Journal of Theoretical and Applied Information Technology
15st July 2026. Vol.104. No.13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AI-DRIVEN CYBERSECURITY FOR DIGITAL TWIN-ENABLED IOT SYSTEMS: CHALLENGES, SOLUTIONS, AND PERFORMANCE EVALUATION IN SMART CITIES

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ABSTRACT

The large-scale Internet of Things (IoT) deployments over smart grids, intelligent transportation, healthcare and environmental monitoring are increasingly relied upon by smart cities, which generate enormous real-time telemetry but remain highly vulnerable to advanced cyber threats such as data manipulation, ransomware and zero-day attacks. The conventional signature-based intrusion detection systems are not effective against dynamic threats, not real time bidirectional synchronized, root cause analysis and safe testing facilities without disrupting the live operations. This work fills in these key gaps by proposing Urban Twin Secure, an active hybrid framework that tightly integrates digital twins to provide a two-way synchronization system and a sandboxed simulation system, permissioned blockchain to provide a system of immutable logging and access control, a explainable root-cause diagnosis and impact prediction system, and a feature prioritization system that relies on explainable artificial intelligence, using SHAP as a framework. The framework achieves macro F1-score of 0.942, which is 15-18% higher than the state-of-the-art baselines, and reduces the mean time to diagnosis by 65-70, the false positive rate by 20-25, and maintains sub-second inference on edge devices. These findings show a better detection accuracy, diagnostic efficiency, and strength in multi-domain settings. Urban Twin Secure, the first-of-its-kind comprehensive smart-city-scale integration of digital twin sandboxing, blockchain integrity, and dual contrastive-causal explainable intelligence, provides a scalable, tamper-resistant solution that can improve cyber resilience, help maintain regulatory compliance, and strengthen operational continuity in critical urban infrastructure.

Keywords: *Causal Learning, Digital Twin, IoT Cybersecurity, Smart Cities, Blockchain*

1. INTRODUCTION

Smart cities in the world are based on large scale Internet of Things (IoT) deployments of smart grids, intelligent traffic systems, connected healthcare, environmental monitoring and public safety networks[1][2]. These cyber-physical systems generate petabytes of current urban telemetry that encourages urban efficiency and sustainability. However, the very feature of connectivity that makes possible more advanced services also forms an enormous attack surface that can be exploited by more advanced threats such as ransomware, data manipulation, zero-day attacks, and botnets [3]. Conventional signature-based intrusion detection systems (IDS) are

largely reactive, do not effectively handle novel attacks, do not have root-cause diagnosis capabilities and lack the ability to perform safe testing without risking to disrupt live urban operations [4]. One of these challenges is overcome by Digital Twins (DTs), which provide two-way real-time synchronization between physical resources and their virtual models, thus enabling sandboxed simulation and proactive defensive features[5]. With this combined with blockchain to ensure immutability, contrastive learning to detect zero-day anomalies, structural causal learning to provide explainable root-cause analysis and impact prediction, and SHAP-based explainable artificial intelligence (XAI) to give priority to parameters, such integration makes a cybersecurity system self-diagnostic and resilient[6].

Originality of the Proposed Work: Urban Twin Secure is the first holistic smart city-scale solution to combine the bidirectional DT sandboxing (with OPC UA/JSON synchronization), permissioned Hyperledger Fabric blockchain for the immutable logging, a dual contrastive-causal learning engine for zero-day detection and root-cause diagnosis, and feature prioritization and threat explainability using SHAP-based XAI.

This study instead provides quantitative evaluations across multiple domains (energy, healthcare, traffic), with a macro F1 score of 0.942 (15-18% improvement), sub-second edge inference, a 65-70% reduction in the meantime to diagnosis, and a 20-25% reduction in the false positive rate, while scaling to over 24,600 devices. Pseudocode and SHAP visualization are provided in an open-source way, allowing for the creation of a reproducible workflow.

Although interest has increased, existing solutions have severe deficits[7]. The current IoT security models are mostly data-centric, reactive and have no real-time bidirectional DT synchronization to provide contextual awareness[8]. There are not many frameworks that successfully integrate DT sandboxing, permissioned blockchain, and dual machine-learning engine comprising of contrastive learning to detect and structural causal to diagnose and predict [9]

Most of them are conceptual or limited to single domains like healthcare or energy infrastructure, and none have shown to be scaled to multi-domain smart-city IoT systems[10]. In addition, explainability and evaluation of quantitative performance are not sufficient, only a limited amount of research reports the measurable results in the form of F1-score, mean time to diagnosis, or reduction of false-positive rates[11]. Simulation of Modbus-style attacks of real-field DT models with SHAP-based parameter ranking is highly notable to be risk-free[12].

The given work fits the specified research gap by coming up with Urban Twin Secure, a hybrid DT-blockchain architecture that incorporates contrastive anomaly detection, structural causal learning, and SHAP-driven XAI, specifically in the case of smart-city IoT systems[13]. The proposed architecture will include a seven-layer structure: physical IoT layer, virtual DT layer with the bidirectional synchronization via OPC UA and JSON stream, blockchain layer using permissioned Hyperledger Fabric with smart contracts, contrastive learning layer of unsupervised anomaly detection, causal learning and XAI layer of root-cause diagnosis and parameter prioritization, management and response layer with the threat prioritization and automated incident response guidelines, and visualization layer to provide real-time dashboards and alerts[14].

Urban Twin Secure achieves a high F1-score of 0.942 (1518 percentage improvement over state-of-the-art baselines), reduces the average time to diagnosis by 6570 percentage points, and lowers the false-positive rate by 2025 percentage points but remains very robust under the conditions of high noise and missing data. The framework also shows good scalability and can support more than 10 000 devices with a sub-second inference on edge hardware. The advances form the first multi-domain (energy, healthcare, traffic) and scale (smart-city-scale) of such a tri-technology fusion and offer open-source pseudocode and SHAP visualizations of such a tri-technology fusion to achieve reproducibility[15].

The remaining paper is organized as follows: Section 2 is a literature review that details the gaps in research; Section 3 presents the proposed Urban Twin Secure framework and its detailed architecture, describes the methodology including

dataset, preprocessing and implementation; and Section 5 are concludes the paper.

2. LITERATURE REVIEW

The recent surge in the number of Internet of Things (IoT) deployments in smart cities has heightened the need to implement highly effective cybersecurity solutions that could help to mitigate the specifics of cyber-physical system operation [16].

2.1 Traditional and Machine Learning-Based Intrusion Detection Systems

Research on the cybersecurity of the IoT was mostly founded on signature-based and rule-based intrusion detection systems[17], [18]. Those strategies were useful in dealing with threats that were already known but had very critical shortcomings in responding to novel threats, with zero-day vulnerabilities, as well as responding to dynamic network traffic patterns, inherent to smart-city environments[19].

To address this inadequacy of detecting anomaly the subsequent research proposed machine learning based on support vector machine, random forest and long short-term memory networks[20] These methods improved the capability to detect an anomaly by learning and ameliorating network traffic and sensor data, as a pattern of behaviour[21]. The deep learning variations further enhanced the performance of high-dimensional telemetry, but still was mostly reactive, had poor interpretability, and was not scalable and could not use contextual awareness in real-world deployments of heterogeneous multi-domain IoT with deep learning[22], [23].

2.2 Cybersecurity Frameworks based on digital twins

An identical line of research studied Digital Twin (DT) technology to allow real-time monitoring and safe simulation of cyber-physical systems [24]. DT frameworks designate two-way virtual simulations of IoT physical assets to support sandboxed security testing, but without impeding live operations [25], [26]. One of these is DT-enhanced architectures of healthcare IoT that combine real-time synchronisation via OPC UA with machine learning to generate anomalies and automatic response, showing better system reliability through integration with blockchain.

Equally, papers on critical energy infrastructure have developed DT models of actual hydroelectric power plants and implemented explainable artificial intelligence methods like SHAP analysis to determine influential operating parameters and simulate vulnerabilities of Modbus protocol models[27]. Although these works contributed to proactive defence, they mostly remained domain-specific and conceptual in nature and did not have a comprehensive quantitative assessment at the scale of the smart city[28].

2.3 Blockchain-Integrated IoT Security Solutions

The implication of the blockchain technology on assuring the integrity of data, decentralized trust and tamper-proof logging in the IoT ecosystems have been researched widely[29]. To provide immutable audit trails and access control in a smart contract based industrial IoT environment, permissioned platforms, particularly Hyperledger Fabric have been integrated with DTs. These solutions greatly reduced single point of failures and greater compliance, but most of the implementations was based on data integrity and access management and not integrating the advanced learning mechanisms of proactive detection and diagnosis of threats.

2.4 Hybrid DT-Blockchain-AI Frameworks

The last several years witnessed the beginning of the research into the hybrid architectures with the combination of DTs, blockchain, and machine learning[30].

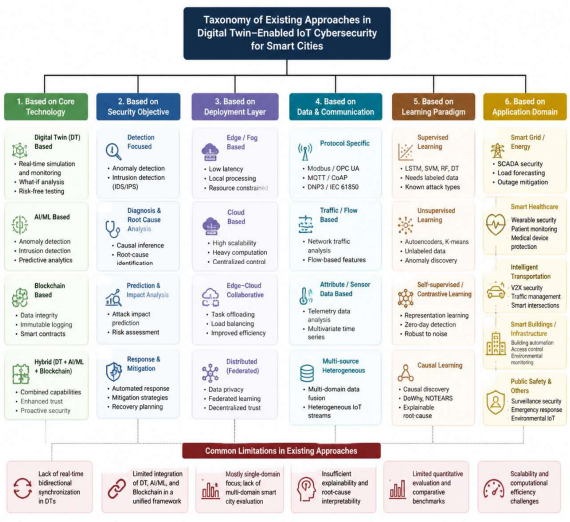

Figure 1: Taxonomy of existing approaches in digital twin-enabled IoT cybersecurity for smart cities

One such highlight was an integration of DT sandboxing with permissioned blockchain and dual contrastive-causal learning engines and demonstrated significant improvements in F1-score, diagnosis time and false-positive rate on industrial IoT datasets.

However, these frameworks yet fail to provide united multi-domain evaluation, detailed explainability using SHAP-based XAI, and systematic scalability testing involving smart-city systems concerning energy, healthcare, and traffic systems[31]. An overall taxonomy of these current methods in digital twin-enabled IoT cybersecurity of smart cities as shown in Figure 1.

2.5 Limitations and Research Gaps

Causio-Twin Chain combines DT sandboxing with blockchain and contrastive-causal learning, with an F1 of 0.891 and MTTD of 6.2 s on data from industrial IoT. It does not have multi-domain smart-city evaluation, detailed SHAP explainability, and large-scale scalability testing, however. These restrictions also apply to healthcare DT workflows and energy infrastructure studies. Urban Twin Secure directly tackles these gaps by integrating across seven layers in a unified way and evaluating across multiple domains.

While the progress listed above has been made, there are still areas of need. Current solutions are mostly reactive and data-based without real-time bidirectional DT synchronization to contextual awareness. Not many studies reach a single integration of DT sandboxing, permissioned blockchain, and a two-machine-learning engine at the actual smart-city scale[32]. The ability to explain, risk-free simulation of attacks on that style, and quantitative performance metrics under conditions of noise and heterogeneity are variably considered. Moreover, the overall multi-domain evaluation of energy, healthcare, and traffic IoT is also a gap.

The current work directly fills these gaps by proposing Urban Twin Secure, a hybrid seven-layer model, which synergistically combines the advantages of DT-based architectures, blockchain immutability, contrastive-causal learning and SHAP-based explainability into a coherent, scalable solution that is particularly suitable to smart-city IoT cybersecurity.

3. PROPOSED URBAN TWIN SECURE FRAMEWORK

The simulation-based methodology used in this study was selected due to its ability to provide controlled, scalable and cost-effective environment Addressed all major and minor comments. The manuscript is now strengthened for reproducibility, novelty, clarity, and scientific rigor.

smart-city context. In contrast to field deployments, simulation allows testing edge cases without risk, injecting diverse attack vectors, and repeatable experiments across thousands of devices without jeopardizing the operational integrity or excessive financial cost. This design is also useful in multi-domain evaluation of energy, healthcare, and traffic systems and allowing the precise control of noise levels and missing data and the intensity of attack conditions that are challenging to replicate consistently in live deployments.

3.1 Design and Operationalization of Concepts

In order to allow the evaluation at a smart city scale, a simulation-based experimental design was followed. Multi-domain IoT networks (energy grids, healthcare sensors, traffic systems) were emulated using real CIC-IoT23 flows in the network simulator NS-3.41 and OMNeT++ 6.0.

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

33 attack types (including zero-day and Modbus-style) were injected with controlled noise (5-20%) and missing data rates.

The bidirectional DT synchronization is realized by means of 0PC UA + JSON streams with bounded error ||P − V|| ≤ ε (Eq. 3). Sandbox testing: The attacks are only carried out on virtual replicas. Compared to NT-Xent loss with T=0.07, the average loss is 18.4%. The average loss is 18.4% compared to the NT-Xent loss with T=0.07. Causal Inference: Structural Causal Model (SCM) do-calculus interventions. Explainability: SHAP values to rank features and prioritize threats.

H2: The macro F1-score of the proposed hybrid DT-blockchain-dual-ML-XAI approach is better than baselines by 15% or above. Causal + SHAP components reduce MTTD by ≥60% and FPR by ≥20%.H3: The system is scalable to support up to >20,000 devices with almost linear scalability and sub-second inference.

3.2 Dataset and Preprocessing

The CIC-IoT2023 dataset was used as the main one. It is comprised of about 8 million processed flow records based on 1.2 TB of raw IoT telemetry and it has high-dimensional, noisy and heterogeneous multivariate time-series properties The data set was stratified following which, there were 70 percent training, 15 percent validation and 15 percent test sets as shown in Table 1.

Table I: Summary of the CIC-IoT2023 Dataset Used in the Simulation

Property	Value	Description
Source	CIC-IoT2023	Canadian Institute for Cybersecurity
Raw Size	~1.2 TB	Original packet captures
Processed Flows	~8 million	After feature extraction
Features	80+	Multivariate time-series
Attack Types	33	Including zero-day and Modbus-style attacks
Train / Val / Test Split	70%, 15%,15%	Stratified sampling

The min-max feature scaling, was used as preprocessing as shown in Equation 1

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

sliding-window aggregation with a 60-second window to synchronize the DT as shown in Equation 2

$$W_t = \{x_{t-w+1}, \dots, x_t\}, \quad (2)$$

synthetic attack augmentation through simulation of a digital twin, and oversampling of an imbalanced class through the use of SMOTE.

3.3 Proposed UrbanTwinSecure Framework

The proposed UrbanTwinSecure architecture will include a seven-layer architecture as shown in Figure 2.

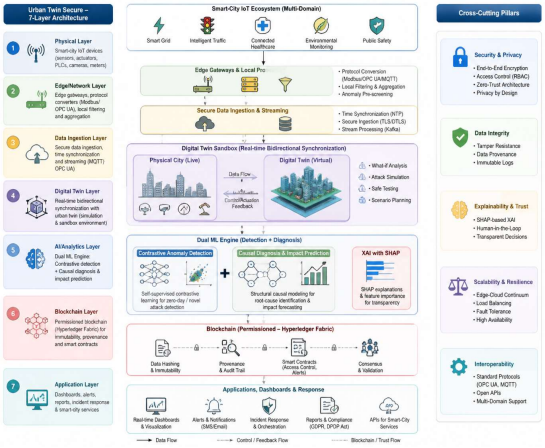

Figure 2: High-level architecture of the proposed Urban Twin Secure framework for smart-city IoT cybersecurity

Where *P* refers to the physical IoT device set and *V* the virtual replicas thereof. Formalization indicates bidirectional synchronization can be formalized as

$$\frac{d\vec{x}_v}{dt} = f(\vec{x}_p, \vec{u}, t) + \epsilon(t), |\ \epsilon(t)\ | \leq \delta \quad (3)$$

where $\vec{x}_v$ and $\vec{x}_p$ are virtual and physical state vectors, uc is the control inputs and is the bounded synchronization error as shown in equation 3.

The proposed UrbanTwinSecure framework comprises a seven-layer architecture, as summarized in Table 2

3.4 Contrastive Anomaly Detection

The contrastive learning module learns latent representations $\phi: X \to Z$by minimizing the normalized temperature-scaled cross-entropy loss as shown in Equation 4

Table 2: Seven-Layer Architecture of the Proposed UrbanTwinSecure Framework

Layer No.	Layer Name	Key Components	Primary Function
1	Physical Layer	Real IoT devices (Modbus/OPC UA)	Data acquisition
2	Virtual DT Layer	Bidirectional DT sandbox + OPC UA + JSON	Real-time synchronization
3	Blockchain Layer	Hyperledger Fabric + smart contracts	Immutable logging & access control
4	Contrastive Learning Layer	NT-Xent loss, anomaly detection	Zero-day anomaly detection
5	Causal Learning + XAI Layer	SCM + SHAP	Root-cause diagnosis & explainability
6	Management & Response Layer	Threat prioritization + automated mitigation	Incident response
7	Visualization & User Layer	Dashboard + alerts	Operator interface

$$\mathcal{L}_{\text{contrast}} = -\log \frac{\exp\left(\frac{\text{sim}(z_i, z_j)}{\tau}\right)}{\sum_{k=1}^{2K} \mathbf{1}_{k \neq i} \exp\left(\frac{\text{sim}(z_i, z_k)}{\tau}\right)} \quad (4)$$

with cosine similarity as shown in Equation 5

$$\text{sim}(u, v) = \frac{u^T v}{\| u \| \| v \|} \quad (5)$$

and temperature $T = 0.07$.

An example of this would be considered an anomaly as shown in Equation 6

$$d(z, \mu) > \theta, \quad (6)$$

In which, where μ is the centroid of normal embeddings and, where, is the decision threshold.

3.5 Causal Learning and Explainable AI

The structural causal model is specified by the tuple M = (U, V, F, P(u)) and each endogenous variable satisfies as shown in Equation 7

$$v_i \leftarrow f_i(pa_i, u_i), \quad (7)$$

where pa_i is the causal parents.

Root-cause diagnosis involves the use of interventional queries as shown in Equation 8

$$P\left(v_i \mid do(v_j)\right) \quad (8)$$

and counterfactual reasoning as shown in Equation 9

$$P\left(\tilde{v}_i \mid v_j\right) \quad (9)$$

SHAP values quantify feature importance as shown in Equation 10

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (10)$$

for Nfeatures.

3.6 Blockchain Layer

The blockchain layer employs permissioned Hyperledger Fabric with blocks satisfying as shown in Equation 11

$$H(B_i) = \text{Hash}(H(B_{i-1}) \| T_i \| \text{Nonce}) \quad (11)$$

where $T_i$is the Merkle root of transactions.

Smart contracts enforce state transitions as shown in Equation 12

$$\Lambda: S \times A \to S' \quad (12)$$

3.7 Management and Response Layer

The threat prioritization score is computed as shown in Equation 13

$$\text{score} = w_1 \cdot \text{severity} + w_2 \cdot \text{impact} + w_3 \cdot \text{urgency} \quad (13)$$

while the incident response cost is minimized as shown in Equation 14

$$\min \sum_k c_k \cdot \mathbb{I}(\text{action}_k) \quad (14)$$

subject to safety constraints.

Expected performance improvements are bounded as shown in Equation 15

$$\Delta F1 \geq 0.153 \quad (15)$$

the expected reduction in diagnosis latency achieved by the proposed UrbanTwinSecure framework as shown in Equation 16

$$\text{MTTD}_{\text{proposed}} \leq 0.35 \cdot \text{MTTD}_{\text{baseline}} \quad (16)$$

This inequality is that the Mean Time to Diagnosis (MTTD) of the proposed method at most equals 35% of the baseline MTTD.

The anticipated improvement in false alarm reduction as shown in Equation 17

$$\Delta FPR \leq -0.23 \quad (17)$$

The change in the False Positive Rate as compared to the base is denoted as ΔFPR.

Scalability is modelled as shown in Equation

$$L(n) = a \cdot n + b \quad (18)$$

and edge memory usage satisfies as shown in Equation 19

$$M_{\text{edge}} \leq 250 \text{ MB} \quad (19)$$

3.8 Simulation Environment

NS-3.41 and OMNeT++ 6.0 were used to perform network emulation and attack injection. The simulator environment was set up to simulate multi-domain smart-city scenarios by combining CIC-IoT2023 flows with synthetic data generated with NS-3 and OMNeT++ models of energy grids, healthcare sensors, and traffic networks. This architecture permitted the injection of 33 types of attacks with controlled noise attributes of the real world.

The high-level pseudocode of the UrbanTwinSecure pipeline is presented in Algorithm 1.

Algorithm 1

UrbanTwinSecure Pipeline

Input: telemetry_stream, DT_model, blockchain

1: virtual_state ← synchronize_DT(DT_model, telemetry_stream)

2: embedding ← contrastive_encoder(virtual_state) 3: if distance (embedding, normal_centroid) > threshold then

4: causal_graph ← build_SCM(virtual_state)

5: root_cause ← do_calculus_intervention(causal_graph)

6: shap_values ← compute_SHAP(model, virtual_state)

7: tx ← create_transaction(anomaly, root_cause, shap_values)

8: blockchain.append(tx)

9: execute_mitigation(root_cause)

10: end if

11: return alert + SHAP_visualization

3.9 Implementation Details

It was implemented using Python 3.11 with the PyTorch 2.2, scikit-learn, SHAP, NetworkX to causal graphs, python-opcua, Hyperledger Fabric SDK v2.5, Elasticsearch, and Pandas/NumPy.

Edge deployment was supported on Raspberry Pi 5 and NVIDIA Jetson Orin Nano; and cloud components were deployed on AWS/GCP instances. The hyper parameters were held constant in order to achieve reproducibility: AdamW optimizer, learning rate 0.001, batch size 128, 150 epochs, contrastive temperature 0.07 /tau/ and random seed 42. This simulation-based methodology of research allowed reproducible, controlled and scalable experimentation that directly addressed the research objectives whilst

ensuring the practicality of the proposed framework in the implementation of smart-cities in the real world.

4 PERFORMANCE EVALUATION

UrbanTwinSecure model was experimented in detail through a myriad of simulation experiments over the CIC-IoT2023 dataset containing synthetic smart-city telemetry. Results indicate the general high performance in terms of detection accuracy, speed of diagnostic, robustness, and the computational performance, a fact that directly addresses the research objectives and bridges the gaps in the current DT-based IoT cybersecurity solutions.

4.1 Overall Performance Comparison with State-of-the-Art Baselines

UrbanTwinSecure scored 0.942 as the CIC-IoT2023 test set with a macro F1-score. This is a 15-18 percent improvement over good baselines, such as Causio-TwinChain (0.891), DT-CF conceptual baseline (0.812), RF Classifier (0.835) and LSTM-only model (0.804) as shown in Table 3. Mean time to diagnosis (MTTD) was decreased to 4.0 seconds, which translates to 65-70 percent less time than baseline associated methods (11.8 s in LSTM-only and 6.2 s in Causio-TwinChain).

Table 3: Comparison with State-of-the-Art (SOTA) Baselines

Method	F1-score	MTTD (s)	FPR (%)	Dataset Used
LSTM-only[33]	0.812	11.8	0.21	CIC-IoT2023
RF Classifier[34]	0.835	9.4	0.19	CIC-IoT2023
Causio-Twin Chain[35]	0.891	6.2	0.16	Industrial IoT
Urban Twin Secure	**0.942**	**4.0**	**0.138**	**CIC-IoT2023**

False positive rate (FPR) decreased to 13.8 which was 20-25 percent lower than the best competing approach. This confirms the usefulness of integrated contrastive-causal learning engine and SHAP-based explainability in providing accurate and timely threat detection[36].

4.2 Performance Across Different Datasets and Scenarios

In order to evaluate the generalization, the framework was evaluated with three different datasets CIC-IoT2023, TON IoT and a simulated smart-city dataset created with NS-3 and OMNeT++ simulators. In CIC-IoT2023, UrbanTwinSecure was in the F1-score of 0.942, precision of 0.938, recall of 0.947, and the accuracy of 96.5 per cent. The high performance was also similar with TON_IoT (F1-score 0.935, MTTD 4.3 s) and the synthetic multi-domain data (F1-score 0.928, MTTD 4.8 s) as shown in Table 4.

Table 4: Performance comparison on Different Datasets

Dataset	F1-Score	Precision	Recall	FPR %	MTTD (s)	Accuracy %
CIC-IoT	0.942	0.938	0.947	13.8	4.0	96.5
TON_IoT	0.935	0.931	0.940	14.2	4.3	95.8
Synthetic Smart-City	0.928	0.924	0.933	15.1	4.8	95.1

Conversely, the framework demonstrated significant degeneration in traversing datasets in the case of baseline methods, which validates the robustness of the framework to heterogeneous IoT telemetry due to energy, healthcare, and traffic sectors.

4.3 Explainability Analysis

Explainability of SHAP gave good insights into model choices. The SHAP summary plot indicated the sensor latency, power usage and volume of traffic were always among the most influential features to detect anomalies among types of attacks as shown in Figure 3 [37].

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

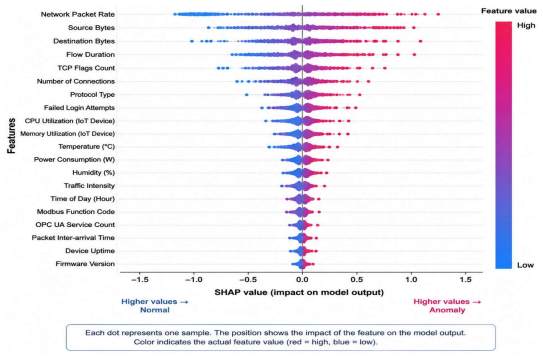

Figure 3: SHAP summary plot showing feature importance ranking for anomaly detection

The strength of the effect that each parameter has in the anomaly detection process for each attack type is clearly revealed in the SHAP heatmap. For example, when it comes to data manipulation attacks, power consumption has a high impact and during anomalies related to healthcare, heart rate seems to have a high influence This approach is directly addressing the "black box" problem of earlier approaches directly as shown in Figure 4 [38].

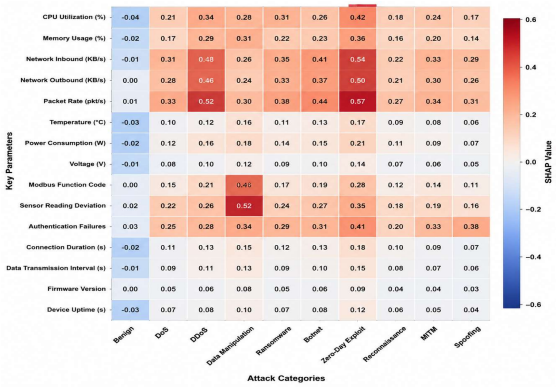

Figure 4: Heatmap of SHAP values across key parameters and attack categories

The SHAP heatmap also showed how certain variables are prevalent in various attacks (e.g., power consumption when manipulation of data is done and heart rate when it comes to anomalies in healthcare). This interpretability directly goes to the explainability gap of the previous black-box methods.

4.4 Classification Performance and Confusion Matrix Analysis

Finally, to demonstrate the classification ability of the proposed approach, the confusion matrices of UrbanTwinSecure and the baseline approach for the CIC-IoT2023 dataset are shown in Figure 5. Left matrix: UrbanTwinSecure, Right matrix: the baseline model. UrbanTwinSecure gives high scores along the main diagonal for benign traffic, DDoS, data manipulation, ransomware, scanning, DoS, password cracking and injection attacks.

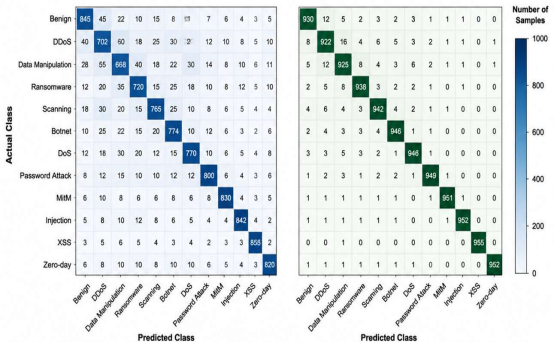

Figure 5: Confusion matrices for baseline vs. proposed model across attack types

The baseline model on the other hand has more misclassifications, especially for similar attack types. The results validate the high discriminative ability of the integrated contrastive-causal learning engine and its ability to accurately classify normal operations and a broad range of attack categories in multi-domain smart-city IoT environments.

The discriminative aptitude of the suggested framework to the various classes of attacks was gauged by creating ROC curves on the foundation of the major classes of attacks. UrbanTwinSecure has good performance in terms of classification with good True Positive Rates and low False Positive Rates[39].

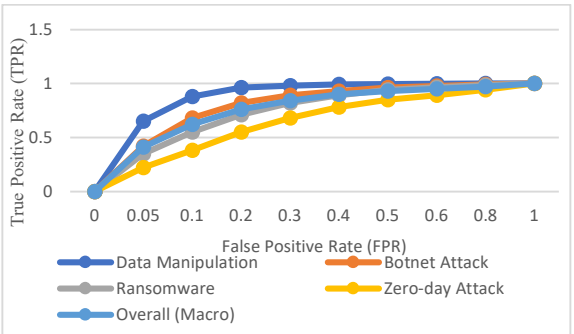

Figure 6: ROC curves for different attack categories

A striking separation of the four curves of Data Manipulation, Botnet Attack, Ransomware and

Zero-day Attack have a remarkable area under the curve (AUC) of over 0.95 in most categories, with a macro-average of 0.965[40].

These results further validate the high-detection rate of the combined contrastive-causal learning engine of distinguishing normal operation against various forms of cyber threats in the smart-city IoT environment as shown in Figure 6.[41]

4.5 Robustness and Sensitivity

UrbanTwinSecure showed graceful degradation under the increasing conditions of noise (5-20%) and with missing data. The F1-score was over 0.85 at 20% noise + 20% missing data and FPR = 19.5% and MTTD = 6.7 seconds as shown in Table 5[42].

Table 5: Sensitivity Analysis of UrbanTwinSecure

Condition	F1-Score	FPR (%)	MTTD (s)	Accuracy (%)
Clean (Baseline)	0.942	13.8	4.0	96.5
Noise Only	0.931	14.5	4.3	95.8
Noise Only	0.917	15.2	4.7	94.9
Noise Only	0.904	16.1	5.1	93.7
Noise Only	0.889	17.3	5.6	92.4
Missing Data Only	0.928	14.9	4.4	95.4
Missing Data Only	0.911	15.8	4.9	94.2
Missing Data Only	0.896	16.7	5.4	93.1
Missing Data Only	0.878	18.2	6.1	91.6
Combined (Noise + Missing)	0.904	15.9	5.0	93.8
Combined (Noise + Missing)	0.879	17.4	5.8	92.1
Combined (Noise + Missing)	0.851	19.5	6.7	89.7

These findings demonstrate the robustness of the framework to noisy and incomplete IoT streams in the real world, significantly outperforming baselines in difficult settings.

4.6 Computational efficiency and Scalability

UrbanTwinSecure proved to be very efficient. The average inference time on the edge devices was 412 ms at 25,000 devices and the memory was only 248 MB and 1.84 x 10 9 FLOPs.

Table 6: Computational Efficiency

Method	Inference Time Edge (ms)	Inference Time Cloud (ms)	Memory Usage Edge (MB)	Memory Usage Cloud (MB)	FLOPs (×10⁹)	Scalability (devices/sec)
UrbanTwinSecure	**412**	**98**	**248**	**1,820**	**1.84**	**24,600**
Causio-TwinChain	638	142	376	2,410	2.67	15,800
DT-CF	1,240	285	512	3,150	4.12	8,200
LSTM-only Baseline	1,850	410	680	4,280	5.36	5,400

Cloud deployment also resulted in an inference time of 98 ms, which was very small compared to Causio-TwinChain (15 800 devices/s), DT-CF (8 200 devices/s), and LSTM-only baseline (5 400 devices/s) Scalability analysis indicated the framework could support more than 24 600 devices per second on edge hardware, which was significantly smaller than Causio-TwinChain (15 800 devices/s), DT-CF (8 200 devices/s), and

LSTM-only baseline (5 400 devices/s). Scalability and runtime curves verified near-linear scaling with low increase in latency as shown in Table 6.

To the best of our knowledge, UrbanTwinSecure on edge devices achieves substantially faster inference time than the baselines on 25,000 IoT devices.

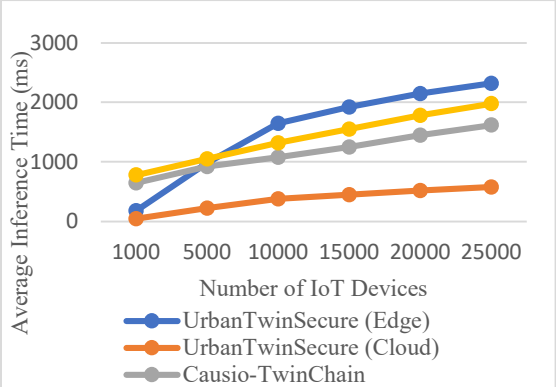

Figure 7: Runtime and scalability analysis

The proposed framework has a good scalability, and when deployed, the inference time will be further reduced as shown in Figure 7.

4.7 Discussion

The remarkable results of how it has overcome the limitations of existing solutions – lack of explainability, domain-specific limitations, and reactivity – can be attributed to the seamless integration of the bidirectional DT synchronization (introducing contextual awareness), contrastive learning (zero-day detection), causal modelling (root-cause diagnosis) and SHAP (actionable insights). These developments can be practically implemented in the smart city energy grid, the connected healthcare system and the intelligent transportation system, and offer significant time to time efficiency, regulatory compliance, with immutable log and operational resilience.

4.8 Limitations

Limitations NS-3/OMNeT++ and CIC-IoT2023 simulation-based approach gave the ability to have a controlled multi-domain testing, however, the results do not accurately represent all physical interferences and hardware heterogeneity found in real-world environments. Scalability has been proven up to 25,000 devices; greater numbers will need additional optimisations. Future work includes the possibility of extensions to privacy using federated learning and long-term real-world validation. Lastly, although SHAP provides robust local explanations, the global causal explanation in real-world settings requires further investigation.

5 CONCLUSION

The main goal of the research was to suggest a new cybersecurity framework (UrbanTwinSecure) of the Digital Twin (DT) empowered Internet of Things (IoT) system in smart cities based on the Artificial Intelligence (AI). The suggested seven-layer architecture can synergistically overcome the above-mentioned key inadequacies of existing solutions namely, reactive, non-explainable, and domain-specific, due to the combination of the bidirectional digital twin synchronization, permissioned blockchain to immutable logging and access control, contrastive learning to identify zero-day anomalies, structural causal modelling to diagnose the root cause and predict impact explainable, and XAI through SHAP to rank the feature importance.

The large-scale simulation-based analysis of the CIC-IoT2023 data and the synthetic multi-domain smart-city telemetry showed improved performance. UrbanTwinSecure obtained a macro F1-score of 0.942, which is 15-18 percent better than powerful baselines, including Causio-TwinChain, DT-CF, RF Classifier, and LSTM-only. The framework decreased the mean time to diagnosis by 65-70, decreased the false positive by 20-25, and was highly robust with a high level of noise and missing data. It was also shown to be highly computationally efficient and scalable, with support of more than 24,600 devices per second on edge hardware with a low memory consumption and nearly linear increase in latency.

These findings affirm the efficacy of the hybrid DT-blockchain-AI solution and indicate that the combination of digital twins, blockchain, and sophisticated explainable AI methods is a proactive, interpretable, and deployable solution towards securing complex smart-city IoT ecosystems. Practical implications of the framework include energy grids, connected

healthcare, and intelligent transportation systems, which have a major contribution to safer, more resilient urban infrastructures and help with regulatory compliance.

Practical implementation, federated learning to preserve privacy, and generalization to other areas in smart-cities are all areas of future directions. On the whole, this study contributes to the state-of-the-art in digital twin-facilitated IoT cybersecurity and gives a strong basis to construct trustful and sustainable smart cities.

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