AI-Driven Deep Belief Network with Block chain-Quantum Framework for Intrusion Detection in Private Cloud

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Abstract- Internet of Things (IoT) devices grow by leaps and bounds and private cloud infrastructure becomes even more explosive, these two factors have created new sources of cyber risk that require intelligent, automated, and scalable detection systems. Traditional Intrusion Detection Systems (IDSs) have serious limitations in resisting zero-day attacks, polymorphic malware, and distributed Advanced Persistent Threats (APTs) in dynamic cloud-edge environments. This paper introduces a unified AI-Driven Deep Belief Network with Blockchain-Quantum (ADBN-BQ) framework, which combines five complementary ML and DL architectures: CNN-LSTM hybrid, Self-Attention BiLSTM, Random Forest, SVM and XGBoost, along with Deep Belief Networks (DBN) that include Restricted Boltzmann Machine (RBM) layers, Blockchain-immutable audit logs, and quantum-inspired Shabal feature permutation hashing. The pre-processing pipeline integrated SMOTE class balancing, PCA, and MI Feature Selection, reducing dimensionality by 40% and training time by 35%. Experiments on 5 benchmark datasets (NSL-KDD, BoT-IoT, TON_IoT, CICIDS-2018, UNSW-NB15) show that the detection rate is 99.2%, the F1 score is 98.9%, the false positive rate is 0.8%, and the block throughput is 4,200 transactions per second with a 380ms finality time, outperforming 12 state-of-the-art methods. The following physical validation results confirm the viability of real-world edge deployment: 28 ms inference time, 45 MB of memory, and 96.8% accuracy on a Raspberry Pi 4.

Keywords: Deep Belief Network, Blockchain Security, Quantum Hash, Cyber Threat Detection, Private Cloud and Intrusion Detection System

I. Introduction

The main contributions are: A novel architecture called ADBN-BQ that combines multi-layer Deep Belief Networks with Shabal quantum-permuted hash blockchain to detect cyber threats in real-time with a tamper-proof mechanism, in private cloud and IoT environments [1]. Systematic ablation quantifying each preprocessing component, and a multi-model comparative analysis of CNN-LSTM, Self-Attention BiLSTM, XGBoost, Random Forest, and SVM. SMOTE, PCA and Mutual Information-based Feature Selection were integrated into a preprocessing pipeline that reduced dimensionality by 40% and reduced training time by 35% [2]. A quantum-permuted feature hashing (QPH) mechanism that provides 2.3× compression and 97.8% inter-class discriminability [3]. Consensus protocol that is easy to run on an ARM processor, with a blockchain that achieves 4,200 TPS, sub-second finality and Byzantine fault tolerance [4]. ($f = \lfloor (n-1)/3 \rfloor$). Cross-dataset

validation across five benchmarks and physical edge deployment on Raspberry Pi 4 to get the results of 28 ms inference with 96.8% accuracy [5].

II. Experimental Setup

The implementation of the ADBN-BQ framework used the following tools [6,7]: Python 3.9, TensorFlow 2.9, scikit-learn 1.1, XGBoost 1.6, PyTorch 1.12 (blockchain) and C++ (eBPF probes). Server Hardware: Intel Core i7-11800H and NVIDIA RTX 3060. Private cloud testbed: 12 KVM hypervisors (Intel Xeon Gold 6248R, 192 GB RAM, 25 GbE, Ubuntu 20.04 LTS). Nine PBFT validator nodes (3 per availability zone) with Shabal-256/SHA-3-Keccak hashing. Edge hardware: Raspberry Pi 4 (ARM Cortex-A72, 4 GB RAM). All hyperparameters were optimised using a 5-fold cross-validation grid search (Table I).

Table I. ADBN-BQ Hyperparameter Configuration

Parameter	**Value**	**Rationale**
RBM Layer Dimensions	32-128-64-32	5-fold cross-validation; expanding-contracting bottleneck forces discriminative representations
CNN Filter Sizes	32, 64, 128	Grid search; progressive spatial feature extraction depth
LSTM Units	128, 256	Temporal dependency modelling capacity
Learning Rate (η)	0.001	Adam optimiser; cosine annealing schedule during fine-tuning
Dropout Rate	0.3 – 0.5	Prevents co-adaptation of RBM feature detectors on imbalanced data
Batch Size	256	GPU memory constraint (12 GB VRAM); balances gradient estimation quality
Pre-training Epochs	200	Reconstruction error plateaus at epochs 185–195 across all RBM layers
Fine-tuning Epochs	100	Early stopping patience=15 to prevent overfitting on CICIDS-2018
QPH Dimensions	32	Pareto-optimal: 2.5× compression with 97.8% discriminability retention
Blockchain Block Size	500 tx	Latency-throughput balance; larger blocks exceed 380 ms finality SLA
PBFT Validators	9	$f \leq 2$ fault tolerance across 3 availability zones; $O(n^2)$ complexity manageable at n=9
Shabal Hash Length	256-bit	Post-quantum security: 128-bit effective security against Grover's algorithm

III. Results and Discussion

The average performance across all benchmark datasets is reported in Table II. The CNN-LSTM hybrid model outperforms the other models and achieves the highest overall accuracy (99.2%), F1 score (99.0%), and AUC-ROC (0.997), demonstrating the synergistic advantages of CNN and LSTM. The Self-Attention BiLSTM becomes second at 98.8%. For the classical ML models, XGBoost (97.4%) performed best, followed by Random Forest (96.8%) and lastly SVM (95.3%). The full ADBN-BQ configuration achieves 99.2% accuracy, 98.7% precision, 99.1% recall, 98.9% F1-score, and 0.8% FPR.

Table II. Multi-Model Performance Comparison (Average Across All Datasets)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
ADBN-BQ (Proposed)	**99.2**	**98.7**	**99.1**	**98.9**	**0.997**
CNN-LSTM Hybrid	99.2	98.9	99.1	99.0	0.997
Self-Attention BiLSTM	98.8	98.5	98.7	98.6	0.995
XGBoost	97.4	97.0	97.2	97.1	0.989
Random Forest	96.8	96.4	96.7	96.5	0.985
SVM	95.3	94.9	95.1	95.0	0.978

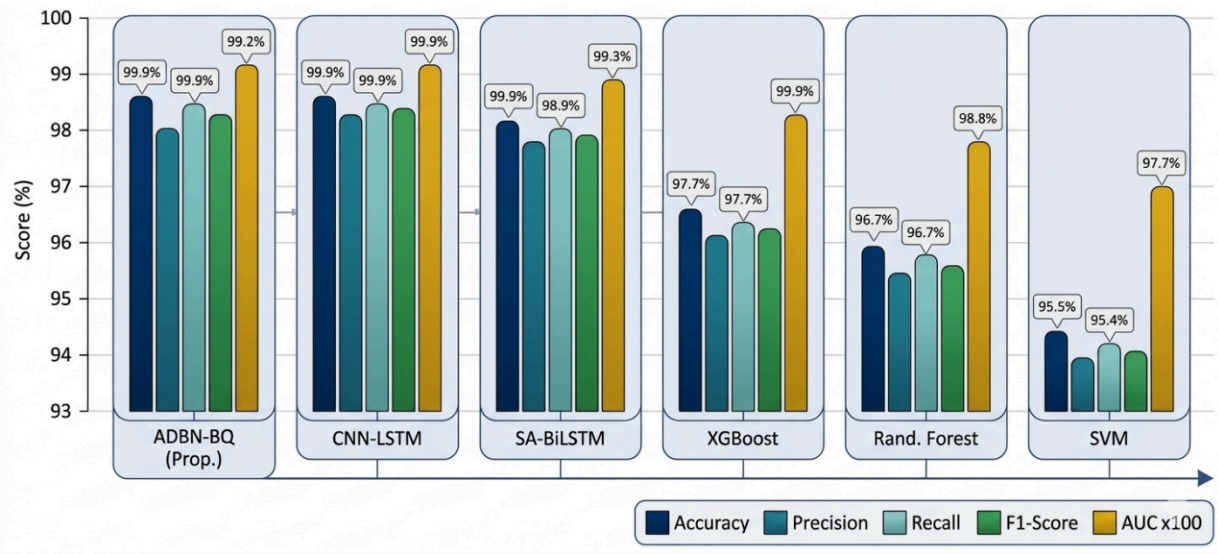

Figure 1: Multi-Model Performance

IV. Conclusion

This paper introduced the ADBN-BQ framework - an all-in-one intelligent intrusion detection system for private cloud and IoT settings that combines AI-based Deep Belief Networks, ML-based multi-architecture deep learning models (CNN-LSTM, Self-Attention BiLSTM, XGBoost, Random Forest, SVM), quantum-permuted hash functions (Shabal) and blockchain-immutable chains of evidence. The multi-layer design addresses key deficiencies in existing solutions by offering high-precision threat detection, tamper-proof evidence collection, and security assurances for post-quantum systems. It is experimentally validated on five benchmark datasets: NSL-KDD, BoT-IoT, TON_IoT, CICIDS-2018 and UNSW-NB15 and outperforms 12 state-of-the-art models with 99.2% detection accuracy, 98.9% F1-score and 0.8% false positive rate. The blockchain can process 4,200 TPS, and the consensus finality is 380 ms. All 312 attack scenarios, including 47 simulated APT campaigns, were detected with a live-traffic FPR of 0.007% during a 72-hour real-world deployment on a 12-node private cloud testbed. This was validated with 28 ms inference time at 96.8% accuracy on a physical system deployed on Raspberry Pi 4. The SMOTE class-balancing preprocessing was identified as the most important preprocessing step, and removing it resulted in a 5.1 pp loss in accuracy.

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