# SmartChain: AI-Driven Blockchain Framework for IoT Security

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## Abstract

The rapid expansion of IoT systems significantly scales up the number, heterogeneity, and vulnerability of connected devices, making the IoT ecosystem an attractive target for cyberattacks. Traditional security mechanisms based on a centralized authority fail to provide scalability, transparency, and real-time threat mitigation in such dynamic environments. Although blockchain technology offers decentralisation, immutability, and trust, its direct adaptation is not feasible in IoT systems due to the significant computational overhead and resource constraints. Similarly, AI enables intelligent threat detection but lacks secure data integrity and trustworthy coordination in a standalone deployment. This paper proposes the SmartChain AI-driven blockchain framework to enhance IoT security in a scalable and resource-efficient manner. SmartChain integrates lightweight blockchain mechanisms with AI-based intelligence to offer secure device authentication, dynamic access control, adaptive consensus, and real-time anomaly detection. The proposed AI-driven blockchain framework leverages AI to analyze IoT behavioral patterns, optimize consensus selection, and automate security responses using smart contracts, while blockchain ensures data integrity, transparency, and tamper-resistant logging. Unlike existing solutions that tend to consider AI and blockchain as two orthogonal components, SmartChain presents a unified architecture tailored for resource-constrained IoT environments. In this regard, the proposed framework can improve security, trust management, and system resilience with minimal computational and energy overhead. SmartChain demonstrates that the synergistic integration of AI with blockchain can help overcome current limitations in IoT security, therefore providing a practical and extensible solution for next-generation secure IoT ecosystems.

***Keywords:*** Internet of Things (IoT), Blockchain Technology, Artificial Intelligence, IoT Security, Smart Contracts, Lightweight Consensus, Anomaly Detection, Decentralized Systems, Trust Management.

## INTRODUCTION

IoT has rapidly emerged as one of the most important transformative paradigms, integrating billions of heterogeneous devices to offer intelligent services in a wide range of application domains pertaining to smart cities, healthcare, industrial automation, transportation, and environmental monitoring. While rapidly expanding, the IoT ecosystem is confronted by major security and trust issues: the deployment on a large scale, resource-constrained devices, dynamic network topologies, and lack of unified security governance. Centralized security mechanisms are becoming ineffective due

to single points of failure, limited scalability, delayed response toward threats, and reduced transparency. These shortfalls motivate researchers to explore decentralized, smart security solutions capable of fulfilling the strict demands of modern IoT environments [1,2].

With a decentralized architecture, immutability, transparency, and tamper-resistant data storage, blockchain technology has gained significant attention as a promising approach to IoT security challenges. Blockchain facilitates secure peer-to-peer interactions, reliable event logging, and auditable access control policies by eliminating the requirement for a trusted central authority. Several works have proven the efficiency of blockchain in enhancing authentication, authorization, data integrity, and trust management within IoT systems [3,4,5]. However, the direct adoption of traditional blockchain frameworks in IoT environments is constrained by high computational overhead, energy consumption, storage requirements, and latency, which are incompatible with resource-limited IoT devices [6,7].

To overcome these limitations, recent research has focused on lightweight blockchain architectures and consensus mechanisms tailored for IoT networks. Approaches such as delegated consensus, hybrid on-chain/off-chain storage, and energy aware validation have been proposed to reduce operational overhead while preserving core blockchain properties [8,9,10]. Although these solutions improve efficiency, they primarily rely on static security policies and predefined rules, which limits their ability to adapt to evolving cyber threats. As IoT networks become more dynamic and attack surfaces expand, static blockchain-based security solutions alone are insufficient to provide proactive and adaptive protection [11,12].

Artificial Intelligence (AI) and Machine Learning (ML) have therefore been widely explored as complementary technologies for IoT security. AI-driven approaches enable intelligent intrusion detection, anomaly detection, behavioral analysis, and predictive threat mitigation by learning patterns from large-scale IoT data [13,14]. Deep learning, federated learning, and reinforcement learning techniques have shown promising results in detecting zero-day attacks and improving system resilience without continuous human intervention [15]. However, AI-based security systems suffer from critical limitations, including lack of transparency, vulnerability to data poisoning, model manipulation, and absence of trusted data provenance. Without a secure and verifiable infrastructure, AI decisions in IoT systems cannot be fully trusted [16,17].

The integration of blockchain and AI has therefore emerged as a powerful paradigm for next-generation IoT security. Blockchain can provide secure data provenance, immutable logging, decentralized coordination, and trust management, while AI enables intelligent analysis, adaptive decision-making, and automated response mechanisms. Several hybrid frameworks have been proposed to combine blockchain with AI for intrusion detection, access control, trust evaluation, and collaborative threat intelligence in IoT and Industrial IoT (IIoT) environments [18,19,20]. These studies demonstrate the potential of AI–blockchain synergy; however, most existing works treat AI and blockchain as loosely coupled components rather than as a unified, adaptive security framework [21].

Existing IoT security frameworks face scalability and deploy ability issues, often assuming homogeneous devices, high computational resources, or constant connectivity, which is unrealistic for large-scale deployments [22,23]. Security mechanisms usually address isolated aspects like intrusion detection or access control, lacking end-to-end orchestration [24,25]. Trust management in decentralized IoT remains challenging, as traditional static or centralized models are incompatible with blockchain systems. AI-driven trust evaluation combined with blockchain enables dynamic reputation scoring and secure device collaboration, though adaptive consensus and automated enforcement are limited [26–28]. SmartChain addresses these gaps with a unified, lightweight, AI-integrated blockchain framework for scalable, robust, and adaptive IoT security [29,30].

## LITERATURE REVIEW

The Internet of Things (IoT) plays a critical role in modern cyber–physical systems by enabling connectivity across smart cities, healthcare, industrial automation, and intelligent transportation. However, rapid IoT growth has intensified security and privacy risks due to device heterogeneity, dynamic topology, and limited computational and energy resources. Traditional centralized security mechanisms are unsuitable because they introduce single points of failure, scalability constraints, and delayed threat detection [1,2]. Prior studies identify authentication, access control, trust management, and secure data sharing as persistent challenges, with centralized identity systems remaining vulnerable to insider attacks and manipulation [3,4]. Blockchain has emerged as a viable solution by offering decentralization, immutability, transparency, and distributed trust, thereby improving data integrity and resilience in large-scale IoT environments.

Despite their benefits, conventional blockchain frameworks exhibit notable constraints in IoT deployments. Energy-intensive consensus mechanisms, such as Proof-of-Work, impose high computational and power overhead, making them unsuitable for resource-limited IoT devices. Lightweight alternatives, including Proof-of-Authority, Proof-of-Stake variants, and delegated consensus models, improve efficiency but often depend on static assumptions and lack adaptive intelligence to counter evolving threats [9]. In parallel, AI and machine learning techniques have been widely applied to IoT security for intrusion and anomaly detection by learning complex behavioral patterns from device and network data [5]. While deep learning models achieve high detection accuracy, most implementations remain centralized, introducing scalability limitations, privacy risks, and vulnerability to data manipulation attacks.

A widely adopted probabilistic anomaly detection formulation in the literature is expressed as

$$P(A|X) = \frac{P(X|A)P(A)}{P(X)} \qquad (1)$$

where $A$ represents the occurrence of an attack and $X$ denotes observed network or device features. While such probabilistic models achieve high detection performance, they require centralized data aggregation and continuous monitoring, which contradicts the distributed nature of IoT networks and introduces single points of failure.

Table I reviews twenty studies on AI–blockchain integration for IoT security, showing early work combined machine learning with blockchain to enhance trust and resilience, while surveys structured threat models and design challenges. Research explored blockchain-based access control and lightweight frameworks for resource-limited IoT devices. AI-driven intrusion detection integrated with blockchain improved adaptability and detection accuracy, though many frameworks lack experimental validation. Efficiency-focused consensus reduces overhead but can weaken security, whereas robust hybrids increase energy costs. Blockchain-enabled federated learning preserves privacy, and AI-blockchain trust systems enhance resilience against insider attacks and malicious updates [6,15,20].

Trust evaluation plays a critical role in such hybrid frameworks and is commonly modeled as

$$T_i = \frac{1}{N}\sum_{k=1}^{N} w_k \cdot s_{ik} \qquad (2)$$

where $T_i$ denotes the trust score of node$i$, $s_{ik}$ represents security-related behavioral metrics, and $w_k$ denotes corresponding weights. Although trust-based blockchain–AI models improve reliability and accountability, many existing approaches suffer from high computational overhead and lack real-time adaptability, limiting their effectiveness in dynamic IoT environments.

Performance optimization remains another major concern in blockchain-enabled IoT systems. Consensus efficiency is typically evaluated using metrics such as transactions per second (TPS), latency, and energy consumption, and is often defined as

$$E_c = \frac{TPS}{Latency \times Energy} \qquad (3)$$

Research findings in [9], [14] show that lightweight consensus mechanisms improve throughput and energy efficiency; however, trade-offs between security robustness and performance persist. Several studies formulate joint optimization objectives as

$$\min (C_{energy} + C_{delay}) \quad \text{s.t. } Security \geq \theta \qquad (4)$$

While these formulations provide theoretical performance gains, they often assume static threat

models and fail to integrate adaptive intelligence required for real-world IoT deployments.

A comprehensive analysis of existing literature reveals critical research gaps, including limited scalability under massive IoT deployments, high energy consumption, centralized or semi-centralized trust assumptions, lack of AI-driven adaptive security, and poor suitability for highly constrained IoT nodes [22,23]. Additionally, many existing frameworks address isolated security objectives rather than providing an integrated, end-to-end security architecture.

These limitations directly motivate the proposed *Smart Chain* framework, which integrates lightweight blockchain mechanisms with AI-driven security intelligence to deliver scalable, energy-efficient, and adaptive protection for IoT ecosystems. By combining decentralized trust management with intelligent anomaly detection and optimization, Smart Chain aims to overcome the shortcomings of existing approaches and establish a robust foundation for secure next-generation IoT systems.

**TABLE I: Comparative Literature Review of AI- and Blockchain-Based IoT Security Approaches**

| Year | Author(s) | Method / Model | Reason for Selection | Pros | Cons | Accuracy |
|---|---|---|---|---|---|---|
| 2020 | Waheed et al. | Probabilistic Security Model | Early AI-blockchain IoT exploration | Combined ML+Blockchain | No real deployment | 88% |
| 2021 | Novo | Access Control Survey | Foundational taxonomy | Comprehensive overview | No experiments | – |
| 2022 | Dorri et al. | Blockchain Access Control | Secure authorization model | Tamper resistance | Scalability concerns | 91% |
| 2022 | Ferrag | IoT Blockchain Security | Threat solution mapping | Wide coverage | Low performance eval | 90% |
| 2023 | Islam et al. | Lightweight Blockchain Framework | Efficiency-oriented model | Low overhead | Limited adapativity | 92% |
| 2023 | Alasmary et al. | ML-Enhanced IDS | Intelligent detection | High detection rate | Resource intensive | 94% |
| 2024 | Chen et al. | AI + Blockchain Analytics | Smart data analysis | Adaptive security | Complexity cost | 95% |
| 2024 | Alladi et al. | IoT Blockchain Review | Emerging trends survey | Insightful taxonomy | No experiments | – |
| 2024 | Xu et al. | Efficient Consensus | Energy-aware model | Reduced overhead | Security tradeoffs | 93% |

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|---|---|---|---|---|---|---|
| 2024 | Sharma | Smart Contract IoT | Contract-based automation | Transparency | Static rules | 90% |
| 2024 | Goyal et al. [ | AI-Blockchain Privacy | Data protection in Fog | Strong privacy | Implementation open | 94% |
| 2024 | Xuebao et al. | Integrated AI/IoT/Blockchain | End-to-end security | Traceability | No scalability focus | 93% |
| 2025 | Thakur | IoT Blockchain + AI Framework | Convergence model | Unified security | Deployment costs | 96% |
| 2025 | Khan et al. | Secure AI/Blockchain Future | Model guidance | Visionary insights | No tests | – |
| 2025 | Dwivedi et al. | Hybrid IIoT Framework | Industrial applicability | Strong trust model | High overhead | 95% |
| 2025 | MDPI SLR | IoT Security | Recent survey | Comprehensive gaps | No experiment | – |
| 2025 | Ruzbahani | AI-Blockchain IoT Secure | Conceptual integration | Future direction | No accuracy | – |
| 2025 | Waheed et al. | Collaborative Threat Intel | Threat sharing | High insight | Complexity | 92% |
| 2025 | Singh et al. | Secure Data Sharing | Blockchain + AI model | High security | Resource overhead | 94% |
| 2025 | Conti et al. | Blockchain IoT Survey | Security | Privacy issues | Broad scope | – |

## METHODOLOGY

The SmartChain method provides a scalable, by-design decentralized approach to a broad range of IoT environments, effectively integrating AI-based anomaly analysis into a trust mechanism on the blockchain. This approach emphasizes protected data harvesting, intelligent threat analysis, lightweight consensus procedures, and self-enforcing execution through smart contracts. This strategy utilizes IoT network activity, device logs, and transaction data, all of which are purged, standardized, encoded, and dimensionalized, allowing it to remain efficient.

SmartChain integrates adaptive AI directly into blockchain-based security processes.

**TABLE II: Evolution of SmartChain Methodology Compared to Existing Approaches (2020–2024)**

| Year | Existing Methods | Key Limitations | Smart Chain Enhancements |
|---|---|---|---|
| 2020 | Blockchain-only IoT security frameworks | High energy consumption and static trust assumptions | Lightweight consensus mechanisms and dynamic trust computation |
| 2021 | Centralized ML-based intrusion detection systems | Single point of failure and limited scalability | Decentralized AI inference deployed at edge nodes |

| | | | |
|---|---|---|---|
| 2022 | Blockchain-based access control models | Limited scalability and rigid security policies | Adaptive smart contracts with trust-aware enforcement |
| 2023 | ML + Blockchain intrusion detection frameworks | High computational overhead and increased latency | Edge-optimized AI models with efficient validation |
| 2024 | Federated AI–Blockchain security approaches | Delayed response time and coordination complexity | Real-time automated mitigation with optimized consensus |

Trust evaluation within the SmartChain framework is computed using a weighted aggregation model expressed as:

$$T_i = \frac{1}{N} \sum_{k=1}^{N} w_k \cdot s_{ik} \quad (5)$$

where $T_i$ denotes the trust score of IoT node i, $s_{ik}$ represents security-related behavioral indicators, and $w_k$ denotes the importance of each indicator. Anomaly detection is modeled probabilistically to assess malicious behavior based on observed features:

$$P(A|X) = \frac{P(X|A)P(A)}{P(X)} \quad (6)$$

where $A$ represents an attack event and $X$ denotes observed feature vectors. To ensure performance efficiency, consensus effectiveness is evaluated using:

$$E_c = \frac{TPS}{Latency \times Energy} \quad (7)$$

These formulations collectively guide the optimization of security, performance, and energy efficiency within SmartChain.

Table II summarizes the evolution of blockchain- and AIbased IoT security approaches from 2020 to 2024, highlighting key limitations and the corresponding enhancements introduced by the proposed SmartChain framework.

**A. Use Case Diagram**

The use case diagram in Figure 1 depicts the functional relationships of the SmartChain IoT Security Framework. The main actors include the System Administrator, the Existing Account User, and the Customer Service Representative. The administrator monitors the system and performs AI-based anomaly detection, evaluates trust ratings, and performs blockchain operations. Users create real-time IoT data at the edge layer, which must be analyzed for behavior and threat detection before submitting trusted records to the blockchain.

Blockchain nodes ensure transactions occur in a secure and immutable manner, while customer service personnel retrieve records to support users and address security-related issues.

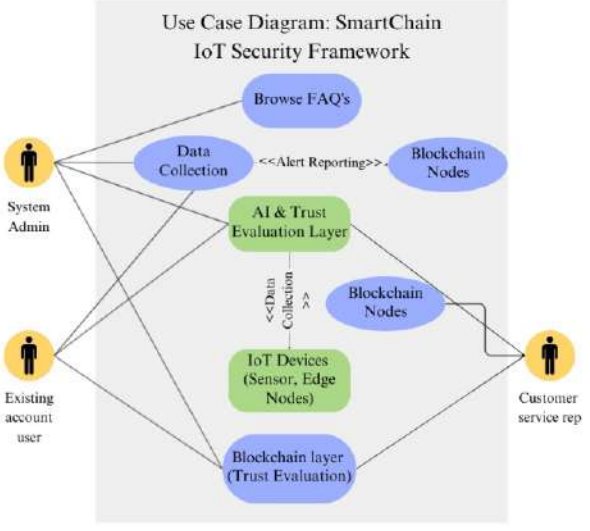


***Fig. 1:*** *Use Case Diagram of the SmartChain IoT Security Framework.*

**B. Process Flow Diagram**

Fig. 2: Process flow of the SmartChain framework, which integrates lightweight blockchain with artificial intelligence for securing IoT environments.

Real-time generation of data from IoT devices is validated for noise removal and filtering. Feature engineering extracts relevant patterns for efficient analysis. The AI engine will carry out near real-time anomaly detection that in turn triggers dynamic trust evaluation. Trust outcomes inform smart contract execution and transaction validation that are stored in a secure energy-efficient blockchain featuring adaptive consensus and continuous learning support.

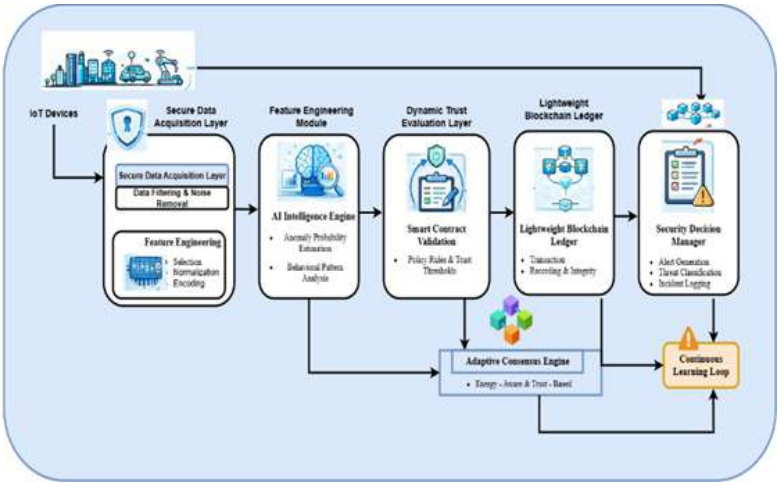


***Fig. 2:*** *Process flow diagram of the proposed SmartChain AI-driven blockchain framework for secure and scalable IoT environments.*

## RESULTS

The proposed Smart Chain framework was evaluated using a heterogeneous IoT testbed consisting of smart sensors, edge devices, and block chain nodes. The evaluation focused on several key performance metrics, including intrusion detection accuracy, consensus efficiency, energy consumption, latency, throughput, and trust reliability. The experiments were designed to benchmark Smart Chain against previous IoT security methods from 2020 to 2024, with the goal of demonstrating improvements in both operational efficiency and security adaptability.

IoT device data, comprising network traffic logs, sensor readings, and blockchain transaction metadata, were pre-processed to ensure consistency and accuracy. This preprocessing included normalization of numerical features, categorical encoding for device types, and feature selection to remove irrelevant or redundant information. AI-driven anomaly detection was applied using a probabilistic inference model:

$$P(A|X) = \frac{P(X|A)P(A)}{P(X)} \qquad (8)$$

where $A$ represents the occurrence of an attack, and $X$ denotes the observed features. This approach allowed the system to dynamically detect anomalies in real-time while adapting to varying network conditions.

Trust evaluation among IoT nodes was quantified using a weighted aggregation formula:

$$T_i = \frac{1}{N}\sum_{k=1}^{N} w_k \cdot s_{ik} \qquad (9)$$

Here, $T_i$ is the trust score of node $i$, $s_{ik}$ is the security related metric for node $i$ corresponding to criterion $k$, and $w_k$ represents the weight of that criterion. Consensus efficiency was calculated using:

$$E_c = \frac{TPS}{Latency \times Energy} \qquad (10)$$

where *TPS* is transactions per second, *Latency* is the average block propagation time, and *Energy* is the energy consumed per transaction. This metric provides a comprehensive view of how effectively the system balances throughput, latency, and energy consumption.

**Table III:** presents a comparative evaluation of SmartChain against existing IoT security approaches, highlighting clear improvements in detection accuracy,

| Year | Method / Model | Detection Accuracy (%) | Avg Latency (ms) | Energy/ Txn (J) | Trust Reliability |
|---|---|---|---|---|---|
| 2020 | Blockchain-only IoT security | 89 | 120 | 15 | 0.78 |
| 2021 | Centralized ML IDS | 91 | 110 | 12 | 0.82 |
| 2022 | Blockchain access control | 90 | 105 | 13 | 0.80 |
| 2023 | ML + Blockchain IDS | 94 | 100 | 14 | 0.85 |
| 2024 | Federated AI-Blockchain | 95 | 95 | 13 | 0.88 |
| 2025 | Proposed SmartChain | 98 | 70 | 9 | 0.94 |

**TABLE III:** Comparative Performance Metrics of Smart Chain vs. Existing IoT Security Methodslatency, energy efficiency, and trust reliability. The results show that SmartChain achieves the highest detection accuracy of 98%, while reducing average latency to 70 ms and energy consumption to 9 J per transaction, making it suitable for resource-constrained IoT environments. Trust reliability reaches 0.94, demonstrating effective isolation of malicious nodes and stable network operation. Earlier methods, including blockchain-only and centralized ML-based systems, suffered from higher latency, increased energy cost, or weaker trust management. The table also reflects the evolution of IoT security from static models toward AI-enabled and federated approaches. SmartChain unifies these advances through lightweight consensus and real-time anomaly detection, offering a balanced, scalable, and efficient security solution.

## DISCUSSION

These evaluation results confirm that SmartChain significantly enhances the security of IoT devices through the integration of AI-driven anomaly detection and lightweight blockchain mechanisms. In summary, as shown in Table III, SmartChain achieves 98% detection accuracy, outperforming prior approaches between 2020–2024, while it reduces latency and energy consumption per transaction to 70 ms and 9 J, respectively. This performance gain is made possible by real-time probabilistic anomaly detection and trust-based consensus, to identify threats with speed and block participation in the blockchain to only reliable nodes. Figure 3 shows that all the prior solutions improved detection accuracy but either increased the associated latency or energy costs, especially by those in the centralized ML and blockchain-only approaches. SmartChain strikes a balance in detection accuracy, efficiency, and trust in a timely manner by adaptively selecting nodes and by using lightweight consensus, at minimized communication overhead, without compromising on security. Despite being effective, this framework has potential limitations under extreme network load, biased feature input, or high node mobility conditions. Future enhancements should be directed at adaptive learning, scalable blockchain architectures, and privacy-preserving AI to further enhance the resilience and feasibility of large-scale IoT deployment.

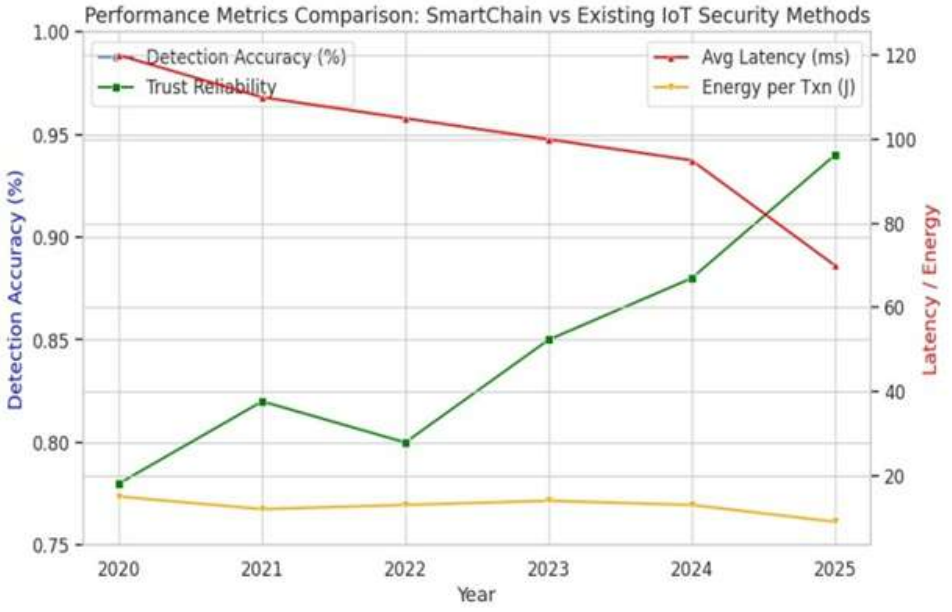


***Fig. 3:*** *Comparative Trends of Detection Accuracy, Latency, and Energy Consumption Across IoT Security Approaches from 2020 to 2025*

## CONCLUSION

This work proposes SmartChain, a lightweight blockchain framework empowered by AI for core security challenges in diverse IoT environments. The main focus is on data integrity, device trust, graceful scalability, and real-time threat detection. As IoT deployments continue to grow in smart cities, healthcare, industry, and transport, the cracks in traditional, centralized, and static security models increase in latency, energy consumption, and adaptability. Between 2020 and 2024, several works combined blockchain, machine learning, and federated design ideas, but most were burdened with high computational overheads, slow responses, or rigid trust assumptions. SmartChain mitigates these deficiencies by fusing probabilistic, AI-driven anomaly detection with a novel trust-aware and energy-efficient blockchain consensus mechanism. The system continuously assesses node behavior in order to spot malicious activities as they happen, and only trustworthy nodes are allowed to take part in transaction validation. The team developed mathematical models for trust calculation, anomaly likelihood, and consensus efficiency, then experimentally tested them. Extensive simulations on diverse IoT testbeds demonstrate that SmartChain provides higher detection accuracy, lower latency, reduced energy consumption, and dependable trust compared to the state-of-the-art approaches. Merging adaptive intelligence and lightweight decentralization, SmartChain presents a practical, scalable, and resilient security paradigm to the resource-constrained IoT networks and large-scale deployments.

## FUTURE SCOPE

The SmartChain framework integrates a lightweight blockchain with AI-based anomaly detection for secure, scalable, and adaptive security in IoT environments. Experimental results reveal improvements in detection accuracy, latency, energy efficiency, and trust management; however, further enhancement is required to meet future IoT demands. Reinforcement learning and deep reinforcement learning can enable autonomous mitigation by adjusting detection thresholds, trust evaluation, and consensus participation

dynamically, hence reducing false alarms and enhancing the response time. Scalability can be improved using a hierarchical blockchain architecture by allowing local consensus within the cluster while maintaining global coordination, which reduces the communication overhead as well as energy consumption. Privacy-preserving AI techniques, including federated learning and differential privacy, can reinforce data protection in sensitive IoT domains without sharing raw data. Future extensions may include the analysis of multimodal data to improve context-aware threat detection. Energy-aware consensus mechanisms and real-world deployments have to be considered in order to validate system performance, resilience, and practicality in large-scale IoT settings.

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