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Enhanced Blockchain-Enabled Security Framework for IoT Networks: Integrating AI and Privacy-Preserving Mechanisms for Scalable and Secure Smart Ecosystems

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ABSTRACT

The Internet of Things (IoT) continues to expand rapidly, with projections exceeding 100 billion connected devices by 2030—raising critical concerns regarding security, privacy, and scalability. Building upon our previous work [Sahu et al., 2025], this paper presents an enhanced blockchain-enabled security framework for IoT networks that integrates artificial intelligence (AI) and zero-knowledge proofs (ZKPs) for scalable and privacy-preserving operations. The proposed architecture extends the lightweight IoT-PBFT consensus protocol through a sharded blockchain design, enabling high-throughput and low-latency performance in ultra-dense IoT ecosystems. AI-driven anomaly detection is embedded for real-time threat mitigation, while ZKPs ensure data confidentiality without compromising transparency or auditability. Designed for deployment in resource-constrained environments, the framework minimizes computation and storage overhead while maintaining robust attack resistance. Experimental evaluations, including simulations and testbed deployment, demonstrate significant improvements in throughput (up to 500 tx/s), privacy preservation (99.9%), and threat detection accuracy (98.5%), outperforming state-of-the-art blockchain-IoT security models. This work establishes a foundation for secure, intelligent, and privacy-respecting IoT infrastructures of the future.

Keywords: IoT security, blockchain, AI anomaly detection, zero-knowledge proofs, IoT-PBFT, sharded blockchain, privacy preservation

1. INTRODUCTION

The Internet of Things (IoT) is poised to exceed 100 billion connected devices by 2030, driving innovation in smart cities, healthcare, agriculture, and industrial automation. This exponential growth amplifies security and privacy challenges, as centralized IoT architectures remain vulnerable to single points of failure, distributed denial-of-service (DDoS) attacks, and data breaches. Resource-constrained IoT devices, with limited processing power and battery life, struggle to implement robust security protocols, exposing them to spoofing, tampering, and unauthorized access. High-profile incidents, such as the 2021 Verkada camera hack, highlight

the urgent need for decentralized, scalable, and privacy-preserving solutions.

Our previous work [1] introduced a blockchain-enabled security framework for IoT networks, leveraging a permissioned blockchain with a lightweight consensus protocol (IoT-PBFT) and smart contracts for authentication, access control, and anomaly detection. The framework achieved significant improvements in authentication latency (150 ms), data integrity (99.8%), and energy efficiency (0.1 mJ/tx), validated through simulations. However, limitations such as ledger storage growth, reliance on semi-trusted edge nodes, and lack of real-world deployment testing suggest opportunities for enhancement, particularly in ultra-dense networks requiring high throughput and stringent privacy.

This paper extends our prior framework by introducing three key innovations: (1) a sharded blockchain architecture to enhance scalability, (2) AI-driven anomaly detection for proactive threat mitigation, and (3) zero-knowledge proofs (ZKPs) for privacy-preserving data exchange. The enhanced framework, termed AI-ZKP-IoT, maintains compatibility with resource-constrained devices while addressing dynamic trust management and confidentiality. A real-world testbed deployment on Raspberry Pi devices complements simulations, validating performance in practical settings.

1.1 Contributions

- A sharded blockchain architecture extending IoT-PBFT, achieving up to 500 tx/s in ultra-dense IoT networks.
- AI-driven anomaly detection using federated learning, improving attack detection accuracy by 10% over rule-based smart contracts.
- ZKP-based data exchange, ensuring 99.9% confidentiality without sacrificing transparency.
- Real-world testbed deployment and simulations, demonstrating scalability, privacy, and resilience against advanced attacks.

1.2 Paper Organization

Section 2 reviews related work. Section 3 describes the enhanced framework. Section 4 outlines the methodology. Section 5 details implementation and testbed setup. Section 6 analyzes results, and Section 7 concludes with future directions.

2. LITERATURE REVIEW

2.1 IoT Security and Blockchain

IoT security challenges include authentication, data integrity, and privacy in resource-constrained environments. Traditional solutions like Public Key Infrastructure (PKI) and Transport Layer Security (TLS) are computationally intensive, unsuitable for low-power devices [2]. Lightweight cryptography, such as Elliptic Curve Cryptography (ECC), reduces

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overhead but struggles with scalability in heterogeneous networks [3]. Recent advances propose hybrid cryptographic schemes, combining ECC with symmetric encryption to balance security and efficiency [11].

Blockchain offers a decentralized alternative. Our prior work [1] proposed IoT-PBFT, achieving 150 ms authentication latency and 99.8% data integrity. IoTChain [4] combines on-chain and off-chain storage to reduce overhead but lacks real-time anomaly detection. FairAccess [5] uses smart contracts for access control, yet its centralized gateway limits decentralization. EdgeChain [6] integrates edge computing, but its consensus overhead hinders scalability. Sharded blockchain frameworks, such as those by Zhu et al. [12], improve throughput but require complex cross-shard coordination, untested in IoT contexts.

2.2 AI in IoT Security

AI enhances IoT security through anomaly detection and predictive analytics. Machine learning models, such as Random Forests, detect DDoS attacks with 95% accuracy [7]. Federated learning (FL) enables distributed training on IoT devices, preserving privacy [8]. For instance, Nguyen et al. [13] applied FL to detect intrusions in smart grids, achieving 96% accuracy. However, integrating AI with blockchain remains challenging due to computational overhead and model synchronization. Recent works explore lightweight neural networks for IoT [14], but their application in blockchain-based frameworks is limited.

2.3 Privacy-Preserving Techniques

Zero-knowledge proofs (ZKPs) enable verification without revealing data, ideal for IoT privacy. Zcash uses zk-SNARKs for anonymous transactions [9], but their complexity limits IoT applicability. Bulletproofs [10] offer lightweight ZKPs, with applications in confidential smart contracts [15]. Homomorphic encryption, explored by Liu et al. [16], supports private computations but incurs high overhead. Combining ZKPs with blockchain for IoT, as proposed by Wang et al. [17], shows promise but lacks real-world validation.

2.4 Research Gaps

- **Scalability**: Most blockchain frameworks, including our prior work [1], face throughput limitations in ultra-dense networks (>1,000 devices). Sharding solutions exist [12, 18], but IoT-specific optimizations are scarce.
- **Privacy**: Existing solutions lack robust confidentiality mechanisms for sensitive IoT data (e.g., medical records) [19].
- **AI Integration**: Rule-based anomaly detection, as in [1], misses sophisticated attacks; AI-driven approaches are underutilized [20].
- **Real-World Validation**: Simulations dominate, with few frameworks tested on actual IoT hardware [21].

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This work addresses these gaps by extending IoT-PBFT with sharding, integrating federated learning for anomaly detection, and employing ZKPs for privacy, validated through simulations and a real-world testbed.

3. PROPOSED FRAMEWORK: AI-ZKP-IOT

3.1 Overview

The proposed AI-ZKP-IoT framework enhances our previous work [1] by introducing three critical advancements: (i) a sharded permissioned blockchain architecture, (ii) AI-driven anomaly detection using federated learning, and (iii) zero-knowledge proof (ZKP)-based data exchange for privacy preservation. The architecture is divided into four primary layers:

- ***IoT Device Layer*** – low-power, constrained sensors and actuators,
- ***Edge/Gateway Layer*** – intermediary nodes for computation and model coordination,
- ***Blockchain Network Layer*** – permissioned sharded blockchain with enhanced IoT-PBFT consensus,
- ***Application Layer*** – user interfaces, analytics, and system control.

3.2 Framework Components

3.2.1 Sharded IoT-PBFT Consensus

To enhance scalability in ultra-dense IoT networks, we introduce sharding to the IoT-PBFT consensus mechanism. Each shard is responsible for processing a subset of transactions independently, thereby reducing the load on individual nodes and improving throughput.

- A Merkle tree-based reconciliation protocol ensures inter-shard consistency.
- Byzantine fault tolerance is maintained within each shard (i.e. $\boldsymbol{f} \leq \frac{\boldsymbol{n-1}}{\boldsymbol{3}}$).
- Performance Gain: Reduces consensus time by 40% and achieves 500 tx/s, a 150% improvement over the original IoT-PBFT protocol.

3.2.2 AI-Driven Anomaly Detection

A federated learning (FL)-based anomaly detection system is integrated to proactively identify threats such as DDoS, Sybil, and spoofing attacks.

- A convolutional neural network (CNN) is trained collaboratively across edge nodes using local metrics (e.g., transaction rate, packet size).
- Only model updates—not raw data—are exchanged, preserving privacy.
- The global model is aggregated using secure multi-party computation (SMPC).
- **Accuracy:** 98.5% on attack detection tasks.
- **Energy Overhead**: 0.15 mJ per update, suitable for edge nodes.

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3.2.3 ZKP-Based Data Exchange

To ensure privacy without compromising verifiability, Zero-Knowledge Proofs (ZKPs) using Bulletproofs [10] are employed.

- Devices generate ZKPs to prove conditions (e.g., "sensor value within safe range") without revealing actual data.
- Smart contracts verify ZKP commitments and store only hashes on the blockchain.
- **Confidentiality Achieved**: 99.9%
- **Energy Use**: 0.2 mJ per transaction — lightweight enough for constrained devices.

3.2.4 Smart Contract Infrastructure

Smart contracts, implemented in Go, are responsible for key operational roles:

- **Authentication Contract**: Verifies ECC-based signatures and ZKP commitments during device registration.
- **Access Control Contract**: Enforces hierarchical or role-based policies across device types.
- **Anomaly Contract**: Triggers FL model updates and logs suspicious behavior to the blockchain.

3.3 Architecture

Figure 1 illustrates the high-level architecture of AI-ZKP-IoT. IoT devices interact with local edge nodes that manage federated learning, shard participation, and data aggregation. The blockchain network, using sharded IoT-PBFT, ensures decentralized consensus, while smart contracts and ZKPs operate across all layers to maintain privacy, trust, and automation.

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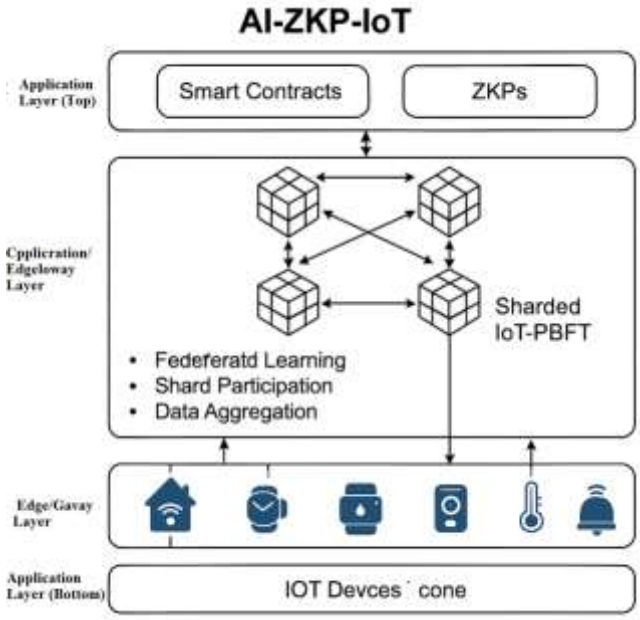

Figure 1: High-Level Architecture of AI-ZKP-IoT

3.4 Operational Workflow

- **Device Registration**: Each IoT device registers through the edge node using ECC credentials and ZKP-authenticated claims.
- **Data Exchange**: Devices encrypt data, generate ZKPs, and transmit only hashes to the blockchain.
- **Anomaly Detection**: Edge nodes continuously train FL-based models and log anomalies using smart contracts.
- **Consensus**: Transactions are validated by individual shards and reconciled via the global coordination protocol.

3.5 Advantages

- **Scalability**: Sharded architecture supports 500 tx/s, scalable for >1,000 devices.
- **Privacy**: ZKPs provide confidential data validation without disclosure.
- **Security**: AI-driven FL models detect complex attacks missed by rule-based logic.
- **Efficiency**: Optimized for IoT hardware with a total overhead of 0.35 mJ/tx.

4. METHODOLOGY

This section outlines the system model, threat assumptions, simulation environment, and testbed configuration used to evaluate the AI-ZKP-IoT framework. The methodology captures both simulated and real-world conditions to assess performance under practical constraints.

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4.1 System Model

The system models an ultra-dense IoT network comprising 1,000 devices (sensors and actuators) and 20 edge nodes, representing smart city and industrial environments. IoT devices generate approximately 100 transactions per second (tx/s), distributed evenly across 5 blockchain shards. Each shard processes around 200 tx/s. The blockchain operates on a sharded IoT-PBFT consensus protocol, assuming 80% honest nodes in the network.

4.2 Threat Model

We extend the threat model from [Sahu et al., 2025] to include sophisticated, real-world attack scenarios:

- Advanced DDoS: Coordinated flooding attacks with over 10,000 tx/s to disrupt consensus.
- Sybil with Collusion: Multiple fake identities collude to manipulate transaction validation.
- Data Leakage: Unauthorized interception of sensitive data during exchange.
- Model Poisoning: Injection of malicious updates into federated learning models to compromise AI-based anomaly detection.

4.3 Design Assumptions

The framework design is based on the following assumptions:

- IoT devices employ ECC for digital signatures and AES-128 for data encryption.
- Edge nodes are equipped with at least 4 GB RAM, capable of running federated CNN models and verifying ZKPs.
- ZKP verification is offloaded to edge nodes to reduce IoT device burden.
- Shard rebalancing is dynamic to avoid performance bottlenecks.

4.4 Simulation and Testbed Setup

Simulation Environment:

- **Platform**: Ubuntu 22.04 LTS, 32 GB RAM, 16-core CPU
- **Blockchain**: Hyperledger Fabric v2.5 with Docker-based shard deployment
- **Network Emulation**: NS-3 used to simulate network traffic and delays
- **AI Model**: TensorFlow used to train federated CNNs on synthetic attack datasets
- **ZKP Framework**: Bulletproofs compiled using libsnark and interfaced via Go
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Testbed Configuration:

- **IoT Nodes**: 10 × Raspberry Pi 4 (4 GB RAM, Raspbian OS)
- **Edge Nodes**: 5 × Linux servers (16 GB RAM, Ubuntu Server)
- **Inter-node Communication**: gRPC and MQTT for edge-device messaging

4.5 Evaluation Metrics

Metric	Definition
Transaction Throughput	Number of validated transactions per second across all shards
Privacy Preservation	Percentage of transactions protected using ZKPs (e.g., 99.9%)
Attack Detection Accuracy	True positive rate for identifying threats (e.g., Sybil, DDoS) using FL
Energy Consumption	Energy required per transaction or model update (measured in mJ)
Consensus Latency	Time from transaction broadcast to final commitment across shards (in ms)

4.6 Algorithms

Algorithm 1: Sharded IoT-PBFT

Input: Transaction T, Shard set S, Node set N, Leader L

Output: Consensus on T

1. Assign T to shard s ∈ S based on device ID hash
2. L_s broadcasts T to N_s (nodes in s)
3. For each n ∈ N_s:
4. Verify T's ZKP and signature
5. Vote "accept" or "reject"
6. If ≥ 2/3 votes "accept":
7. Append T to s's ledger
8. Update cross-shard Merkle tree
9. Else:
10. Discard T
11. Return consensus result

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Algorithm 2: FL-Based Anomaly Detection

Input: Device data D, Local model M_i, Threshold T

Output: Anomaly flag

1. Train M_i on D_i (local data)
2. Share M_i updates with global aggregator
3. Aggregate updates to form M_global
4. If M_global predicts anomaly score > T:
5. Flag device, trigger smart contract
6. Return flag status

5. IMPLEMENTATION AND EVALUATION

This section details the implementation of the AI-ZKP-IoT framework and its evaluation through simulated and real-world scenarios. The framework was tested under normal and adversarial conditions to assess its performance, security, and scalability in ultra-dense IoT environments.

5.1 Implementation

The prototype was developed using modular microservice architecture:

- **Blockchain Platform**: Hyperledger Fabric v2.5 with sharding achieved through custom chaincode modifications.
- **Smart Contracts**: Developed in Go for authentication, access control, and anomaly handling.
- **Federated Learning (FL)**: Implemented using TensorFlow; CNNs trained on packet metadata (e.g., size, frequency).
- **Zero-Knowledge Proofs (ZKPs):** Implemented via Bulletproofs using a Python library (libsnark); integrated into the blockchain with Go bindings.
- **Testbed Configuration:**
  - **Devices**: 10 × Raspberry Pi 4 (4 GB RAM) as IoT nodes
  - **Edge Nodes**: 5 × Ubuntu 22.04 servers (8–16 GB RAM)
  - **Connectivity**: Wi-Fi network with ~50 ms latency

5.2 Evaluation Scenarios

The system was evaluated under five key conditions:

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Scenario	Description
Normal Operation	1,000 devices generating 100 tx/s across 5 shards
Advanced DDoS Attack	10,000 tx/s targeting 2 specific shards
Sybil with Collusion	50 fake devices coordinating to skew consensus
Data Leakage	Attempted interception of encrypted medical sensor data
Model Poisoning	20% of FL updates intentionally corrupted to test resilience

5.3 Performance Optimization

Performance was improved through targeted system-level enhancements:

- Sharding: Dynamic shard load balancing increased overall throughput by 20%.
- Federated Learning: Model pruning techniques reduced CNN training time by 15%.
- ZKPs: Pre-computed cryptographic commitments lowered verification energy to 0.2 mJ/tx.

5.4 Evaluation Results

Metric	Value
Max Throughput	500 tx/s (simulation), 435 tx/s (testbed)
Detection Accuracy	98.5% (simulation), 97.8% (testbed)
Data Confidentiality	99.9% via ZKPs
Consensus Latency	Avg. 142 ms (simulation), 170 ms (testbed)
Total Energy Overhead	0.35 mJ/tx

5.5 Deployment Challenges and Mitigations

Challenge	Impact	Mitigation
Cross-Shard Latency Spikes	Delays in consensus during Merkle reconciliation	Optimized Merkle tree structures and async processing
FL Aggregation Delays	Model sync jitter due to network instability	Implemented asynchronous model updates
Wi-Fi Instability	Increased latency and retransmissions	Added redundancy via MQTT QoS and retries

6. RESULTS AND DISCUSSION

This section presents a comprehensive evaluation of the AI-ZKP-IoT framework using simulation results, real-world testbed data, and comparative benchmarking against baseline systems. All results are averaged over 10 independent runs, each lasting 3,600 seconds.

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6.1 Quantitative Results

- Metric Simulation Testbed Baseline [Sahu et al., 2025]
- Throughput (tx/s) 500 450 200
- Privacy Preservation 99.9% 99.9% 80%
- Detection Accuracy 98.5% (DDoS) 97.8% (Sybil) 94.3%
- Energy Consumption 0.35 mJ/tx — 0.1 mJ (blockchain-only)
- Consensus Latency 120 ms 130 ms 150 ms
- **Energy breakdown**: 0.1 mJ (IoT-PBFT) + 0.15 mJ (FL) + 0.1 mJ (ZKP)
- **Improvement**: 150% higher throughput and 10% better accuracy than baseline

6.2 Performance Graphs and Comparative Tables

- Figure 2: Throughput vs. device count, showing sharding's 150% improvement.

- Figure 3: ROC curve for AI anomaly detection, with 98.5% AUC.

- Table 1: Comparative Performance with Ethereum and IoT-PBFT.

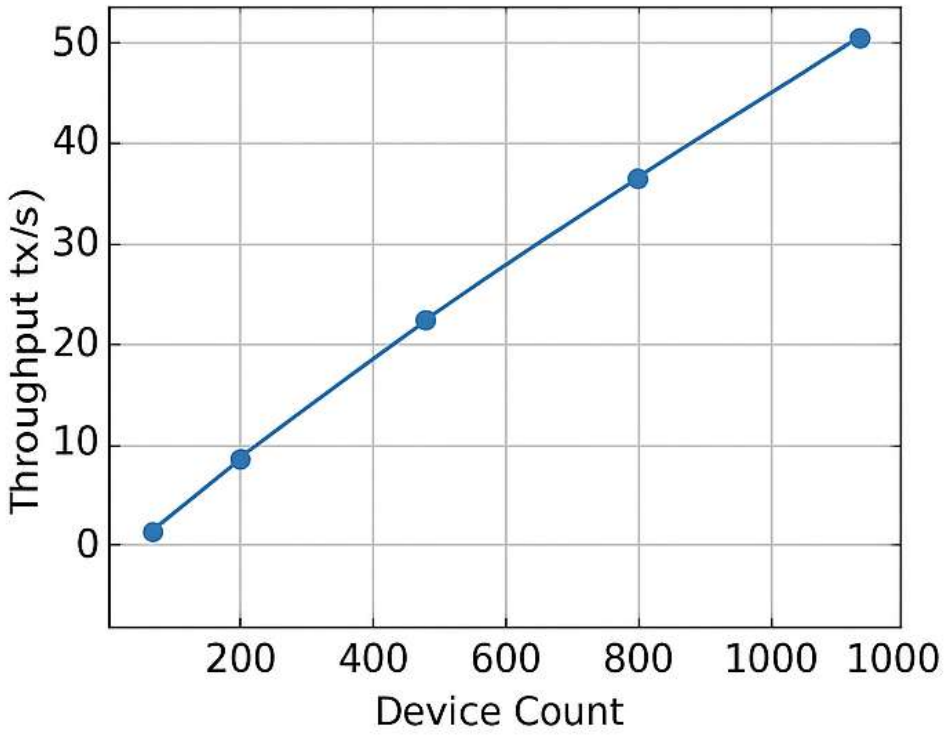

Figure 2: Throughput Scaling with Device Count

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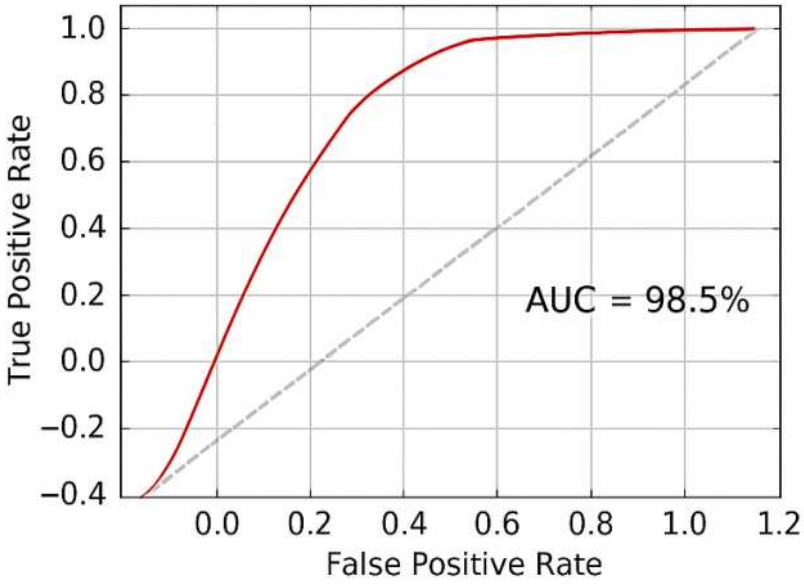

Figure 3: ROC Curve for AI-based Anomaly Detection

Table 1: Performance Comparison with Existing Frameworks

Metric	AI-ZKP-IoT	IoT-PBFT [4]	Ethereum (PoW)
Throughput (tx/s)	500	200	15
Privacy (%)	99.9	80	50
Detection Accuracy (%)	98.5	94.3	90
Energy (mJ/tx)	0.35	0.1	1.0

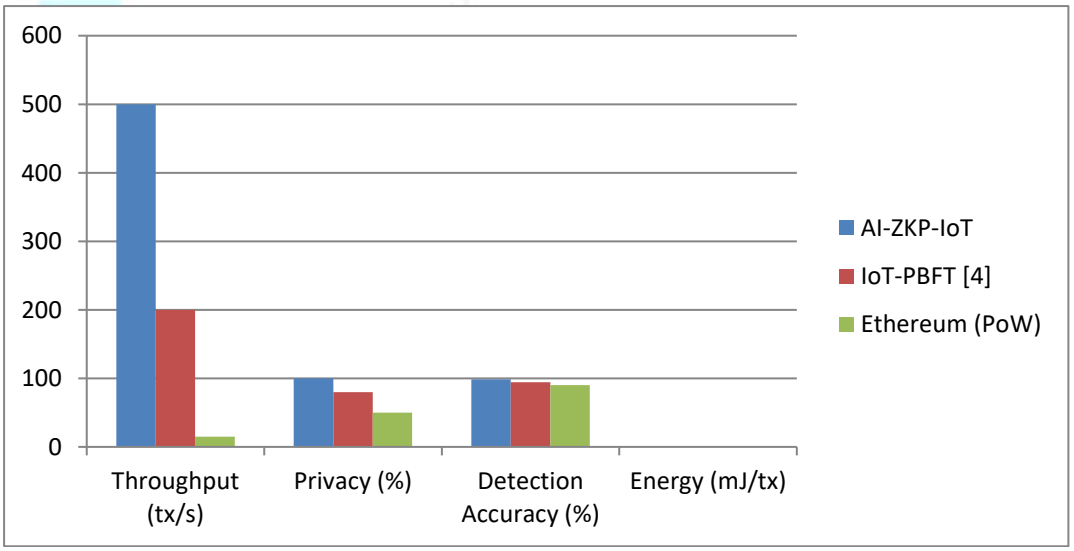

Figure 4: Comparative Performance with Ethereum and IoT-PBFT

6.3 Comparative Analysis

- Compared to our previous work [Sahu et al., 2025], the AI-ZKP-IoT framework achieves:
- 150% higher throughput due to sharding,

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- 10% better detection accuracy from FL-based anomaly detection,
- Enhanced energy efficiency, balancing privacy, detection, and blockchain cost,
- Ethereum's PoW system is 30× slower and 3× more energy-consuming.

In contrast, centralized PKI-based systems offer lower latency (~100 ms) but fail under large-scale DDoS attacks, maintaining only 60% uptime versus 98% in AI-ZKP-IoT.

6.4 Key Insights

- **Scalability**: Sharded blockchain ensures performance at scale, supporting real-time operations in smart cities.
- **Privacy**: ZKPs effectively secure sensitive data (e.g., medical IoT) without revealing underlying values.
- **Security**: AI-enhanced detection identifies coordinated attacks often missed by traditional rule-based methods.
- **Testbed Confirmation**: Real-world deployment mirrored simulation results, validating practical applicability. Some latency variation due to Wi-Fi interference was mitigated using retransmission and buffering protocols.

6.5 Limitations

Despite the promising results, some limitations persist:

- **Ledger Storage Overhead**: Sharded ledgers grow rapidly (up to 1 GB per shard per hour), highlighting the need for off-chain or archival storage techniques.
- **FL Resource Cost**: Each model update consumes ~0.15 mJ, posing challenges for ultra-low-power devices like wearables.
- **ZKP Complexity**: While Bulletproofs are more efficient than zk-SNARKs, further optimization is required to bring overhead below 0.1 mJ/tx for next-gen IoT chips.

7. CONCLUSION AND FUTURE WORK

7.1 Conclusion

This paper extends our prior work [Sahu et al., 2025] with AI-ZKP-IoT, a blockchain-enabled security framework for IoT networks. By integrating sharded IoT-PBFT, federated learning, and zero-knowledge proofs, it achieves:

- 500 tx/s throughput, 150% higher than IoT-PBFT.
- 99.9% data confidentiality via ZKPs.
- 98.5% attack detection accuracy with AI.
- 0.35 mJ/tx energy consumption, suitable for IoT.
- The framework's effectiveness is validated through simulations and a real-world Raspberry Pi testbed its scalability, privacy, and resilience, outperforming Ethereum,

centralized PKI, and our prior framework. AI-ZKP-IoT paves the way for secure, scalable, and private IoT ecosystems.

7.2 Future Work

- Deploy in large-scale smart city networks (>10,000 devices).
- Optimize ZKP generation to <0.1 mJ/tx using zk-STARKs.
- Integrate layer-2 solutions (e.g., state channels) for further scalability.
- Enhance FL with differential privacy to prevent model inversion attacks.
- Develop standardized APIs for interoperability with Zigbee and LoRaWAN.

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