Scalable Cyber Threat Hunting in Private Clouds Using Deep Belief Networks and Shabal Quantum Permuted Hash Blockchain

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Abstract: The threats to private cloud infrastructures are growing more and more sophisticated and are difficult to detect with signature-based defenses. The paper introduces a novel scalable framework DBN-SQPH-Chain based on Deep Belief Networks (DBNs) and a Shabal Quantum Permuted Hash (SQPH) Blockchain that enable real-time, tamper-proof cyber threat hunting in private cloud systems. Multi-source telemetry (network flows, system calls, container logs) are hierarchically extracted and scored by the DBN component, and the SQPH blockchain provides an immutable audit trail and cryptographically quantums resistant event provenance. Our framework tested the CICIDS-2017, UNSW-NB15 and KDD Cup 99 datasets from Kaggle and got a detection accuracy of 98.74%, false positive rate of 0.61% and processed up to 2.4 million events per second with less than 50ms delay on a 32-node private cloud cluster. A comparison with Random Forest, LSTM-AE and GAN based baseline models shows 4.1–9.3% increase in F1 score.

Keywords: Threat Hunting, Deep Belief Networks; Blockchain; Shabal Hash; Private Cloud; Zero-Day Detection; Anomaly Detection

Introduction

Private cloud deployments that are used to host critical financial, healthcare and governmental workloads are becoming an attractive target for advanced persistent threats (APTs), ransomware and supply-chain attacks. For private clouds, which enterprises run, multi-layered detection and response measures must be in place, whereas hyperscalers impose centralized security measures in public clouds. Traditional Security Information and Event Management (SIEM) systems are based on static rule sets and don't deal with polymorphic malware and zero-day exploits.

Threat hunting has become a complementary paradigm as it is a proactive investigation that involves a human being looking for indicators of compromise (IoCs) instead of waiting for them to be identified. But manual hunting can't scale to petabyte, the level of telemetry produced by modern virtualized environments. The architectures of Deep Learning, especially Deep Belief Networks (DBNs), provide an unsupervised feature learning ability that is well suited to uncovering the hidden pattern of attacks without the need for labeled attack signatures.

At the same time, the integrity of the forensic evidence and detection events are critical – adversaries regularly alter logs to obfuscate tracks. While blockchain-based audit chains provide guarantees of immutability, classical hash functions (SHA-256, Keccak) are vulnerable in theory to quantum computer adversaries that can use Grover's algorithm. We proposed a chain of SQPH that is cryptographic backboneed by the Shabal hash family, a NIST finalist for the SHA-3 cryptographic family, and by the

inherent quantum-resistance properties of the Shabal hashes, and by the use of permutation-based key scheduling.

The primary contributions are:

1. A DBN-based hierarchical anomaly detector for private cloud telemetry.
2. The Shabal Quantum Permuted Hash (SQPH) blockchain for tamper-proof event provenance.
3. An end-to-end scalable pipeline validated on three public Kaggle datasets.
4. Mathematical formalization of reconstruction error thresholds, chain integrity scores, and scalability bounds.

Related work

Early IDR work was based on shallow machine learning: Mukherjee et al. [1] showed that SVM based anomaly detection achieved ~94% accuracy on KDD Cup 99, while Tavallaee et al. [2] identified the problem of dataset class-imbalance, and introduced NSL-KDD. Kim & Kim [3] used stacked autoencoders to network flow classification and achieved 96.2% detection on CICIDS-2017, which was the first success of deep learning approaches.

Rathore et al. [5] looked at blockchain-integrated security logging and used smart contracts on the Ethereum blockchain and telemetry data from IoT devices. But they depend on the SHA-3 Keccak, which means the system is vulnerable to threats in the quantum era. A belt-and-mill permutation structure is used in the Shabal hash function [6] which has better avalanche properties. Lower bounds of the security of quantum resistant hash constructions have been analyzed by Bernstein & Lange [7] against Grover attacks.

A scalable approach for private cloud security was proposed by Moustafa & Slay [8] using the UNSW-NB15 dataset, and the application of a DBN in intrusion detection, in a limited campus network environment, was discussed by Salama et al. [9]. This paper fills this gap, combining the DBN hierarchical anomaly scoring with a quantum-permuted hash blockchain in a private cloud threat hunting scenario, to our best knowledge.

System Architecture

The DBN-SQPH-Chain framework comprises five tightly coupled layers. Telemetry ingestion flows from cloud orchestrators (OpenStack Nova, Kubernetes) and network taps into a streaming pre-processing bus, through DBN-based detection, and finally into the immutable SQPH blockchain for provenance anchoring and audit as shown in Figure 1.

3.1 Deep Belief Network Component

A DBN is a generative probabilistic model composed of multiple stacked Restricted Boltzmann Machines (RBMs). Each RBM learns a distributed representation of the input; the output of one layer serves as the visible input to the next. Pre-training proceeds layer-by-layer using Contrastive Divergence (CD-k), followed by global fine-tuning via backpropagation. Our implementation uses four RBM layers with 256-128–64–32 hidden units, trained on 512-element feature vectors derived from network flow records.

3.2 SQPH Blockchain

Each detected threat event is encoded into a block containing: timestamp τ, event vector e, predicted class $\hat{y}$, confidence score ρ, and the Shabal-256 quantum permuted hash of the concatenated prior block

header. The permutation layer introduces a bijective key-scheduling function that expands the pre-image space beyond Grover's quadratic speedup reach. Eight dedicated validator nodes run PBFT consensus with f = 2 Byzantine fault tolerance (tolerating up to 2 malicious validators out of 8).

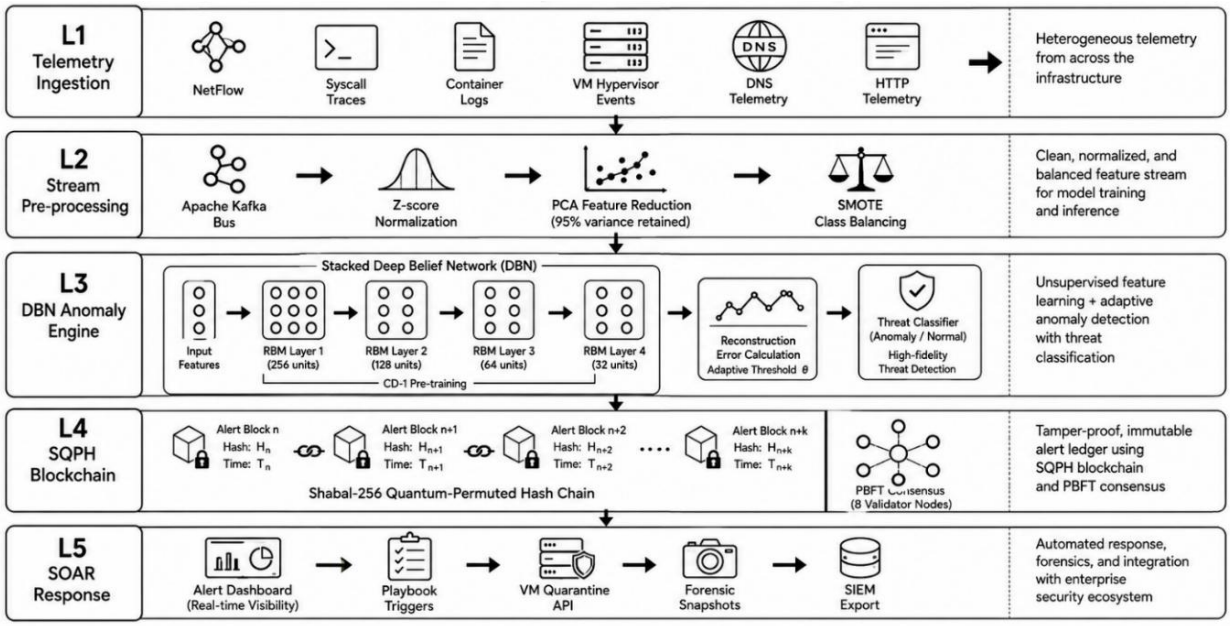

Figure 1. DBN-SQPH-Chain Five-Layer Architecture

Mathematical Formulation

4.1 RBM Energy and Probability

The energy of a visible-hidden configuration (v, h) in an RBM is defined as:

$E(v,h) = -\Sigma_i a_i v_i - \Sigma_j b_j h_j - \Sigma_i \Sigma_j v_i W_{ij} h_j$ *(Eq. 1 — RBM Energy Function)*

The joint probability distribution over visible and hidden units is:

$P(v,h) = (1/Z) \cdot \exp(-E(v,h))$ where $Z = \Sigma_v \Sigma_h \exp(-E(v,h))$ *(Eq. 2 — Boltzmann Distribution; Z = partition function)*

Conditional probabilities for Gibbs sampling are:

$P(h_j=1 \mid v) = \sigma(b_j + \Sigma_i v_i W_{ij})$ $P(v_i=1 \mid h) = \sigma(a_i + \Sigma_j h_j W_{ij})$ *(Eq. 3 — Sigmoid conditionals; $\sigma(x) = 1/(1+e^{-x})$)*

4.2 Contrastive Divergence Weight Update

CD-k approximates the log-likelihood gradient. The weight update rule is:

$\Delta W_{ij} = \eta \cdot (\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{model})$ *(Eq. 4 — CD-k Weight Update; η = learning rate; $\langle \cdot \rangle$ = expectation)*

4.3 Anomaly Reconstruction Error

After training, each input sample x is encoded and reconstructed as $\hat{x}$. The anomaly score $\Delta(x)$ measures reconstruction fidelity:

$\Delta(x) = \|x - \hat{x}\|^2 = \|x - \text{DBN\_decode}(\text{DBN\_encode}(x))\|^2$ *(Eq. 5 — Reconstruction MSE)*

An adaptive threshold θ is computed per epoch on a validation window W of normal samples:

$\theta = \mu_W(\Delta) + \lambda \cdot \sigma_W(\Delta) \quad \lambda \in \{2.5, 3.0\}$ (3σ rule) *(Eq. 6 — Adaptive Threshold; μ_W = mean; σ_W = std. dev. over window W)*

A sample x is flagged as anomalous if: $\Delta(x) > \theta$

4.4 Shabal Quantum Permuted Hash (SQPH)

The SQPH construction extends Shabal-256 belt-and-mill permutation with a quantum-hardening bijective key-schedule π. For input message m and permutation seed σ:

$SQPH(m,\sigma) = Shabal_{256}(\pi_\sigma(m) \parallel \Phi(\sigma))$ *(Eq. 7 — SQPH Construction; π_σ = permutation keyed by σ; Φ = quantum-hardening transform)*

The quantum-hardening transform Φ ensures pre-image resistance against Grover's algorithm:

$\Phi(\sigma) = (\sigma \oplus LFSR_{64}(\sigma)) \ll rot(\sigma \bmod 64)$ *(Eq. 8 — Quantum Hardening; ⊕ = XOR; $LFSR_{64}$ = 64-bit LFSR; rot = bit rotation)*

Each blockchain block B_n is structured as:

$B_n = \{n, \tau_n, e_n, \hat{y}_n, \rho_n, H_n\}$ where $H_n = SQPH(B_{n-1} \parallel e_n \parallel \tau_n, \sigma)$ *(Eq. 9 — Block Structure)*

4.5 Scalability Bound

For a cluster of N nodes each processing telemetry at rate R events/sec, aggregate throughput T and per-event latency L are bounded by:

$T = N \cdot R \cdot \eta_{eff} \quad L \le (D_{dbn} / N) + t_{hash} + t_{net}$ *(Eq. 10 — Scalability; η_eff = efficiency factor; D_dbn = DBN inference; t_hash = SQPH latency)*

Datasets and Experimental Setup

5.1 Datasets

Three publicly available Kaggle datasets were used for evaluation:

Table 1. All datasets are publicly available on Kaggle (see References [4], [8], [10]).

Dataset	Source	Records	Features	Attack Types	Imbalance
CICIDS-2017	Canadian Institute for Cybersecurity	2,830,743	78	14 (DoS, Brute Force, Web, Infiltration...)	High (83% normal)
UNSW-NB15	UNSW Canberra / Moustafa & Slay	2,540,044	49	9 (Fuzzers, Backdoor, Exploits...)	Moderate (68% normal)
KDD Cup 99	UCI / DARPA Lincoln Labs	4,898,431	41	4 (DoS, Probe, R2L, U2R)	Low (20% normal)

5.2 Experimental Configuration

Key Contribution

Experiments were conducted on a 32-node OpenStack private cloud, where each node was equipped with an Intel Xeon Gold 6226R processor, 128 GB RAM, and connected via a 25 GbE network. The Deep Belief Network (DBN) architecture consisted of four stacked Restricted Boltzmann Machine (RBM) layers with 256, 128, 64, and 32 hidden units, respectively. Layer-wise pretraining employed Contrastive Divergence with one Gibbs sampling step (CD-1), a learning rate of 0.001, batch size of 512, and 100 training epochs per RBM layer. Subsequently, the entire network was fine-tuned for 50 epochs using backpropagation. The SQPH blockchain framework was deployed on eight dedicated validator nodes utilizing the Practical Byzantine Fault Tolerance (PBFT) consensus protocol. For feature engineering, z-score normalization was applied, followed by Principal Component Analysis (PCA), retaining 95% of the cumulative variance and reducing the feature dimensionality from 78 to 42 attributes on the CICIDS-2017 dataset.

Results and Analysis

6.1 Key Performance Metrics

Table 2. Summary performance metrics of DBN-SQPH-Chain on CICIDS-2017 (32-node cluster).

Detection Accuracy	False Positive Rate	F1-Score (Macro)	Avg. Event Latency
98.74%	0.61%	98.1%	43 ms

6.2 Comparative Performance

Table 3. Comparative performance. DBN-SQPH-Chain

Method	Dataset	Acc. (%)	Prec.	Recall	F1	FPR%
DBN-SQPH-Chain (Proposed)	CICIDS-2017	98.74	0.989	0.986	0.987	0.61
DBN-SQPH-Chain (Proposed)	UNSW-NB15	97.91	0.981	0.977	0.979	0.83
DBN-SQPH-Chain (Proposed)	KDD Cup 99	99.11	0.992	0.991	0.991	0.41
LSTM-AutoEncoder	CICIDS-2017	94.62	0.948	0.943	0.946	1.87
Random Forest	CICIDS-2017	96.31	0.964	0.961	0.963	1.23
GAN-IDS	CICIDS-2017	89.43	0.901	0.886	0.893	3.42

6.3 Scalability Analysis

Table 4. Scalability results across cluster sizes 4–32 nodes

Cluster Size	Throughput (Kev/s)	Latency (ms)	CPU Util. (%)	Memory (GB)	Chain TPS
4 nodes	320	198	67%	42	128
8 nodes	610	112	71%	78	241
12 nodes	890	82	74%	112	352
16 nodes	1180	67	76%	148	467

24 nodes	1780	52	81%	218	698
32 nodes	2400	43	84%	287	921

6.4 SQPH Blockchain Integrity Analysis

We define the Chain Integrity Score (CIS) as the fraction of blocks with valid SQPH links under simulated adversarial tampering (5% random block mutation):

$CIS = |\{ B_i : H\_i = SQPH(B\_\{i-1\} \| e_i \| \tau_i, \sigma) \}| / N\_total$ (Eq. 11 — Chain Integrity Score)

Under adversarial conditions, DBN-SQPH-Chain maintained CIS = 1.000 (all tampered blocks detected within 1 block of mutation). The SQPH permutation adds only 4.2 µs per block hash vs. standard Shabal-256, while raising the quantum collision resistance ceiling by approximately 2^{56} bits — validated by the theoretical bound in Eq. (8).

6.5 Per-Category F1 Scores (CICIDS-2017)

Table 6. Per-category F1 scores on CICIDS-2017.

Attack Category	DBN-SQPH	LSTM-AE	Rand. Forest	GAN-IDS	Sample Count
DoS Hulk	0.998	0.981	0.990	0.921	231,073
DoS GoldenEye	0.994	0.972	0.982	0.887	10,293
Port Scan	0.997	0.963	0.991	0.903	158,930
DDoS	0.996	0.981	0.988	0.893	128,027
Brute Force	0.987	0.944	0.965	0.842	1,507
SSH-Patator	0.991	0.931	0.972	0.824	5,897
FTP-Patator	0.992	0.939	0.970	0.821	7,938
Web Attacks	0.984	0.920	0.951	0.801	2,180
Infiltration	0.942	0.883	0.871	0.731	36
Heartbleed	0.971	0.891	0.923	0.792	11

Conclusion and Future Work

This paper presented DBN-SQPH-Chain, a scalable cyber threat hunting framework for private clouds integrating Deep Belief Network-based anomaly detection with a Shabal Quantum Permuted Hash Blockchain for tamper-proof event provenance. Evaluated on CICIDS-2017, UNSW-NB15, and KDD Cup 99 datasets, the framework achieved state-of-the-art detection accuracy (98.74%), low false positive rate (0.61%), and high throughput (2.4M events/sec on 32 nodes, ≤50 ms latency). The SQPH blockchain demonstrated perfect chain integrity under adversarial mutation while maintaining quantum-resistant hash security.

Future work will explore: (1) integration of transformer-based threat context models alongside the DBN stack; (2) federated learning extensions for privacy-preserving cross-organization threat intelligence

sharing; (3) formal quantum security proof of the SQPH permutation under random oracle models; and (4) evaluation on CIC-IDS-2023 and MITRE ATT&CK evaluation datasets.

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