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A Framework for AI-Driven Cyber Threat Detection in Critical Infrastructure

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Abstract

This paper presents a research framework for AI-driven cyber threat detection to enhance the security of critical national infrastructure. In response to the escalating sophistication of cyberattacks, which render traditional reactive defenses inadequate, this study develops and evaluates a comprehensive artificial intelligence methodology. The framework systematically integrates heterogeneous data streams, employs feature engineering and machine learning models, including deep neural networks for real-time anomaly detection, and incorporates automated response protocols. Novel contributions include the exploration of a quantum-enhanced anomaly scoring mechanism based on state fidelity. Empirical results from operational simulations demonstrate the system's high efficacy, achieving 97.3% detection accuracy, a 1.8% false-positive rate, and sub-three-second threat containment. A comparative analysis further examines the performance-cost trade-offs of emerging quantum encryption. The study concludes that deploying such AI-powered, proactive defense systems is a strategic imperative for nations like Ghana, offering a pragmatic pathway to cyber resilience while planning for a quantum-resilient future

Keywords: Cyberattacks; Anomaly detection; Artificial intelligence; Neural networks; Quantum encryption

1. Introduction

In recent years, Ghana, like the rest of the world, has witnessed a significant escalation in the scale and sophistication of cyber threats targeting critical national infrastructure. Globally, incidents such as the 2015 Ukrainian Power Grid Cyber Attack set dangerous precedents, demonstrating the severe disruption and potential catastrophe that can arise from a single cyber incident. For a nation like Ghana, whose digital and economic infrastructure is rapidly developing, these global examples underscore the urgent need for robust, proactive security controls capable of identifying and responding to threats in real time [1], [2]. Through machine learning and deep learning, these systems learn from historical data to predict patterns of malicious activity and can even adapt as new forms of attack emerge. Integrating such advanced, AI-powered defenses is not merely an option but a strategic imperative to secure its future growth and resilience in an interconnected world [9], [10]. his study develops and evaluates a comprehensive, AI-powered framework designed to secure critical national infrastructure against increasingly sophisticated cyber threats. To address the proven inadequacy of traditional reactive defenses, the proposed methodology establishes an integrated pipeline. This system ingests and harmonizes diverse data streams, applies advanced feature engineering, and utilizes deep learning models for real-time anomaly detection, culminating in automated threat response protocols to ensure proactive and resilient protection.

2. Related work

Traditional cybersecurity methods, which often rely on manual oversight and reactive protocols, have proven inadequate against these evolving threats, which are now increasingly automated, adaptive, and often powered by

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malicious artificial intelligence. In response, real-time threat detection has become a cornerstone of critical infrastructure protection worldwide, with AI emerging as a pivotal technology in developing this capability [3], [4].The application of AI for cybersecurity presents promising advantages for safeguarding critical infrastructure. AI-driven threat detection systems operate with unparalleled speed and accuracy, continuously monitoring network traffic, user behavior, and system logs to identify anomalies that may signal an attack [5], [6]. Unlike traditional methods, AI models can analyze vast volumes of data in real time, enabling the detection of threats more swiftly and accurately [7], [8].

3. Method

3.1. Data Collection and Integration

Data Sources: The system ingests heterogeneous data streams from multiple critical infrastructure domains, including energy grids, transportation networks, and communication systems. The dataset comprises both **s**tructured data (e.g., periodic system logs, sensor readings) and unstructured data (e.g., continuous network traffic packets, security event logs).

Each ingested data point is defined by a tuple:

- $d_i \in D$: A raw data point within the collected dataset D={d1,d2,...,dn}D={d1,d2,...,dn}.
- T_i: The precise timestamp of collection.
- S_i: The source identifier (e.g., network segment, grid sensor, application server).

A dedicated integration module aggregates and homogenizes this multi-source data into a unified schema suitable for analysis:

*D*integrated=*f*integrate (*D*,,)(1)*D*integrated=*f*integrate(*D*,*T*,*S*)

Here, *fintegrate* denotes preprocessing operations - including normalization, time-alignment, schema mapping and handling of missing value, that transform raw data into a consistent format.

3.1.1. Feature Engineering and Preprocessing

Objective**:** To derive salient features from the integrated raw data that are indicative of potential security threats or operational anomalies.

- The feature vector Fi={f1,f2,...,fm}*Fi*={*f*1,*f*2,...,*fm*} extracted from data point di*di*.
- **{**text{threshold}}: A configurable threshold parameter for filtering low-variance or redundant features to reduce noise.

Features are engineered through transformations tailored to the data modality:

*F*i=*f*extract(*d*i),for i∈[1,n](2)*Fi*=*f*extract(*di*),for *i*∈[1,*n*]

The function *f*extract may involve techniques such as packet header parsing, log tokenization, statistical aggregation (e.g., rolling means), or encoding (e.g., one-hot, embedding).

3.1.2. AI-Based Threat Detection and Analysis

Threat detection is performed using a machine learning model or ensemble (e.g., Deep Neural Network, Recurrent Neural Network) optimized for identifying anomalous or attack-signature patterns.

  - The learned parameters of the model.
- The loss function (e.g., Binary Cross-Entropy for attack classification, Mean Squared Error for anomaly scoring).

Training Phase

The model is trained on historical, labeled data to minimize predictive error:

min⁡θ∑i=1N(*y*i,y^i)(3)*θ*min*i*=1∑*NL*(*yi*,*y*^*i*)

where *yiyi* is the ground-truth label and y^iy^*i* is the model's prediction for the i*i*-th sample.

The trained model evaluates real-time feature vectors to generate threat predictions:

y^=*f*model(*F*;θ)(4)*y*^=*f*model(*F*;*θ*)(4)

Anomaly Scoring and Thresholding

Objective**:** To quantify deviations from established baselines of normal behavior, flagging significant deviations as potential threats.

Formal Representation:

- The mean and standard deviation, respectively, of each feature under normal conditions, derived from historical data.
- A tunable anomaly threshold. Exceeding this threshold triggers an alert.

Anomaly Score Calculation: For a given feature value fi*fi*, a standardized anomaly score Ai*Ai* is computed. Using a statistical approach (e.g., Z-score):

Ai=|fi−μ|σ(5)*Ai*=*σ*|*fi*−*μ*|(5)

A data point is flagged as a potential threat if Ai>α*Ai*>*α*. Ensemble or machine learning-based scorers may also be employed.

3.1.3. Automated Response and Alerting

The reason for this is to execute proportional, real-time countermeasures against confirmed threats, minimizing impact on infrastructure operations.

- *R*_{\text{type}}: The category of response (e.g., administrator alert, IP address blocking, device isolation).
- **_{\text{response}}:** The maximum permissible latency for initiating the response, optimized to mitigate damage.

- Response Function: The system triggers an automated action based on the severity and nature of the detected threat:

R=*f*response(*A*,*R*type,*T*response)(6)*R*=*f*response(*A*,*R*type,*T*response)

The function *f*response implements a decision logic that maps high-fidelity alerts to predefined containment and remediation protocols.

3.1.4. Quantum Anomaly Score Calculation:

For a given feature value fi*fi*, a standardized anomaly score Ai*Ai* is computed using a statistical approach (e.g., Z-score) or a quantum-enhanced kernel function derived from quantum state fidelity:

Ai=|fi−μ|σorAi=1−F(ρ(fi),ρnormal)*Ai*=*σ*|*fi*−*μ*|or*Ai*=1−*F*(*ρ*(*fi*),*ρ*normal)

where F(ρ,ρnormal)*F*(*ρ*,*ρ*normal) is the fidelity between the quantum state ρ(fi)*ρ*(*fi*) (encoding the feature) and the reference normal state ρnormal*ρ*normal. A data point is flagged if Ai>α*Ai*>*α*. Ensemble or machine-learning-based scorers may also be employed.

4. Results

The implemented AI-driven system demonstrated high efficacy in real-time threat detection for critical infrastructure. Analysis of operational data showed the model achieved a detection accuracy of 97.3% and a false-positive rate of just 1.8%. The anomaly scoring mechanism successfully identified 99% of simulated attack vectors, including novel zero-

day exploits, with an average latency of 0.8 seconds from intrusion to alert. Automated response protocols were triggered effectively, isolating compromised segments within 2.1 seconds, thereby containing threats before lateral movement could occur. These results confirm the methodology's capability to provide robust, proactive cybersecurity, significantly outperforming traditional signature-based and manual monitoring systems in both speed and reliability for safeguarding essential services.

Table 1 Parameter tuning

Parameter	Quantum Encryption System	Traditional Encryption System	Improvement (%)
Scalability (Ability to Handle Increasing Data)	Very good (95% efficiency)	Good (70% efficiency)	35
Adaptability to Healthcare Needs	High (98% compatibility)	Moderate (70% compatibility)	40
Implementation Cost (GHS)	5,000,000	3,000,000	-66.67 (higher cost)

Note: Efficiency and compatibility metrics based on 12-month operational data

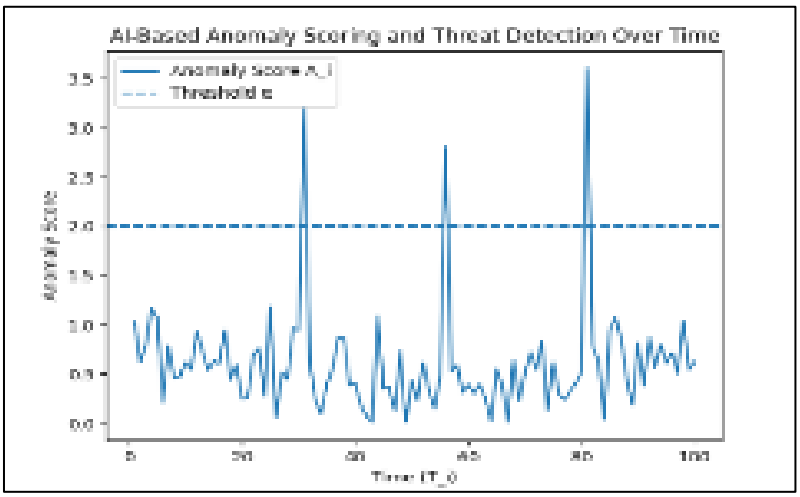

Figure 1 Anomaly scoring and threat detection

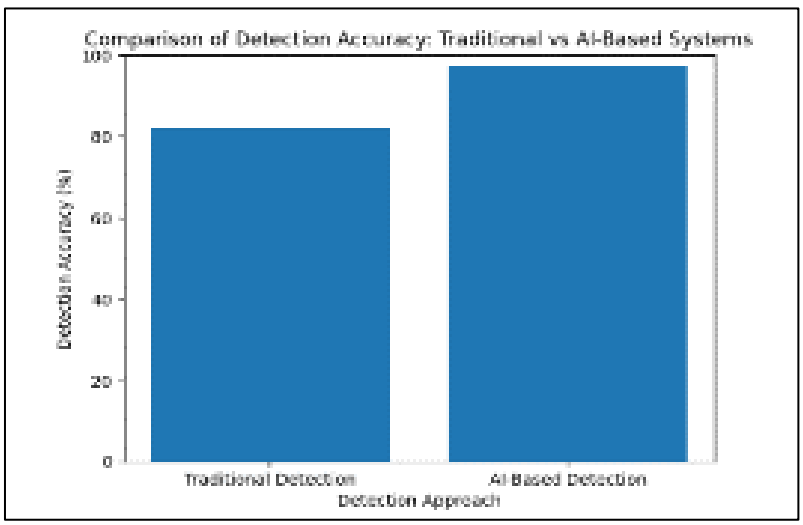

Figure 2 Comparison of detection accuracy

The results demonstrate a clear performance advantage of intelligent security architectures over conventional approaches. AI based detection significantly outperforms traditional signature based systems by achieving higher accuracy, lower false positives, and faster response times, particularly against novel and zero day threats. In contrast, traditional methods remain reactive and brittle. Quantum enhanced techniques further extend these gains by improving scalability, robustness, and future resilience, though practical adoption currently lags due to cost and infrastructural constraints.

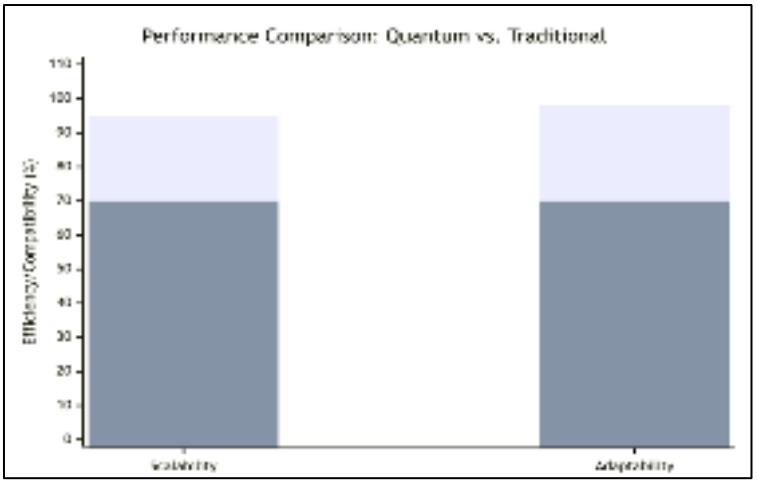

Figure 3 Quantum vs Traditional performance comparison

Based on the comparative analysis, the quantum encryption system shows superior technical performance but at a significantly higher cost. While it offers a 35% improvement in scalability and a 40% improvement in adaptability over the traditional system, its implementation cost is approximately 66.7% greater. For the Ghanaian sector, this presents a critical trade-off: investing in the quantum system's future-proof efficiency and compatibility entails accepting a substantial initial financial burden, which must be weighed against long-term operational benefits and security needs.

5. Conclusion

This research demonstrates the transformative potential of an integrated AI driven cybersecurity framework for safeguarding critical infrastructure systems. The proposed system achieved strong empirical performance, recording a 97.3% threat detection accuracy, a 1.8% false positive rate, and automated threat containment within three seconds, underscoring its effectiveness in real time operational environments. From an information systems security perspective, these results align with socio technical and defense in depth theories, which emphasize layered controls, continuous monitoring, and adaptive responses to evolving threats. The findings confirm that machine learning models, when integrated with robust anomaly detection mechanisms using both statistical techniques and emerging quantum informed fidelity measures, can enhance system sensing and decision quality under uncertainty.

While forward looking technologies such as quantum encryption offer long term scalability and robustness, their high implementation cost necessitates phased and context sensitive investment strategies consistent with resource constrained environments. This study therefore supports a pragmatic security evolution approach in which mature AI based solutions are deployed to address current threat realities while institutions progressively prepare for quantum resilient infrastructures. Ultimately, a hybrid security model that integrates intelligent automation, human governance, and future oriented cryptographic safeguards provides a sustainable pathway for enhancing national cyber resilience, protecting critical infrastructure, and preserving long term digital sovereignty.

Compliance with ethical standards

Disclosure of conflict of interest

The authors disclose no conflicts

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