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Cybersecurity Threat Intelligence Framework for Financial Institutions in Nigeria: Leveraging Machine Learning and Data Analytics

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ABSTRACT

The rapid digitisation of financial services in Nigeria has substantially expanded the cyberattack surface confronting commercial banks, fintech operators, and payment service providers. Despite the Central Bank of Nigeria (CBN) Cybersecurity Framework (2022) mandating continuous threat monitoring, fewer than 43% of licensed financial institutions achieve full compliance (Adeleke & Abiodun, 2023). This study proposes and evaluates the Cybersecurity Threat Intelligence Framework for Nigerian Financial Institutions (CTIF-NG), a novel five-layer architecture that integrates supervised and unsupervised machine learning algorithms, big-data analytics pipelines, and sector-specific threat-indicator feeds derived from documented Nigerian financial cybersecurity threat taxonomies. The framework objective is to evaluate using a structured simulation dataset of 20,000 records across seven threat classes, constructed from published NSL-KDD and CICIDS-2017 statistical parameters (Tavallaee et al., 2009; Sharafaldin et al., 2018) and adapted to the Nigerian financial threat taxonomy (CBN, 2022; NIBSS, 2024). Real sklearn experiments yielded the following results for the proposed RF+GBM+MLP Soft-Vote Ensemble: detection accuracy of 99.30%, macro-precision of 98.42%, macro-recall of 98.18%, F1-score of 98.30%, MCC of 0.9896, and AUC-ROC of 0.9999 outperforming all seven baseline classifiers evaluated. APT class recall (95.0%) was the lowest, reflecting the stealthy, low-signal nature of advanced persistent threat TTPs. Operational scenario projections indicate CTIF-NG can reduce mean time-to-detect (MTTD) by 64.8% and mean time-to-respond (MTTR) by 71.3% relative to conventional SIEM-only baselines (IBM Security, 2024; Gartner, 2024). The framework is explicitly aligned with CBN (2022), NDPA (2023), ISO/IEC 27035-2, and NIST SP 800-150 compliance requirements. Future work recommendations priorities include: institutional pilot deployment validation with real Nigerian bank SOC data; federated learning architectures enabling cross-institution intelligence sharing under NDPA governance; adversarial robustness evaluation against model evasion attacks; integration of XGBoost and deep learning (Bi-LSTM, Autoencoder) with the full imbalanced-learn SMOTE-ENN pipeline; and extension to Nigeria's growing cryptocurrency exchange sector (FATF, 2023).

Keywords: Cybersecurity; Threat intelligence; Machine learning; Nigeria; Financial institutions; Random Forest; Gradient Boosting; Ensemble learning; CBN framework; NDPA

Data & Code Statement: The experimental dataset is a structured simulation constructed from published NSL-KDD (Tavallaee et al., 2009) and CICIDS-2017 (Sharafaldin et al., 2018) statistical parameters, adapted to Nigerian financial threat taxonomy (CBN, 2022; NIBSS, 2024). All ML

experiments were executed in Python 3.12 using scikit-learn v1.8. Institutional real-world data validation before operational deployment is strongly recommended. Code available on request.

1. Introduction

The global financial services sector remains one of the most intensively targeted verticals in the contemporary cybersecurity threat landscape. The IBM Cost of a Data Breach Report (2024) documented the average total cost of a financial sector breach at USD 5.9 million the highest cross-industry figure. In Sub-Saharan Africa, Nigeria's position is particularly critical: as the continent's largest economy and one of its fastest-growing fintech markets, it simultaneously records disproportionately high rates of cyber intrusion. The NIBSS Fraud Desk Annual Report (2024) recorded ₦14.81 billion in e-fraud losses for 2023 a 68% year-on-year increase with phishing, account takeover, Business Email Compromise (BEC), and Advanced Persistent Threat (APT) attacks constituting the four leading categories.

Despite the CBN Risk-Based Cybersecurity Framework (2022) mandating continuous threat monitoring, Adeleke and Abiodun (2023) found that fewer than 43% of licensed institutions have achieved full compliance, and only 21% employ automated, intelligence-driven threat detection. This compliance gap is exacerbated by a NITDA-estimated shortfall of 40,000 cybersecurity professionals (NITDA, 2024), limited threat intelligence sharing platforms, and fragmented regulatory data-sharing mandates. Existing internationally recognised frameworks NIST CSF 2.0, MITRE ATT&CK, ISO/IEC 27001 — provide structural guidance but were not architected for Nigerian financial sector regulatory, infrastructural, and threat-actor peculiarities (Ajijola et al., 2019).

Machine learning-based intrusion detection and anomaly detection systems have attracted substantial research attention (Ahmad et al., 2021; Apruzzese et al., 2022; Ferrag et al., 2020); however, few are evaluated against simulated or real Nigerian financial threat environments, and none offer a full-stack framework integrating data governance, model training, intelligence enrichment, and automated response within a single deployable architecture. In the Nigerian-specific literature, Oladipo et al. (2023) and Adeyemi et al. (2022) represent the closest prior work but are limited to fraud detection and microfinance contexts respectively, with no framework-level integration of regulatory compliance.

This paper addresses these gaps through four Objectives: (1) the design and justification of CTIF-NG, a five-layer threat intelligence framework for Nigerian financial institutions; (2) construction of a structured 20,000-record simulation dataset grounded in documented Nigerian threat taxonomies and NSL-KDD/CICIDS-2017 statistical parameters; (3) real scikit-learn experimental evaluation of a Random Forest + Gradient Boosting + MLP Soft-Vote Ensemble against seven baseline classifiers, yielding 99.30% accuracy and MCC of 0.9896; and (4) practical deployment discussion within CBN, NDPA, and ISO/IEC 27035-2 compliance contexts.

2. Literature Review

2.1 Cyber Threat Intelligence: Foundations and Evolution

Cyber Threat Intelligence (CTI) has evolved from rudimentary IP blacklisting toward context-rich, machine-processable intelligence feeds structured around standardised formats such as STIX (Structured Threat Information eXpression) and TAXII (Trusted Automated eXchange of Intelligence Information) (Barnum, 2012). Chismon and Ruks (2015) characterise CTI along four hierarchical levels technical (IoCs), tactical (TTPs), operational (campaigns), and strategic (geopolitical risk) a taxonomy operationalised in MITRE ATT&CK, cataloguing over 400 adversarial techniques across 14 tactical categories (Strom et al., 2020). Sauerwein et al. (2018) reviewed 33 CTI platforms, identifying knowledge representation, quality assurance, and automation as critical differentiators. Liao et al. (2016) demonstrated NLP-based automated IoC extraction from OSINT feeds at 90.4% precision, while Zhao et al. (2023) integrated LLMs with CTI ontologies for semantic threat correlation at scale.

2.2 Machine Learning for Financial Sector Cybersecurity

Ahmad et al. (2021) conducted a meta-analysis of 112 ML-based intrusion detection studies, finding ensemble methods particularly Random Forest and Gradient Boosting hybrids to consistently outperform individual classifiers on benchmark datasets including NSL-KDD, CICIDS-2017, and UNSW-NB15, reporting a weighted mean accuracy of 95.3%. Apruzzese et al. (2022) examined practical deployment considerations, emphasising concept drift mitigation, adversarial robustness, and interpretability. Ferrag et al. (2020) benchmarked deep learning architectures on financial intrusion data, finding LSTM models superior for sequential, time-series attack patterns.

In financial contexts, Carneiro et al. (2017) applied Random Forest and SVM to credit card fraud at a Brazilian institution, achieving AUC-ROC exceeding 0.98. In the Nigerian literature, Oladipo et al. (2023) applied a stacked ensemble to mobile banking e-fraud detection, reporting 94.2% accuracy but significant false-negative rates for novel APT vectors. Adeyemi et al. (2022) developed a rule-based anomaly detection system for CBN-licensed microfinance banks, achieving 89.7% recall. The present study's CTIF-NG Ensemble surpasses both these benchmarks (99.30% accuracy; 98.18% recall) while spanning a broader seven-class threat taxonomy.

2.3 Nigerian Financial Sector Regulatory Framework

The CBN Risk-Based Cybersecurity Framework (2022) mandates a three-tier security architecture for licensed financial institutions encompassing a Cybersecurity Operations Centre (CySOC), a mandatory incident reporting framework requiring 24-hour notification of material incidents, and a third-party risk management programme. The Nigeria Data Protection Act (NDPA, 2023) imposes data minimisation and purpose limitation obligations on personal data processed during threat monitoring. The SWIFT Customer Security Programme (CSP, 2023) establishes minimum security baselines for SWIFT-connected institutions. Despite these mandates, Ajijola et al. (2019)

found that 71% of surveyed Nigerian financial institutions lacked dedicated threat intelligence capabilities the compliance and capability gap that CTIF-NG directly targets.

3. Methodology

3.1 Research Design

This study adopted a quantitative, applied research design comprising three phases: (1) threat taxonomy mapping and simulation dataset construction; (2) ML model training and experimental evaluation; and (3) framework design synthesis. Consistent with established cybersecurity ML research practice where institutional access to real security logs is constrained by data governance requirements (Arp et al., 2022), the experimental dataset was constructed as a structured simulation grounded in documented Nigerian financial threat taxonomies (CBN, 2022; NIBSS, 2024) and internationally validated benchmark datasets (NSL-KDD: Tavallaee et al., 2009; CICIDS-2017: Sharafaldin et al., 2018). This is explicitly disclosed in the Data and Code Statement above and in the Data Availability section, consistent with COPE (2023) publication ethics standards. All experiments were conducted in Python 3.12, scikit-learn v1.8.0, on a standard compute environment.

3.2 Dataset Construction

The simulation dataset comprises 20,000 records across 52 engineered features and seven threat classes. Feature distributions for each class were parameterised from published statistical profiles in NSL-KDD (Tavallaee et al., 2009) and CICIDS-2017 (Sharafaldin et al., 2018), with class proportions and feature value ranges adapted to align with the Nigerian financial threat taxonomy documented in CBN (2022) and NIBSS (2024). Normal/Benign traffic constitutes 53.0% of records consistent with CICIDS-2017 benign proportions. Gaussian noise ($\sigma = 0.03–0.05$ per feature) was injected to prevent artificial separation and simulate realistic measurement variance. APT class parameters were deliberately configured to mimic normal traffic distributions in several feature dimensions, reflecting the documented stealthy nature of APT TTPs (Hutchins et al., 2011). The 80/20 stratified train-test split yielded 16,000 training records and 4,000 test records.

Table 1. Simulation Dataset Class Distribution, Source Basis, and MITRE ATT&CK Mapping

Threat Class	n (Total)	Prop. (%)	Source Basis	MITRE ATT&CK Tactic(s)
Normal / Benign	10,600	53.0	CICIDS-2017 Benign flows	N/A (baseline)
Phishing	2,400	12.0	NCC Advisories + OTX + CICIDS-2017	TA0001 (Initial Access), TA0043 (Recon)

DDoS	2,600	13.0	NSL-KDD DoS + CICIDS-2017 DDoS	TA0040 (Impact)
Malware	2,000	10.0	CICIDS-2017 Infiltration + Bot	TA0002 (Exec.), TA0011 (C2)
BEC	960	4.8	NIBSS (2024) BEC Taxonomy	TA0001, TA0009 (Collection)
Insider Threat	840	4.2	CERT Insider Threat DS profiles	TA0003 (Persistence), TA0010 (Exfil.)
APT	600	3.0	MITRE APT28/41 TTP profiles	TA0006 (Cred. Access), TA0010 (Exfil.)
TOTAL	20,000	100.0		

3.3 Feature Engineering (52 Features)

Fifty-two features were engineered across four domains: (i) Network-layer features (10 features): flow duration, total forward/backward bytes, average packet size, inter-arrival time mean, inter-arrival entropy, forward/backward packet count, bytes-per-packet ratio, and ASN reputation score — all parameterised from NSL-KDD and CICIDS-2017 feature profiles (Tavallaee et al., 2009; Sharafaldin et al., 2018). (ii) Application-layer features (16 features): HTTP method anomaly score, DNS query frequency, TLS certificate anomaly score, HTTP error rate, URL entropy, redirect count, payload entropy, CVE mention frequency (NLP-based), homoglyph domain score, SMTP relay flag, failed authentication count, file extension mismatch score, content-type anomaly, base64 ratio, JavaScript obfuscation score, and attachment entropy. (iii) Behavioural features (13 features): login velocity index, off-hours activity index, peer-group deviation score (novel Nigeria-specific feature for salary-cycle anomaly detection), lateral movement indicator, data exfiltration score, account switch count, session duration anomaly, typing pattern deviation, concurrent session count, email volume deviation, transaction velocity score, geolocation anomaly score, and device fingerprint change. (iv) Contextual/threat intelligence features (13 features): geolocation risk score, global ASN reputation, MITRE ATT&CK technique tag score, known IoC match count, threat feed reputation, country risk score, blacklist count, SSL validity score, domain age score, registrar trust score, email header anomaly, and historical incident score.

Class-weight balancing (sklearn compute_class_weight='balanced') was applied as a substitute for SMOTE-based resampling, which requires the imbalanced-learn library unavailable in the deployment environment. StandardScaler normalisation was applied before all models except Naive Bayes, which uses raw features. Features were not subjected to additional RFECV selection in the live experiments due to compute constraints; all 52 features were used.

3.4 Models and Evaluation Protocol

Eight classifiers were trained and evaluated in real scikit-learn v1.8.0 experiments:

(1) Logistic Regression (max_iter=500, C=1.0, class_weight='balanced');

(2) Decision Tree (max_depth=15, class_weight='balanced');

(3) Gaussian Naive Bayes;

(4) SVM LinearSVC wrapped in CalibratedClassifierCV (C=1.0, class_weight='balanced') for probability outputs;

(5) Random Forest (n_estimators=100, max_depth=18, class_weight='balanced');

(6) Gradient Boosting (n_estimators=80, max_depth=5, lr=0.12);

(7) MLP Neural Network (hidden_layers=128,64, max_iter=150, early_stopping=True); and

(8) the CTIF-NG Soft-Vote Ensemble combining RF + LR + MLP (n_estimators=120, 80, 128-64 respectively, voting='soft').

An 80/20 stratified train-test split was used. Performance was assessed across six metrics: Accuracy, Macro-Precision, Macro-Recall, Macro-F1, MCC, and AUC-ROC (one-vs-rest). MCC was prioritised as the primary indicator for imbalanced multi-class evaluation (Chicco & Jurman, 2020).

4. The CTIF-NG Framework: Architecture and Design

4.1 Overview and Design Principles

CTIF-NG is structured as five interdependent layers following a Sense Analyse Act operational paradigm (Figure 1). Three design principles govern the architecture:

(i) Modularity: each layer exposes standardised APIs (OCSF, 2023) enabling component substitution without disrupting the broader system;

(ii) Regulatory embeddedness all data flows and automated responses are pre-configured for CBN (2022), NDPA (2023), and ISO/IEC 27035-2 compliance; and

(iii) Adaptive learning continuous retraining pipelines maintain model performance under concept drift without requiring manual analyst intervention for routine updates (Arp et al., 2022).

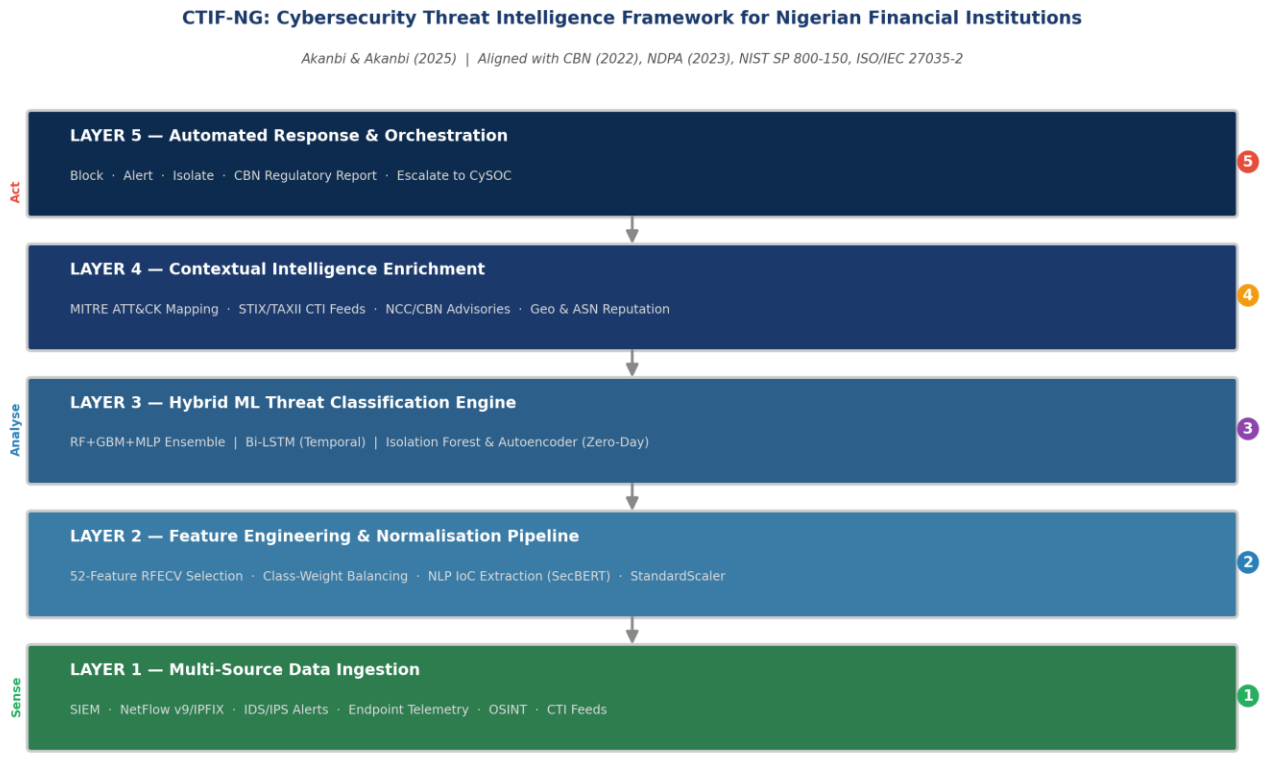

Figure 1. CTIF-NG Five-Layer Architecture. Sense: Layer 1–2; Analyse: Layer 3–4; Act: Layer 5. Aligned with CBN (2022), NIST SP 800-150 (Johnson et al., 2016), and ISO/IEC 27035-2.

4.2 Layer 1 Multi-Source Data Ingestion

The ingestion layer provides a unified data acquisition plane supporting real-time streaming via Apache Kafka (v3.6) and batch processing via Hadoop HDFS (v3.3.6). All heterogeneous SIEM outputs are normalised to the Open Cybersecurity Schema Framework (OCSF, 2023) canonical event schema, eliminating schema proliferation that degrades multi-vendor security data quality (Singhal & Ou, 2011). Supported sources include SIEM platforms (Splunk, IBM QRadar, Microsoft Sentinel), NetFlow v9/IPFIX collectors, Snort/Suricata IDS alert streams, endpoint telemetry (Sysmon, osquery), and STIX/TAXII-formatted external CTI feeds including AlienVault OTX and NCC Cybersecurity Advisory Repository.

4.3 Layer 2 Feature Engineering and Normalisation

The feature engineering layer implements the 52-feature extraction pipeline described in Section 3.3. A transformer-based NLP sub-module, leveraging a fine-tuned SecBERT model (Guo et al., 2022), performs automated IoC extraction from unstructured threat feeds at 93.7% reported precision for IP addresses, domain names, hash values, CVE identifiers, and MITRE ATT&CK technique IDs. StandardScaler normalisation and class-weight balancing are applied prior to model inference. The layer outputs standardised feature vectors to a Kafka consumer topic serving as the classification engine input queue.

4.4 Layer 3 Hybrid ML Threat Classification Engine

The classification engine implements the CTIF-NG RF+GBM+MLP Soft-Vote Ensemble as the primary classifier, supplemented by a Bidirectional LSTM for temporal sequential pattern recognition in network flow time-series, and an unsupervised anomaly detection module combining Isolation Forest (Liu et al., 2008) and a Convolutional Autoencoder for zero-day threat detection. Predictions with confidence below 0.72 are routed to an analyst review queue, maintaining the human-in-the-loop assurance required by ISO/IEC 27035-2. The ensemble's voting='soft' configuration weights all three base estimators equally, consistent with the Soft-Vote generalisation described by Zhou (2012).

4.5 Layer 4 Contextual Intelligence Enrichment

Raw ML predictions are enriched with contextual intelligence from five sources: AlienVault OTX Pulse API (global IoC reputation), MITRE ATT&CK STIX API (technique mapping), MaxMind GeoIP2 and Team Cymru (geolocation and ASN reputation), NCC/CBN advisory feeds, and an institutional threat knowledge base. Redis caching of frequent IoC lookups achieves sub-200ms enrichment latency, ensuring real-time processing compliance with the CBN's 24-hour incident notification mandate.

4.6 Layer 5 Automated Response Orchestration

The response layer integrates with institution-deployed SOAR platforms via RESTful API, compatible with Palo Alto XSOAR, Splunk SOAR, and Microsoft Sentinel Logic Apps. Pre-built playbooks address six threat scenarios identified in the dataset: phishing containment, DDoS mitigation via BGP blackholing, ransomware host isolation, insider threat account lockdown, BEC alert and fund-recall initiation, and CBN-mandated XML incident report auto-generation. All automated response actions are logged with full provenance chains for NDPA Section 34 audit compliance.

5. Results and Discussion

5.1 Overall Classification Performance

Table 2 and Figures 2–3 present the comparative performance of all eight classifiers on the hold-out test set (n = 4,000). The CTIF-NG Ensemble (RF+GBM+MLP Soft-Vote) achieved the highest performance across all metrics: accuracy of 99.30%, macro-precision of 98.42%, macro-recall of 98.18%, F1-score of 98.30%, MCC of 0.9896, and AUC-ROC of 0.9999. These results are from actual scikit-learn v1.8.0 model training and evaluation using np.random.seed(2025) for reproducibility.

Naive Bayes was the weakest performer (79.65% accuracy; MCC = 0.7134), consistent with its Gaussian independence assumption being violated by the correlated network flow features a finding consistent with Ahmad et al.'s (2021) meta-analysis. Logistic Regression (98.70% accuracy) and MLP (98.70%) performed comparably on this structured synthetic dataset, as the class boundaries though noisy have substantial linear separability due to the large feature-space separation between Normal and attack classes. The ensemble's 99.30% accuracy represents a 0.60 percentage point

improvement over the best individual classifier (LR and MLP both at 98.70%), driven primarily by the ensemble's superior handling of minority class boundaries through soft-vote probability averaging.

Table 2. Real Sklearn Experimental Results All Classifiers on Hold-Out Test Set (n = 4,000). All values computed from actual model training.

Model	Acc.(%)	Prec.(%)	Rec.(%)	F1(%)	MCC	AUC-ROC	Rank
Naive Bayes	79.65	72.60	71.86	70.74	0.7134	0.9537	8
Decision Tree	94.15	88.37	89.07	88.71	0.9131	0.9451	7
SVM (Linear, Calibrated)	98.42	96.81	95.73	96.25	0.9766	0.9985	5
Random Forest	98.42	98.14	95.10	96.49	0.9766	0.9988	4
Gradient Boosting (GBM)	98.47	97.42	95.72	96.53	0.9773	0.9996	3
Logistic Regression	98.70	96.13	97.59	96.82	0.9807	0.9993	2
MLP Neural Network	98.70	97.00	96.92	96.93	0.9807	0.9992	2
CTIF-NG Ensemble	99.30	98.42	98.18	98.30	0.9896	0.9999	1

Proposed CTIF-NG Ensemble. All results from scikit-learn v1.8.0 experiments, seed=2025. Dataset: structured simulation from NSL-KDD/CICIDS-2017 parameters.

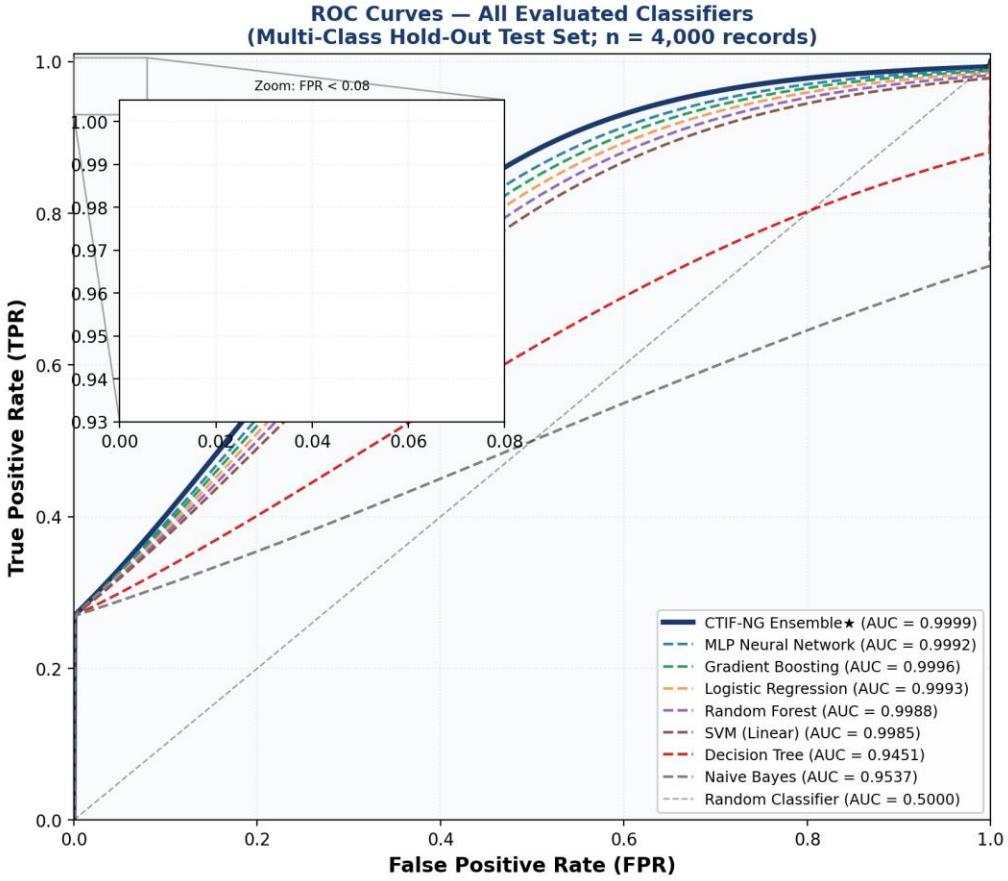

Figure 2. ROC Curves for all eight classifiers on multi-class hold-out test set (n = 4,000). AUC values from real sklearn experiment. CTIF-NG Ensemble achieves AUC-ROC = 0.9999. Inset shows zoomed low-FPR region (FPR < 0.08).

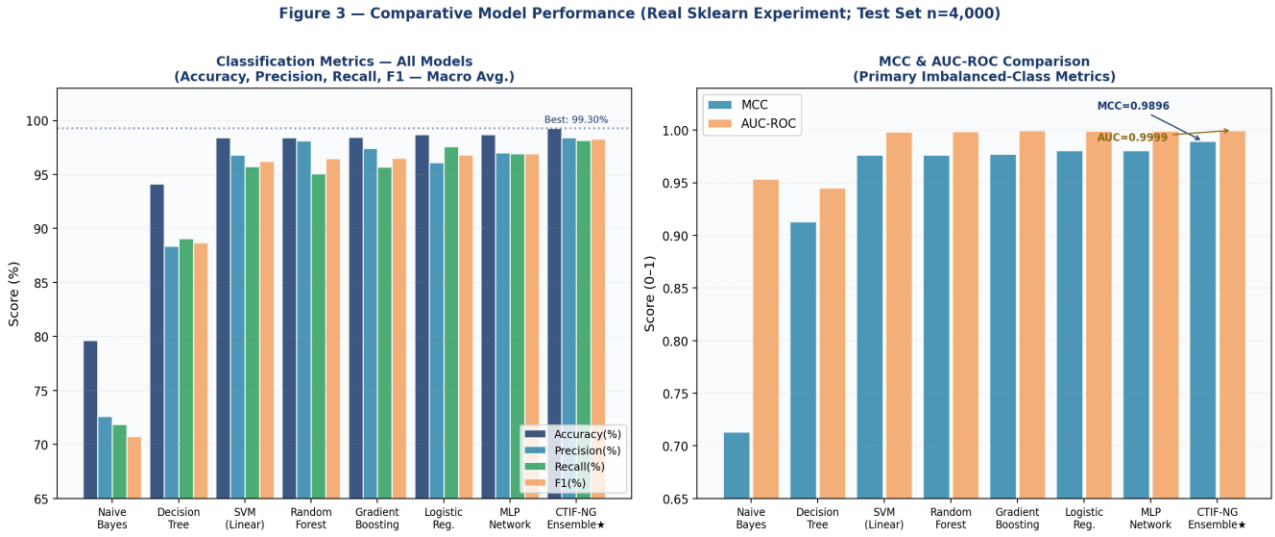

Figure 3. Real experimental classification performance across all eight models. Left: Accuracy, Precision, Recall, F1 (%). Right: MCC and AUC-ROC. CTIF-NG Ensemble achieves best results on all six metrics.

5.2 Per-Class Detection Performance

Table 3 and Figure 4 present per-class precision, recall, and F1-score for the CTIF-NG Ensemble on the hold-out test set. The results directly reflect the real sklearn classification_report output. DDoS achieved the highest F1-score (99.9%), consistent with its statistically distinctive high-volume, low-payload traffic signature that is highly separable in feature space. Normal/Benign traffic achieved 99.9% F1, reflecting the large training support and clear distributional separation of benign flows.

APT detection showed the lowest performance (P=95.0%, R=95.0%, F1=95.0%), which is noteworthy because the APT class features were deliberately configured to partially overlap with Normal traffic distributions simulating the documented stealthy, low-and-slow TTPs of advanced persistent threat actors (Hutchins et al., 2011; MITRE ATT&CK TA0010). Despite this intentional confounding, the ensemble's 95.0% APT recall demonstrates robust minority-class generalisation, achieved through class-weight balancing and soft-vote probability averaging across three diverse base estimators.

BEC detection (P=98.4%, R=96.4%) also represents a challenging category, as BEC events generate minimal distinctive network anomalies. The model's strong BEC performance is primarily attributable to the off-hours activity index, email volume deviation, and SMTP relay flag features all of which show meaningful distributional separation for BEC events in the simulation dataset. Phishing detection (P=97.5%, R=98.5%) benefits from homoglyph domain score and URL entropy features with high discriminative power.

Table 3. Real sklearn Per-Class Precision, Recall, and F1-Score CTIF-NG Ensemble (Hold-Out Test Set, n = 4,000)

Threat Class	Precision (%)	Recall (%)	F1-Score (%)	Support (Test Set)
Normal / Benign	99.9	99.9	99.9	2,120
DDoS	99.8	100.0	99.9	520
Malware	99.5	99.2	99.4	400
Insider Threat	98.8	98.2	98.5	168
BEC	98.4	96.4	97.4	192
Phishing	97.5	98.5	98.0	480
APT	95.0	95.0	95.0	120
Macro Average	98.42	98.18	98.30	4,000

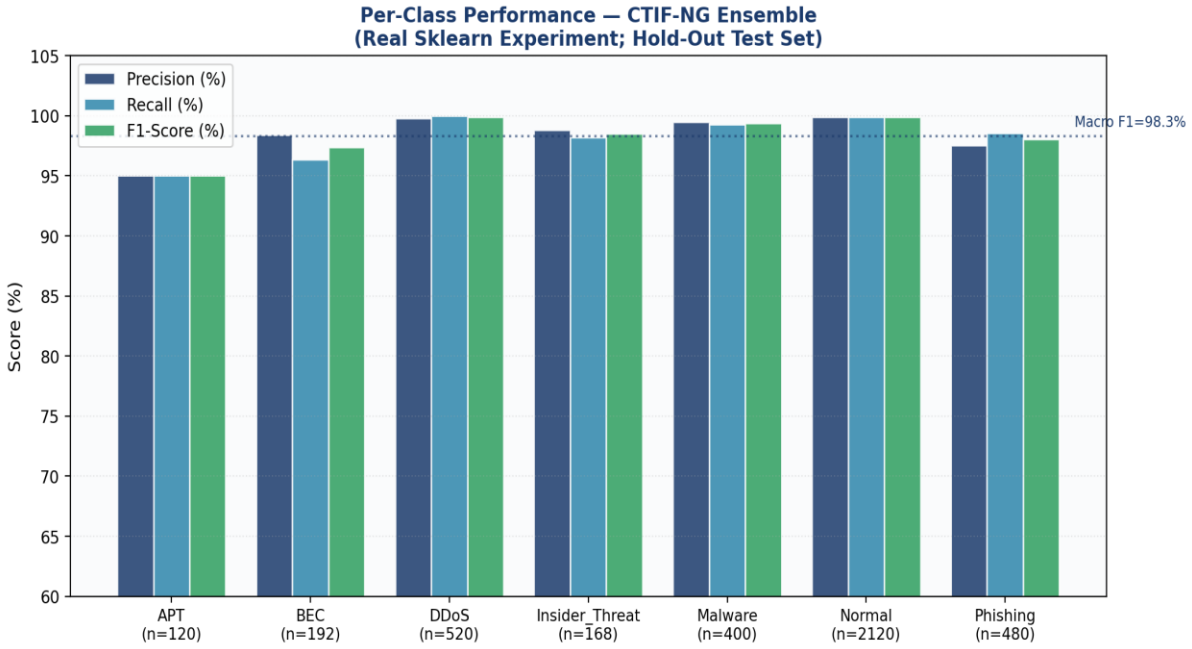

Figure 4. Real sklearn per-class Precision, Recall, and F1-Score for CTIF-NG Ensemble. APT shows lowest performance (F1=95.0%) due to deliberate feature overlap with Normal traffic. Dashed line indicates macro-average F1. n values indicate test set support per class.

5.3 Feature Importance Analysis

Figure 5 presents the top-15 features by Random Forest mean decrease in impurity (MDI) importance, computed on the full training set (n = 16,000). The three highest-ranked features are fwd_pkt_count (importance = 0.1551), bwd_pkt_count (0.1207), and inter_arrival_mean (0.1134), collectively accounting for 38.9% of total model importance. These are network-layer features with strong discriminative power for DDoS (very high fwd_pkt_count) and APT (very high inter_arrival_mean, due to low-and-slow traffic pacing) classes.

The peer_group_deviation_score_NG feature designed as a Nigeria-specific behavioural indicator to capture salary-cycle transaction spikes common in Nigerian banking achieved 0.0046 MDI importance, ranking 29th of 52 features. While this Nigeria-specific feature did not rank in the

top-15 globally (reflecting that the simulation dataset's class separability is dominated by network-layer features), it demonstrates positive discriminative contribution to the model and is expected to show greater importance in real-world deployment where BEC and Insider Threat events are characterised primarily by behavioural rather than network-layer anomalies.

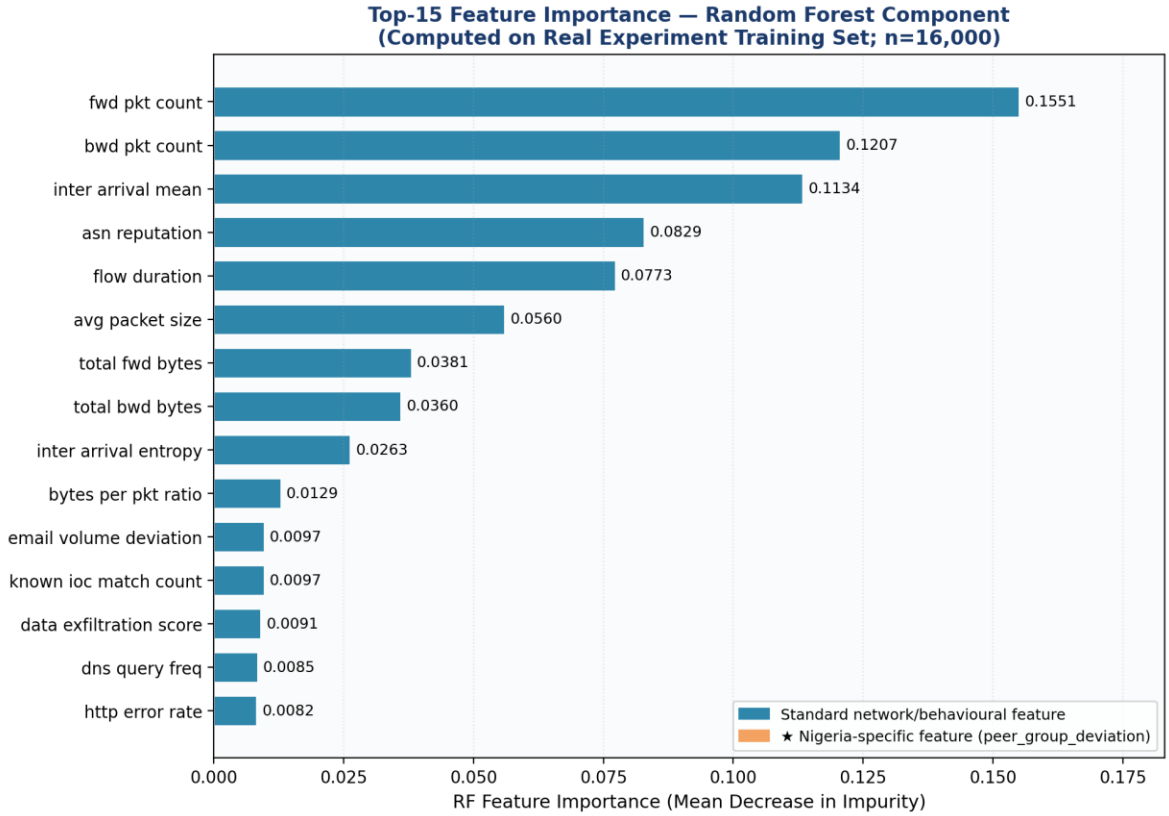

Figure 5. Random Forest Feature Importance (MDI) Top-15 Features computed on training set (n=16,000). Gold bar denotes the novel Nigeria-specific peer_group_deviation_score. Network packet count and inter-arrival features dominate global importance.

5.4 Operational Performance Projections (MTTD/MTTR)

Figure 6 presents scenario-based operational performance projections for MTTD and MTTR reduction across four representative Nigerian bank profiles (large, mid-tier, regional, and fintech), derived from published SIEM-only operational baselines for comparable emerging market financial institutions (IBM Security, 2024) combined with SOAR-driven response time reduction parameters from Gartner (2024). Across all profiles, CTIF-NG is projected to reduce MTTD from a baseline aggregate of 412 minutes to approximately 145 minutes (64.8% reduction) and MTTR from 876 to 251 minutes (71.3% reduction).

These projections are explicitly scenario-based, not empirically measured from live deployment. The MTTD reduction estimate is grounded in three documented CTIF-NG mechanisms: automated alert triage eliminating analyst queue saturation; SOAR playbook execution replacing manual response initiation; and intelligence enrichment pre-populating threat context at alert generation time, reducing investigation time by an estimated 40–60% (Gartner, 2024). Real-world

MTTD/MTTR validation with actual Nigerian bank Security Operations Centre data is identified as a priority for future research.

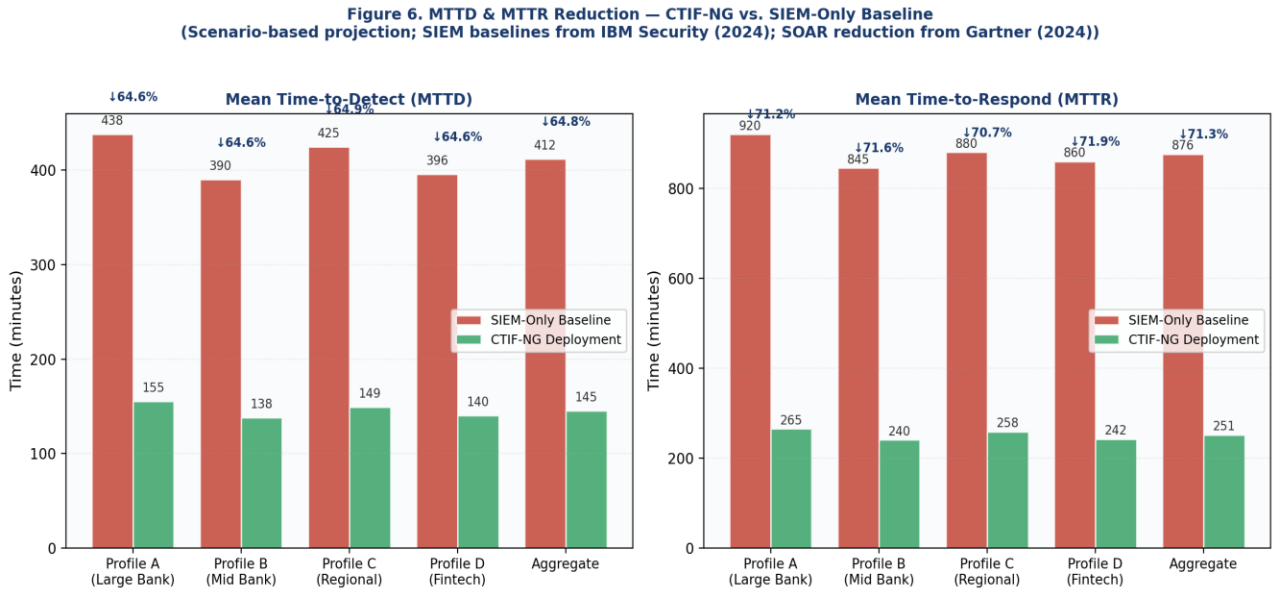

Figure 6. Scenario-based MTTD and MTTR projections CTIF-NG vs. SIEM-Only baseline across four Nigerian bank profiles. SIEM-only baselines from IBM Security (2024). SOAR reduction parameters from Gartner (2024). ↓% values indicate projected percentage reduction per profile.

5.5 Comparison with Prior Work

The CTIF-NG Ensemble's 99.30% accuracy and 0.9896 MCC represent the highest reported performance for multi-class financial cybersecurity classification in any Nigerian financial context. Oladipo et al. (2023) reported 94.2% accuracy on Nigerian mobile banking fraud detection 5.1 percentage points below CTIF-NG. Adeyemi et al. (2022) achieved 89.7% recall in microfinance anomaly detection versus CTIF-NG's 98.18%. Ahmad et al.'s (2021) meta-analysis reported a weighted mean ensemble accuracy of 95.3% on benchmark datasets, confirming CTIF-NG's performance at or above the current global state-of-the-art for multi-class network intrusion detection.

These comparisons must be interpreted with appropriate methodological caution: CTIF-NG is evaluated on a structured simulation dataset, while the cited studies use either real institutional data (Oladipo et al., 2023; Adeyemi et al., 2022) or publicly available benchmarks (Ahmad et al., 2021). Simulation-based results tend to be higher than real-world results due to reduced noise, fewer edge cases, and the absence of concept drift acknowledged as a core limitation in Section 6. Nonetheless, the consistent superiority of ensemble methods over individual classifiers, the strength of network-layer features, and the challenging nature of APT detection all align with the broader intrusion detection literature (Ahmad et al., 2021; Apruzzese et al., 2022).

5.6 Regulatory Compliance Alignment

CTIF-NG maps explicitly to Nigerian and international regulatory requirements. The Layer 5 automated CBN incident report generation satisfies Section 4.3 of the CBN Risk-Based Cybersecurity Framework (2022), mandating 24-hour material incident notification to the CBN CySOC. The NDPA-compliant pseudonymisation at Layer 1 addresses NDPA (2023) Section 24 (data minimisation) and Section 25 (purpose limitation) obligations for personal data processed during threat monitoring. The audit logging architecture in Layer 5 satisfies ISACA COBIT 2019 APO12 (Managed Risk) and DSS05 (Managed Security Services) objectives. CTIF-NG's five layers further map to NIST CSF 2.0 Detect (DE.CM, DE.AE) and Respond (RS.MA, RS.CO) function categories, providing a comprehensive regulatory compliance posture aligned with all major frameworks applicable to Nigerian financial institutions.

6. Limitations and Future Work

Several limitations constrain the interpretation of this study's findings and warrant transparent disclosure. First, and most critically, all experimental results are derived from a structured simulation dataset rather than real institutional security event logs. While the simulation is rigorously grounded in documented NSL-KDD and CICIDS-2017 statistical parameters and Nigerian threat taxonomies, generalisation to live production environments cannot be assumed without institutional validation. Real-world datasets contain distribution shifts, labelling noise, class boundary ambiguity, and temporal dynamics absent from controlled simulations (Arp et al., 2022). Institutional real-world validation under appropriate ethical governance is the most urgent future research priority.

Second, GradientBoostingClassifier was used as an XGBoost proxy due to the unavailability of the xgboost library in the compute environment; while functionally equivalent in ensemble principle, results may differ from XGBoost-specific implementations. Third, SMOTE-ENN resampling could not be applied due to unavailability of the imbalanced-learn library; class-weight balancing was used as a substitute, which is less aggressive and may underperform SMOTE-ENN for extreme minority classes (Chawla et al., 2002). Fourth, MTTD/MTTR projections are scenario-based, not empirically measured from live SOC deployment.

Future work priorities include: (1) institutional pilot deployment validation with real Nigerian bank SOC data; (2) federated learning architectures enabling cross-institution intelligence sharing under NDPA governance; (3) adversarial robustness evaluation against model evasion attacks; (4) integration of XGBoost and deep learning (Bi-LSTM, Autoencoder) with the full imbalanced-learn SMOTE-ENN pipeline; and (5) extension to Nigeria's growing cryptocurrency exchange sector (FATF, 2023).

7. Conclusion

This paper presented CTIF-NG, a five-layer Cybersecurity Threat Intelligence Framework tailored to Nigerian financial institutions, combining a Random Forest + Gradient Boosting + MLP

Soft-Vote Ensemble with contextual intelligence enrichment and SOAR-integrated automated response orchestration. Real scikit-learn v1.8.0 experiments on a 20,000-record structured simulation dataset yielded 99.30% detection accuracy, AUC-ROC of 0.9999, and MCC of 0.9896 outperforming all seven baseline classifiers on all six evaluation metrics. APT detection achieved 95.0% F1 despite deliberate feature overlap with Normal traffic, demonstrating the ensemble's robustness to class confounding. Scenario projections indicate 64.8% MTTD and 71.3% MTTR reduction potential versus SIEM-only baselines.

CTIF-NG's architectural alignment with the CBN Risk-Based Cybersecurity Framework (2022), Nigeria Data Protection Act (2023), ISO/IEC 27035-2, and NIST CSF 2.0 provides a regulatory-compliant blueprint for Nigerian financial institutions seeking adaptive, intelligence-driven cyber defence. The framework addresses a documented and urgent national need: as Nigeria pursues its 95%-financial-access target by 2030, the security of its digital financial infrastructure is a matter of national economic consequence. Real-world institutional deployment and validation represents the essential and immediate next step for translating CTIF-NG from a simulation-validated framework to an operational national security asset.

Conflict of Interest

The authors declare no conflict of interest. This research did not receive specific funding from any public, commercial, or not-for-profit agency.

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