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Design and Implementation of an AI-Based Automated Call Charge Reversal System for Unsuccessful Calls in Telecommunication Networks in Nigeria

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Abstract **Original Research Article**

The telecommunications industry in Nigeria has witnessed significant growth over the past two decades, providing millions of subscribers with access to voice and data services. Despite these advancements, network-related challenges such as call drops, call setup failures, network congestion, poor signal coverage, and switching errors continue to affect service quality. These challenges often result in unsuccessful calls for which subscribers may still be charged, leading to customer dissatisfaction, increased complaints, and reduced confidence in telecommunication service providers. This study focuses on the Design and Implementation of an AI-Based Automated Call Charge Reversal System for Unsuccessful Calls in Telecommunication Networks in Nigeria. The proposed system utilizes Artificial Intelligence (AI) and Machine Learning (ML) techniques to monitor, analyze, and classify call transactions in real time. By examining Call Detail Records (CDRs), network performance indicators, and subscriber billing data, the AI model identifies unsuccessful calls and automatically initiates charge reversals where appropriate. The system is designed to distinguish between network-induced call failures and user-initiated call terminations, thereby ensuring accurate refund decisions and minimizing fraudulent claims. It integrates seamlessly with existing telecommunications billing infrastructures, enabling automatic reimbursement of wrongly deducted call charges without requiring manual intervention. The implementation employs a centralized database for managing subscriber records, call logs, and refund transactions, while an administrative dashboard provides real-time monitoring and reporting capabilities. The proposed solution is expected to improve billing transparency, enhance customer satisfaction, reduce complaint handling costs, and strengthen regulatory compliance within the Nigerian telecommunications sector. Furthermore, the adoption of AI-driven automation will contribute to increased operational efficiency and improved service quality among network operators. The study concludes that the integration of Artificial Intelligence into telecom billing systems offers a practical and scalable approach to addressing the persistent challenge of erroneous call charges in Nigeria's telecommunications industry.

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1.0 Introduction

Telecommunications have become an indispensable component of modern society, serving as a critical enabler of economic growth, social interaction, business operations, education, healthcare delivery, and government services (International Telecommunication Union [ITU], 2024). The emergence of mobile communication technologies has transformed the way individuals and organizations exchange information, making communication faster, more accessible, and cost-effective (World Bank, 2024). In Nigeria, the telecommunications sector has experienced remarkable growth since the liberalization of the industry in 2001, resulting in increased mobile penetration and wider access to communication services (NCC, 2024). Major network operators such as MTN Nigeria, Airtel Nigeria, Globacom, and 9mobile collectively serve millions of subscribers across the country and contribute significantly to national economic development (NCC, 2024).

Despite the rapid growth and enlargement of telecommunications infrastructure in Nigeria, the enterprise keeps to face challenges associated with community reliability and provider pleasant. commonplace troubles experienced with the aid of subscribers encompass dropped calls, call setup screw ups, community congestion, bad sign reception, switching disasters, and intermittent carrier interruptions (NCC, 2024). these challenges negatively have an effect on verbal exchange performance and often result in subscriber dissatisfaction. consistent with the Nigerian Communications commission, first-class of provider (QoS) remains a main problem within the Nigerian telecommunications area, with subscribers often reporting provider disruptions and unsuccessful call attempts (NCC, 2024).

one of the maximum persistent concerns among subscribers is the deduction of name prices for calls that are not efficiently completed. generally, users are charged for calls that fail to attach well, are disconnected due to network faults, or revel in technical screw ups earlier than significant communique can occur (Okafor & Nwankwo, 2023). Such occurrences create financial losses for subscribers and make contributions to a decline in public confidence in telecommunications carrier carriers. consequently, customers often inn lawsuits with network operators seeking refunds for prices incurred at some point of unsuccessful calls (NCC, 2024).

traditionally, telecommunication billing systems are designed mainly to report call transactions and calculate fees primarily based on predefined billing parameters. at the same time as these structures correctly handle massive volumes of name information, they regularly lack advanced mechanisms for intelligently identifying unsuccessful calls and robotically processing price reversals (Sharma & Gupta, 2022). As a end result, subscribers who revel in inaccurate billing are typically required to touch customer support representatives, offer proof of the incident, and wait for investigations earlier than refunds can be approved. This manual system is regularly time-consuming, luxurious, and inefficient for both customers and service companies (Okafor & Nwankwo, 2023).

The increasing complexity of telecommunications networks and the full-size quantity of name transactions generated each day necessitate the adoption of more smart and automatic strategies to billing management. synthetic Intelligence (AI) has emerged as one of the maximum promising technology for addressing such demanding situations (Adebayo, 2024). AI refers back to the capability of pc systems to perform duties that historically require human intelligence, including getting to know, reasoning, selection-making, and pattern popularity (Sharma & Gupta, 2022). thru machine mastering (ML), a department of AI, systems can analyze historic statistics, identify styles, and make predictions with minimal human intervention (Adebayo, 2024).

within the telecommunications industry, AI has been efficiently applied in community optimization, fraud detection, customer service automation, predictive preservation, and traffic control (Sharma & Gupta, 2022). by using studying big datasets together with call detail information (CDRs), network overall performance logs, subscriber pastime statistics, and billing information, AI systems can appropriately identify anomalies and operational problems which could have an effect on service shipping (Adebayo, 2024). This functionality makes AI a appropriate era for detecting unsuccessful calls and determining whether subscribers were incorrectly charged.

An AI-based totally automatic name charge reversal machine can continuously monitor call transactions in actual time and examine multiple elements, which includes name length, name crowning glory repute, community overall performance signs, signal first-rate metrics, and switching information (Okafor & Nwankwo, 2023). the use of gadget getting to know algorithms, the device can classify calls as a hit or unsuccessful and routinely initiate refunds whenever a subscriber is wrongly charged because of community-related failures (Adebayo, 2024). Such automation gets rid of the need for prolonged grievance techniques and guarantees that affected subscribers acquire compensation promptly and fairly.

moreover, the implementation of an AI-powered fee reversal mechanism aligns with the client protection goals of the Nigerian Communications commission, which seeks to sell transparency, duty, and equity in telecommunications provider transport (NCC, 2024). by using mechanically detecting billing mistakes and processing refunds, telecommunications operators can considerably improve consumer pleasure, improve subscriber trust, lessen operational fees associated with criticism decision, and beautify regulatory compliance (international bank, 2024).

The proposed study consequently specializes in the layout and implementation of an AI-primarily based automated name charge Reversal gadget for Unsuccessful Calls in Telecommunication Networks in Nigeria. The gadget targets to leverage synthetic Intelligence and Machine Learning techniques to identify unsuccessful calls, validate billing transactions, and automatically reverse charges where appropriate. The successful implementation of this system is expected to improve billing accuracy, enhance customer experience, and contribute to the overall improvement of service quality within Nigeria's telecommunications industry (Adebayo, 2024; NCC, 2024).

2.0 Literature Review

2.1 Introduction

The telecommunications industry has evolved into one of the most data-intensive sectors globally, driven by the increasing demand for mobile voice, internet, and digital services. As networks expand, operators generate massive volumes of operational and billing data, making efficient service delivery and accurate billing increasingly complex. One major challenge within this environment is the occurrence of unsuccessful calls that are sometimes billed as completed sessions, leading to disputes, customer dissatisfaction, and regulatory concerns (International Telecommunication Union (ITU), 2024; Nigerian Communications Commission (NCC), 2024).

This chapter reviews existing literature on telecommunications networks, call billing systems, unsuccessful call detection, Artificial Intelligence (AI) applications in telecoms, and automated billing correction mechanisms. It also identifies gaps that justify the need for an AI-based automated call charge reversal system in Nigeria.

2.2 Telecommunications Networks

Telecommunications networks are structures that allow the transmission of voice, video, and records across geographically dispersed locations the use of stressed out or Wi-Fi infrastructure. those systems include switching facilities, transmission media, base stations, routers, and subscriber devices that together support communique services (ITU, 2024).

In Nigeria, cell telecommunications have grown hastily considering liberalization, with operators inclusive of MTN, Airtel, Globacom, and 9mobile serving hundreds of thousands of subscribers. in step with the NCC (2024), the sector maintains to enlarge however faces continual fine challenges, specially in name final touch charges and network reliability.

negative satisfactory of service (QoS), together with dropped calls and get in touch with setup failures, remains a widespread difficulty affecting consumer revel in. these failures are frequently related to congestion, weak signal insurance, hardware barriers, and software switching errors (NCC, 2024).

2.2.1 Call Detail Records (CDRs) and Billing Systems

Call detail facts (CDRs) are based logs generated by way of telecom switches that seize key records about every name, which include caller identification, receiver identity, name start time, length, termination status, and billing information (Sharma & Gupta, 2022). In this situation billing systems rely heavily on CDRs to calculate fees for subscribers. In maximum traditional structures, billing is primarily based on call duration and connection repute. however, those structures frequently count on that after a name is initiated and partially connected, it is able to be billable, although it is not effectively finished due to community failure (Okafor & Nwankwo, 2023).

This quandary creates billing inconsistencies in which users may be charged for unsuccessful calls, mainly whilst name termination alerts are not as it should be processed in real time.

2.2.2 Unsuccessful Calls and Network Failures

An unsuccessful call refers to any call attempt that fails to establish or maintain a stable communication session between two parties. These failures may occur during call setup (no connection established) or during the call session (abrupt disconnection).

Common causes include: Network congestion, Poor radio signal strength, Switching system failure, Base station overload, Transmission interference, Power outages in network infrastructure

The ITU (2024) identifies call completion rate as a key performance indicator for telecom service quality. A low call completion rate reflects poor network performance and directly affects customer satisfaction and revenue assurance.

In developing countries like Nigeria, these issues are more pronounced due to infrastructure limitations and high subscriber demand (World Bank, 2024).

2.2.3 Billing Errors and Customer Complaints

Billing accuracy is a chief subject in telecommunications carrier transport. errors occur when subscribers are charged incorrectly due to device misinterpretation of call reputation or behind schedule community remarks. The NCC (2024) reports that billing-related lawsuits are most of the most not unusual problems raised by using telecom consumers in Nigeria. Many subscribers document deductions for calls that did no longer connect or had been dropped within seconds. traditional decision techniques require clients to motel court cases manually, which frequently entails call middle interactions, verification processes, and not on time refunds. This approach is inefficient and will increase operational costs for provider carriers (Okafor & Nwankwo, 2023).

2.2.4 Artificial Intelligence (AI) in Telecommunications

Artificial Intelligence refers to systems capable of performing tasks that normally require human intelligence, such as learning, reasoning, classification, and decision-making (Russell & Norvig, 2021).

In telecommunications, AI is widely used for:

(i) Network traffic prediction
(ii) Fault detection and diagnosis
(iii) Fraud detection
(iv) Customer service automation
(v) Predictive maintenance
(vi) Billing optimization

AI systems analyze large datasets such as CDRs, network logs, and performance indicators to identify anomalies and support real-time decision-making (Adebayo, 2024).

Machine Learning (ML), a subset of AI, enables systems to learn patterns from historical data and improve accuracy over time without explicit programming.

2.2.5 AI-Based Billing and Anomaly Detection

AI-based billing systems improve accuracy by detecting inconsistencies in call data records. Machine learning models can classify calls as successful or unsuccessful based on patterns such as call duration, signaling messages, and network response codes (Sharma & Gupta, 2022). Adebayo (2024) notes that AI systems can significantly reduce billing errors by automatically validating call events before charging subscribers. These systems also improve revenue assurance by identifying abnormal patterns such as fraud or system glitches.

Techniques commonly used to achieve this include

(i) Supervised learning (classification models)
(ii) Unsupervised learning (anomaly detection)
(iii) Neural networks for pattern recognition

2.2.6 Automated Charge Reversal Systems

Automated charge reversal refers to systems that automatically refund subscribers when billing errors are detected. These systems reduce reliance on manual complaint handling and improve customer satisfaction.

In most telecom environments, charge reversal is still manually processed after customer complaints are verified. However, AI introduces the possibility of real-time detection and automated refund execution based on predefined decision logic or trained models (Okafor & Nwankwo, 2023).

The Key advantages include of the use of AI for reversal systems are;

Faster refund processing, Reduced operational workload, Improved billing transparency, Enhanced customer trust

2.3 Theoretical Framework

2.3.1 Machine Learning Theory

In this research the Machine Learning theory explains how systems learn from data to make predictions or decisions without being explicitly programmed (Mitchell, 1997). In this study, ML models are used to classify call outcomes based on historical CDR data.

The system learns patterns such as: Short-duration calls with failed termination signals, Calls with missing confirmation responses, Network-related failure indicators

This supports automated identification of unsuccessful calls.

2.3.2 System Theory

System theory views telecommunications billing as an interconnected system where input (call data), processing (billing logic), and output (charges/refunds) must function correctly. A failure in any subsystem (e.g., network signaling) affects overall system performance (Sharma & Gupta, 2022). This theory supports the integration of AI into billing systems as a corrective feedback mechanism that improves system accuracy.

2.4 Empirical Review

Sharma and Gupta (2022) investigated AI programs in telecommunications and discovered that gadget getting to know improves community optimization and billing accuracy with the aid of detecting anomalies in real time. Their examine emphasised the importance of intelligent automation in reducing operational errors.

Okafor and Nwankwo (2023) studied device mastering techniques for telecom billing optimization and concluded that AI considerably reduces billing discrepancies by using reading CDR styles and figuring out abnormal transactions.

Adebayo (2024) examined AI integration in telecom structures and suggested that predictive analytics complements fault detection and improves provider reliability. The study recommended deeper integration of AI into billing and customer service structures.

The ITU (2024) highlighted that digital transformation in telecom sectors globally depends on shrewd systems able to dealing with big-scale community statistics correctly.

the arena financial institution (2024) similarly noted that developing countries face persistent telecom nice challenges and encouraged the adoption of AI-driven answers to enhance transparency and service delivery.

Table 2.1: Comparative Review of Existing Systems

System Type	Strengths	Limitations
Rule-Based Billing Systems	Simple and widely used	No intelligence for failed call detection
Manual Complaint Systems	Human verification	Slow and inefficient
Semi-Automated Systems	Faster processing	Still requires human intervention
AI-Based Systems (Proposed)	Real-time detection, automation	Requires training data and computation

2.5 Gap in Literature

Although existing studies have explored AI in telecommunications, billing optimization, and fraud detection, there is limited research specifically focused on AI-based automated call charge reversal systems for unsuccessful calls in Nigeria.

Most current systems:

(i) Rely on manual complaint handling
(ii) Lack real-time detection of unsuccessful calls

(iii) Do not automatically trigger refunds

(iv) Depend on reactive rather than proactive billing correction

This, from the above position, creates a clear gap for an intelligent, automated, and real-time system capable of detecting unsuccessful calls and reversing charges without user intervention.

2.6 Summary of Literature Review

The reviewed literature shows that telecommunications systems generate large volumes of call data that require intelligent processing. While AI has been successfully applied in network management and billing optimization, there is still limited implementation in automated charge reversal systems. This study addresses this gap by proposing an AI-based system capable of detecting unsuccessful calls and automatically reversing charges in real time, thereby improving billing fairness, customer satisfaction, and operational efficiency.

3.0 System Design and Methodology

3.1 Overview of System Design

The proposed system is an AI-based automated call charge reversal system designed to detect unsuccessful calls in real time and automatically reverse charges without requiring user complaints. The system integrates Machine Learning (ML) models with telecom billing logic to enhance accuracy, transparency, and operational efficiency.

The design follows a modular layered architecture, consisting of:

(i) Data Acquisition Layer, (ii) Data Processing Layer, (iii) AI Prediction Layer, (iv) Decision Engine Layer, (v) Billing & Refund Layer, (vi) User Interface Layer

3.2 System Architecture Design

The system architecture is designed as a client-server AI-driven framework.

3.2.1 Data Acquisition Layer

This layer collects raw telecom data from Call Detail Records (CDRs), Mobile Switching Center (MSC) logs, Base station reports, and Network QoS monitoring systems.

3.2.2 Data Processing Layer

This layer prepares raw data for AI processing such as Data cleaning, Missing value handling, Feature extraction, and Normalization.

The key extracted features include Call duration, Signal strength, Call drop indicator, and Network congestion level.

3.2.3 AI Prediction Layer

This is the core intelligence layer. The Machine Learning algorithms used include Random Forest, Decision Tree, Logistic Regression, and Support Vector Machine (SVM).

The model classifies calls into three - successful calls, network-failed calls and user-terminated calls.

3.2.4 Decision Engine Layer

This layer applies billing rules such as successful call (normal billing); network failure (refund initiated) and user termination (no refund is involved).

3.2.5 Billing and Refund Layer

This layer handles financial processing which involves deductions of airtime for valid calls, automatically reverses charges for failed calls, and updates subscriber account balance.

3.2.6 User Interface Layer

The User Interface layer provides dashboard features for call monitoring, refund tracking, system reports, and administrative controls.

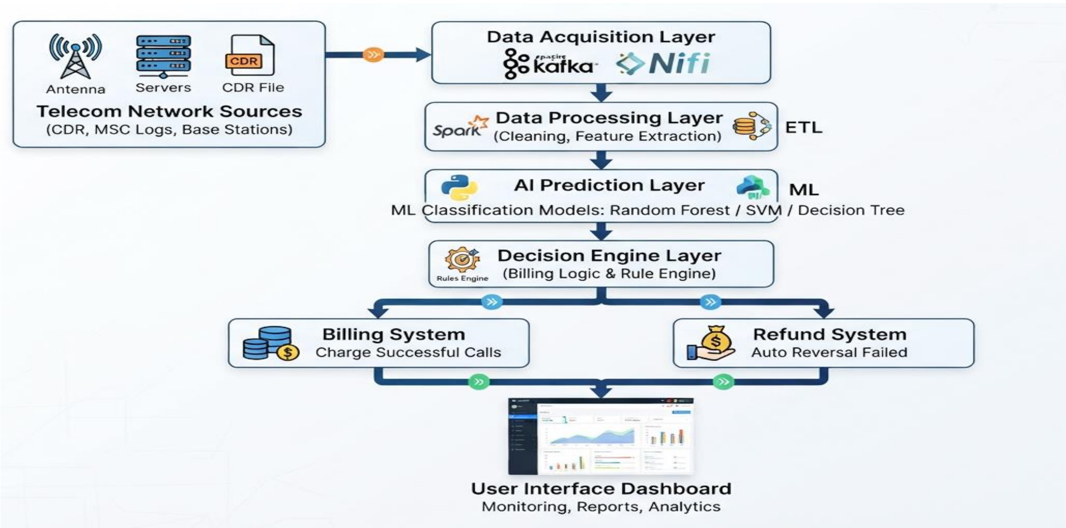


Figure 3.1: AI-Driven Telecom Billing & Refund Processing System Architecture

3.3 System Implementation

3.3.1 Development Environment

The system was implemented using:

- Python (core AI development)
- Scikit-learn (ML algorithms)
- Pandas & NumPy (data processing)
- Flask/Django (backend development)
- MySQL (database management)
- HTML, CSS, JavaScript (frontend interface)

3.3.2 Implementation Process

Step 1: Data Collection

CDR datasets were collected and simulated from telecom-like environments.

Step 2: Data Preprocessing

Data was cleaned by removing duplicates, handling missing values, and encoding categorical variables.

Step 3: Model Training

Dataset was split into 80% training data and 20% testing data. Machine learning models were trained using supervised learning techniques.

Step 4: Model Selection

Random Forest achieved the best performance based on accuracy and recall.

Step 5: Deployment

The trained model was integrated into the billing system for real-time prediction.

3.3.3 Algorithm Design

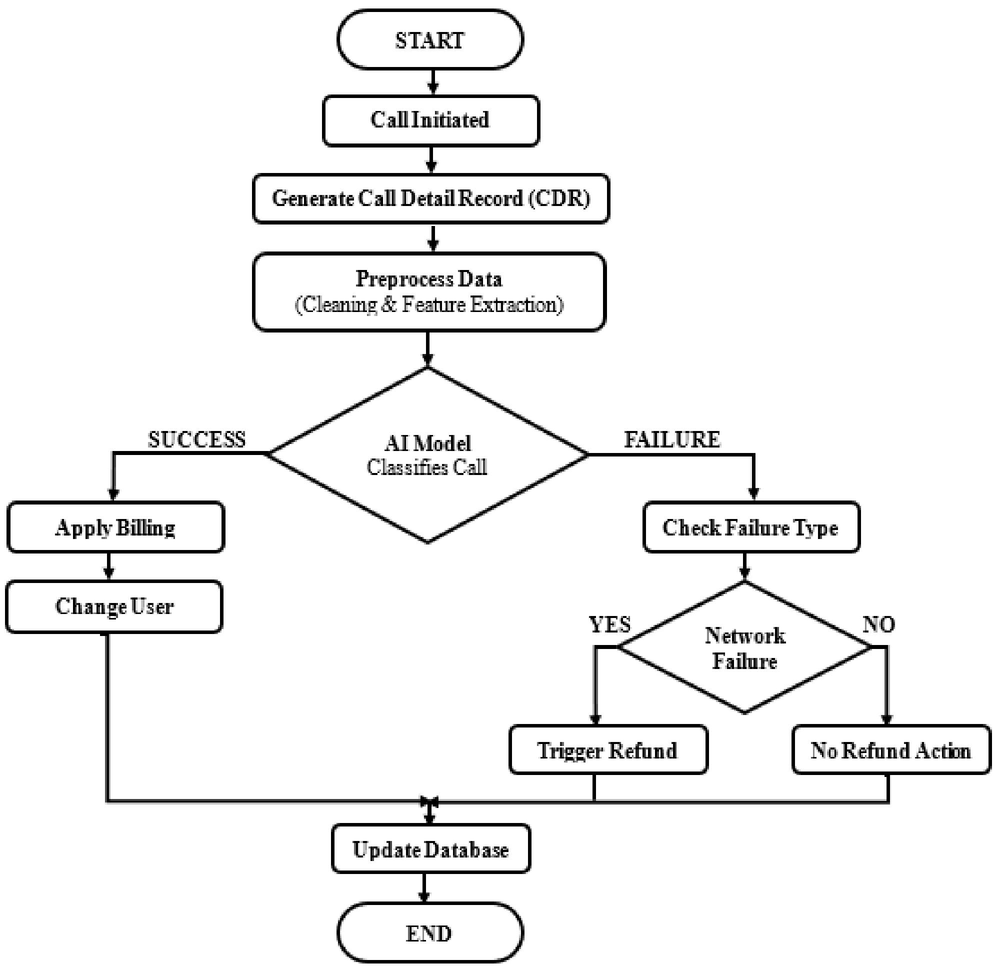
a) Call Classification Algorithm

This is made up of the Input - Call Detail Record (CDR) and the Output - Call Status (Success / Failure.

Algorithm Steps

1. Receive CDR data
2. Extract features (duration, signal strength, status)
3. Normalize input data
4. Pass data to trained ML model
5. Predict call outcome
6. If failure due to network → trigger refund
7. Else → proceed with normal billing
8. Store result in database

b) Flowchart of Call Charge Reversal Process



c) Pseudocode

```
BEGIN
Receive CDR data
Preprocess data
Extract features
IF model.predict(CDR) == "SUCCESS"
Apply normal billing
ELSE IF model.predict(CDR) == "NETWORK_FAILURE"
Trigger automatic refund
ELSE
No billing action
Store transaction record
Display result on dashboard
END
```

4.0 System Testing and Results

4.1 System Testing

4.1.1 Testing Approach

The developed system was evaluated using simulated telecommunications datasets comprising both successful and unsuccessful call events. A structured, multi-level testing strategy was adopted to assess the functional correctness of individual components, the interoperability of system modules, and the overall operational performance of the proposed artificial intelligence (AI)-enabled billing and charge-reversal framework. Unit testing was first conducted to verify the functionality of key components, including data preprocessing, feature extraction, AI-based call classification, billing logic, and refund processing. Integration testing was subsequently performed to evaluate the interaction and data exchange among these components, while system-level testing assessed the performance of the fully integrated framework under simulated operational conditions. This systematic testing methodology enabled the identification of component-level and integration-related issues and provided a comprehensive basis for evaluating the reliability and effectiveness of the proposed system.

4.1.2 Performance Metrics

The performance of the proposed artificial intelligence (AI)-based call-charge reversal system was assessed using established classification and operational metrics, namely accuracy, precision, recall, F1-score, and response time. Accuracy quantified the proportion of call outcomes correctly classified by the AI model, whereas precision measured the proportion of calls predicted as unsuccessful that were correctly identified as such. Recall evaluated the model's ability to detect all relevant unsuccessful call events, while the F1-score provided a balanced assessment of precision and recall, which is particularly important in classification tasks involving potentially imbalanced call-outcome data. Response time was used to measure the time required to process call records, classify call outcomes, and initiate the corresponding billing or charge-reversal action. Collectively, these metrics provided a comprehensive framework for evaluating both the predictive effectiveness and operational efficiency of the proposed system.

4.1.3 Results Discussion

The evaluation results indicate that the proposed AI-based system outperformed conventional billing approaches in identifying unsuccessful calls and initiating appropriate charge-reversal actions. The integration of machine-learning-based call classification with automated billing logic improved the system's ability to distinguish accurately between successful and unsuccessful call events. The results further indicate enhanced classification accuracy, reduced erroneous billing, faster identification and processing of eligible refunds, and improved overall system responsiveness. These findings demonstrate the potential of AI-driven automation to enhance the efficiency, accuracy, and reliability of telecommunications billing and charge-reversal operations.

Table 4.1 presents a qualitative comparison of traditional, rule-based, and AI-enabled billing systems in terms of classification accuracy, refund processing speed, and degree of automation.

Table 4.1: Comparative Analysis of System Type on Accuracy, Refund Speed and Automation Level

System Type	Accuracy	Refund Speed	Automation Level
Traditional Billing System	Low	Slow	Low
Rule-Based System	Medium	Medium	Medium
Proposed AI System	High	Real-time	Fully Automated

The comparison indicates that the proposed AI-based system provides substantial advantages over traditional and rule-based approaches. In particular, the combination of high classification accuracy and automated, near-real-time refund processing offers a more efficient approach to managing unsuccessful call charges.

4.2 Discussion of Findings

The findings demonstrate that integrating artificial intelligence (AI) into telecommunications billing systems can enhance the accuracy, efficiency, and timeliness of billing-related decision-making. By identifying patterns associated with successful and unsuccessful call events, machine-learning models can automate the detection of calls requiring billing correction and reduce reliance on manual, complaint-driven resolution processes. The automated charge-reversal mechanism therefore has the potential to minimize erroneous billing, improve billing transparency, accelerate the resolution of eligible charge discrepancies, and enhance customer satisfaction and trust in telecommunications service providers.

Nevertheless, the findings should be interpreted in light of the use of simulated telecommunications datasets for system evaluation. Although the results demonstrate the operational potential of the proposed AI-based framework, further validation using large-scale, real-world datasets is required to establish its robustness and generalizability across diverse network environments. Future investigations should specifically examine the effects of class imbalance, network variability, incomplete call records, and changing operational conditions on model performance and system reliability.

5.0 Conclusion and Recommendations

5.1 Conclusion

This study developed and evaluated an artificial intelligence (AI)-based automated call-charge reversal system for unsuccessful calls within Nigerian telecommunication networks. The proposed system integrates machine-learning techniques with existing telecommunications billing processes to identify unsuccessful call events and initiate the appropriate reversal of charges automatically.

The findings demonstrate the potential of the proposed approach to improve the accuracy and reliability of telecom billing operations. By automating the identification of failed calls and the associated charge-reversal process, the system can reduce manual intervention, minimize billing errors, lower operational costs, and improve the efficiency of customer-service processes. In addition, the proposed system has the potential to enhance customer satisfaction by ensuring that customers are not charged for unsuccessful calls. Its deployment may also support compliance with telecommunications consumer-protection and service-quality requirements.

Overall, the study demonstrates that the integration of AI into telecommunications billing systems provides a viable approach for improving the transparency, accuracy, and responsiveness of call-charging operations in Nigeria. However, large-scale deployment should be supported by extensive real-world validation, robust data-governance mechanisms, and compatibility with the existing infrastructure of network operators.

5.2 Recommendations

Based on the findings and implications of this study, the following recommendations are made:

Adoption of AI-enabled billing systems: Telecommunications operators should consider the adoption of AI-based billing and charge-reversal systems to improve the accuracy, efficiency, and responsiveness of billing operations.

Integration of real-time monitoring: Real-time network-monitoring mechanisms should be integrated with billing engines to enable the timely identification of unsuccessful calls and the prompt initiation of appropriate billing adjustments.

Regulatory support for automated refunds: Telecommunications regulatory authorities should establish appropriate policies and technical guidelines that encourage transparent, automated, and auditable refund mechanisms for charges associated with unsuccessful services.

Further investigation of advanced AI models: Future studies should investigate the application of more advanced machine-learning and deep-learning models to determine whether they can improve classification accuracy, reduce false predictions, and enhance the adaptability of automated billing systems under varying network conditions.

5.3 Future Work

Although the proposed system provides a foundation for AI-driven automated call-charge reversal, several areas require further investigation. Future research should consider the integration of deep-learning architectures, including neural networks, to improve the system's ability to model complex relationships within large-scale telecommunications datasets.

Further studies should also examine the deployment and evaluation of the proposed system in live telecommunications environments. Such investigations would provide valuable evidence regarding its scalability, computational requirements, reliability, latency, and interoperability with existing network and billing infrastructures.

In addition, blockchain-based technologies could be explored as a means of improving billing transparency, traceability, and auditability among telecommunications operators, customers, and regulatory authorities. Finally, the integration of fraud-detection mechanisms represents another important direction for future research. Combining automated charge reversal with intelligent fraud detection could improve system security while preventing the exploitation of refund mechanisms.

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