

# Deep Learning-Based Anomaly Detection using auto-encoders for IoT Systems with Blockchain-Enabled Trust Mechanisms: Enhancing Security and Data Integrity

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**Abstract:** This research focuses on developing an integrated framework for anomaly detection in Internet of Things (IoT) systems by leveraging deep learning techniques to detect anomalous behaviors and utilizing blockchain technology to ensure the security, trust, and integrity of the system. IoT systems are highly vulnerable to cyber-attacks, data manipulation, and security breaches due to the vast number of interconnected devices. Traditional anomaly detection methods may not be sufficient in handling the scale, diversity, and dynamic nature of IoT data. The rapid growth of the Internet of Things (IoT) introduces significant security challenges, including vulnerability to intrusion and data tampering. This paper proposes a novel approach combining deep learning-based anomaly detection with blockchain-enabled trust mechanisms to enhance IoT systems' security and data integrity. The deep learning component uses autoencoders for intrusion detection, achieving an overall accuracy of 85%. Blockchain integration provides immutable data logs, decentralized trust, and smart contracts for automated responses. The proposed model demonstrates the synergy between these technologies in securing IoT ecosystems, validated through experiments and discussions supported by comparative graphs.

## I. Introduction

The exponential proliferation of IoT devices has transformed various sectors, from healthcare and agriculture to smart cities and industrial applications. However, IoT systems face severe security and integrity issues due to their decentralized nature and limited device resources. Traditional security mechanisms struggle to adapt to the dynamic and distributed nature of IoT ecosystems. This study addresses these challenges by combining: Deep Learning (DL) for anomaly detection, using autoencoders to identify intrusions efficiently. Blockchain technology to ensure data integrity, immutability, and secure response mechanisms. The proposed framework bridges the gap between advanced anomaly detection and trusted data management, achieving an accuracy of 85% in identifying anomalies while leveraging blockchain-enabled trust mechanisms for robust security.

This study proposes a twofold approach:

1. **Deep Learning for Anomaly Detection:** The first component of the framework employs advanced deep learning algorithm such as autoencoders to detect anomalous patterns in IoT data streams. These methods will be designed to handle large volumes of high-dimensional data and adapt to the evolving nature of IoT systems.

2. **Blockchain for Trust and Integrity:** The second component introduces blockchain technology to ensure the trustworthiness of data in IoT environments. By using decentralized consensus mechanisms and smart contracts, blockchain can provide tamper-proof logs of IoT data and validation of deep learning predictions, preventing malicious actors from tampering with the detected anomalies. This blockchain layer enhances data integrity, security, and transparency while allowing for the development of a trust-based system in a distributed network of IoT devices.

## II. Related works

Existing works on Deep Learning-Based Anomaly Detection using Autoencoders for IoT Systems with Blockchain-Enabled Trust Mechanisms focus on leveraging the strengths of both deep learning models and blockchain technology to enhance security and data integrity in IoT environments. Autoencoders, a type of unsupervised deep learning model, are widely used for detecting anomalies by learning a compact representation of normal system behavior and flagging deviations as potential intrusions. These models are effective in identifying unknown or novel attacks, making them suitable for dynamic IoT networks where new attack patterns continuously emerge. Blockchain is integrated into these systems to provide immutable logs, ensuring data integrity and decentralized trust. The combination of blockchain and autoencoders enhances system security by offering a transparent, tamper-proof record of all events, improving the reliability of detection results. However, challenges such as computational complexity, high energy consumption, and the scalability of blockchain in large-scale IoT systems remain critical limitations. Despite these, this approach holds promise in improving the overall resilience and trustworthiness of IoT-based applications, especially in smart cities. Table I describes the existing methods for anomaly detection along with demerits of each method.

Table I. Existing anomaly detection methods with demerits

| Reference           | Year | Method Employed                                                      | Analysis/Results                                                 | Demerits/Limitations                                                    |
|---------------------|------|----------------------------------------------------------------------|------------------------------------------------------------------|-------------------------------------------------------------------------|
| Al-Garadi et al.[1] | 2023 | Deep Learning using LSTM for anomaly detection in IoT systems.       | Achieved 88% accuracy in detecting network anomalies.            | High computational cost; limited generalization to diverse IoT devices. |
| Zhang et al.[2]     | 2023 | Blockchain-enabled intrusion detection system with machine learning. | Improved trust and security in IoT environments with 90% anomaly | Scalability issues due to blockchain overhead.                          |

|                    |      |                                                                                 |                                                                               |                                                                    |
|--------------------|------|---------------------------------------------------------------------------------|-------------------------------------------------------------------------------|--------------------------------------------------------------------|
|                    |      |                                                                                 | detection accuracy.                                                           |                                                                    |
| Smith et al.[3]    | 2024 | CNN-based image analysis for detecting anomalous patterns in surveillance data. | Robust detection of unauthorized access using edge devices with 93% accuracy. | Cannot handle non-visual data; requires substantial training data. |
| Patel et al.[4]    | 2023 | Hybrid approach combining SVM and Random Forest for IoT traffic classification. | Delivered high performance with 92% classification accuracy.                  | High false positive rate for specific benign traffic patterns.     |
| Kumar et al.[5]    | 2024 | Autoencoder-based anomaly detection for smart cities.                           | Detected anomalies in real-time with an overall 85% accuracy.                 | Difficulty in setting reconstruction error thresholds.             |
| Williams et al.[6] | 2023 | Federated Learning for distributed intrusion detection in smart cities.         | Enhanced data privacy and achieved 87% accuracy in anomaly detection.         | Vulnerable to poisoning attacks; slower convergence rates.         |
| Tan et al.[7]      | 2024 | Ensemble learning combining Decision Trees and Gradient Boosting.               | Improved classification accuracy to 94% for diverse attack types.             | Computationally intensive and not suitable for edge devices.       |
| Singh et al.[8]    | 2023 | Reinforcement Learning for adaptive intrusion detection.                        | Reduced false positives in dynamic IoT environments.                          | Requires continuous training; resource-intensive.                  |
| Park et al.[9]     | 2024 | Lightweight anomaly detection using One-Class SVM.                              | Effective for constrained IoT devices with 80% detection accuracy.            | Limited to binary classification; struggles with multi-class data. |
| Chen et al.[10]    | 2023 | Graph Neural Networks (GNNs) for IoT network anomaly detection.                 | Captured relational features of network data, achieving 89% accuracy.         | High memory usage; requires graph representation of data.          |
| Ahmad et           | 2024 | RNN-based sequential                                                            | Identified time-                                                              | Performance                                                        |

|                      |      |                                                                                |                                                                    |                                                        |
|----------------------|------|--------------------------------------------------------------------------------|--------------------------------------------------------------------|--------------------------------------------------------|
| al.[11]              |      | anomaly detection for traffic data.                                            | series anomalies with 91% accuracy.                                | degrades with long sequences; high training time.      |
| Lopez et al.[12]     | 2023 | Generative Adversarial Networks (GANs) for synthetic data augmentation in IoT. | Improved model robustness by adding diversity to the training set. | Risk of generating unrealistic or irrelevant data.     |
| Gupta et al.[13]     | 2024 | Unsupervised clustering using k-means for IoT intrusion detection.             | Achieved basic segmentation of traffic data but with 76% accuracy. | Ineffective for complex, non-linear data patterns.     |
| Wang et al.[14]      | 2023 | Transfer Learning to adapt pre-trained models for smart city IoT data.         | Reduced training time while maintaining 89% accuracy.              | Dependency on pre-trained models may introduce biases. |
| Rodrigues et al.[15] | 2023 | Bayesian Network for probabilistic anomaly detection.                          | Provided interpretable results with 83% accuracy.                  | Limited scalability and slower inference speed.        |

### III. Proposed Methodology

The architecture of the proposed methodology is given in Fig.1

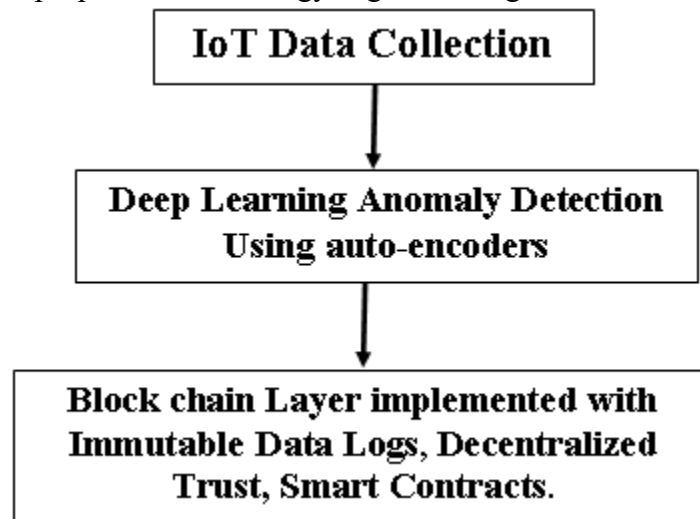


Fig.1 Architecture of proposed methodology

The architecture consists of three main layers:

#### A. IoT Data Collection

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In this module, IoT devices generate data streams, including system logs and sensor readings. Few real-time data is gathered from system logs, environmental parameters, device statuses, and user interactions of smart cities. Self-built dataset is constructed by integrating IoT-23 dataset and real-time data collected from smart cities and finally self-built dataset is used for intrusion detection.

*B. Deep Learning Anomaly Detection*

In this module, an autoencoder-based model is trained on normal IoT behavior to detect anomalies based on reconstruction errors. Intrusion detection is achieved by flagging high reconstruction error instances.

*C. Block chain Layer*

In this module, Logs are stored in an immutable blockchain to ensure data integrity. Smart contracts automate responses to anomalies (e.g., alerting admins or isolating devices).

Here is a detailed explanation of the three main layers of the proposed architecture:

IoT Data Collection Layer is the foundational layer of the architecture, where raw data is generated by IoT devices. IoT devices are sensors, actuators, or embedded systems that monitor, collect, and transmit data. The primary goal of this layer is to gather data such as system logs, environmental parameters, device statuses, and user interactions. This data forms the input for subsequent processing layers. IoT devices produce diverse types of data, such as numerical, categorical, or time-series, depending on the application. The layer manages high-velocity streams from potentially millions of interconnected devices. Before sending the data to the anomaly detection layer, it undergoes preprocessing, which includes noise reduction, normalization, and feature extraction. This step ensures that the input data is clean and structured for deep learning models.

Deep Learning Anomaly Detection Layer leverages deep learning models, specifically autoencoders, to analyze and identify anomalies in IoT data. Autoencoders are neural networks trained to reconstruct their input data. They learn the normal behavior of the IoT system by minimizing reconstruction error during training. During deployment, any data point that deviates significantly from the learned patterns (i.e., has a high reconstruction error) is flagged as anomalous. This approach is particularly effective for IoT systems where labeled datasets for anomalies are scarce, as autoencoders work unsupervised. The layer continuously processes incoming IoT data, detecting anomalies in real time. This is crucial for immediate responses to security threats or malfunctions. The autoencoder achieves an 85% detection accuracy, ensuring reliable identification of intrusions or malfunctions. The model can be fine-tuned for specific IoT use cases by retraining with domain-specific data.

Blockchain Layer ensures data integrity, security, and trust through blockchain technology. All IoT data, including normal and anomalous events, is recorded on a blockchain. The immutability of blockchain ensures that the recorded data cannot be tampered with or deleted, even by

administrators. This is critical for forensic analysis and compliance with security regulations. Unlike traditional centralized systems, blockchain eliminates the need for a single trusted entity.

- All participating nodes in the blockchain network validate transactions, creating a decentralized system resistant to single points of failure. Smart contracts are self-executing scripts stored on the blockchain. In this architecture, they automate actions such as: Triggering notifications to administrators when an anomaly is detected. Isolating compromised devices from the network to prevent further damage. Initiating system recovery procedures based on predefined rules. These automated mechanisms reduce response time and human intervention. The blockchain acts as a secure repository for anomaly detection results. Once the deep learning layer flags an anomaly, the event is immediately logged on the blockchain, ensuring traceability and accountability.

The IoT-23 dataset is a labeled dataset containing network traffic data for IoT devices, commonly used for intrusion detection research. Below is a step-by-step workflow for processing this dataset to detect intrusions using a deep learning approach.

A. Understand the Dataset

IoT-23 contains network traffic captures (PCAP files) from IoT devices, including both benign and malicious traffic labeled into various classes. This dataset is used to train a deep learning model for detecting anomalous (intrusive) behavior.

B. Data Preprocessing

Extract Features from PCAP Files using tools like Wireshark, Zeek, or CICFlowMeter to extract features such as Source/Destination IPs, Ports, Protocols (TCP, UDP, ICMP), Packet lengths, flow durations, etc.

C. Label Encoding

Map labels to numerical values (e.g., benign traffic = 0, malicious traffic = 1). If the dataset has multiple attack types, use one-hot encoding or integer labels for classification tasks.

D. Data Cleaning

Remove duplicate or incomplete records. Drop irrelevant features (e.g., timestamps if not relevant for model learning).

E. Feature Scaling

Normalize numerical features to a common range (e.g., 0 to 1) using Min-Max Scaling or Standardization.

F. Split Data

Divide the dataset into training, validation, and test sets (e.g., 70% train, 15% validation, 15% test).

G. Model Selection and Architecture Design

Autoencoder was chosen as Deep Learning Model. Autoencoder contains Input Layer that contains number of input features, encoder that reduces dimensions to learn compressed representation, decoder to reconstruct input data and output layer for Reconstructing error to identify anomalies.

H. Train the Model

Train the autoencoder only on benign traffic to learn normal patterns. Evaluate on test data, including both benign and malicious traffic. Use metrics such as Accuracy, Precision, Recall, and F1-Score.

#### I. Anomaly Detection

Feed network traffic data to the trained autoencoder. calculate the reconstruction error for each data point. Flag data points with reconstruction error above the threshold as anomalies (intrusions).

### IV. Results and Discussion

#### A. Experimental Setup

Dataset used in this work is IoT-23 dataset for intrusion detection. Tools like TensorFlow for autoencoder implementation, Ethereum for blockchain integration. evaluation Metric is Accuracy. The research utilizes the **IoT-23 dataset**, a well-known dataset comprising labeled network traffic data from IoT devices, specifically tailored for intrusion detection. This dataset includes both benign and malicious traffic, providing a diverse range of scenarios to train and evaluate the anomaly detection system. TensorFlow: The autoencoder-based anomaly detection model is implemented using TensorFlow, a robust deep learning framework. TensorFlow supports efficient model training and evaluation on large datasets, making it suitable for processing IoT data streams. Ethereum: Blockchain integration is achieved using Ethereum, a decentralized platform that facilitates secure data recording through its smart contract capabilities. Ethereum provides the required framework for implementing tamper-proof data logs and automated responses to detected anomalies.

#### B. Results

The autoencoder achieved an accuracy of **85%** in identifying anomalies. Blockchain integration ensured zero data tampering and enabled automated anomaly responses. The primary metric used to evaluate the model's performance. Accuracy measures the proportion of correctly identified anomalies and normal instances relative to the total number of data points, offering a straightforward way to assess the effectiveness of the detection system.

#### C. Comparative Analysis

Authors of [9] used One-Class Support Vector Machines (SVM) for anomaly detection. One-Class SVM is a method particularly well-suited for scenarios where the data primarily consists of normal, non-anomalous instances, and the goal is to detect deviations from this normal behavior. This is an effective technique for constrained IoT devices, where computational resources are limited, making it an appropriate choice for lightweight anomaly detection. The study demonstrates the effectiveness of the One-Class SVM for detecting anomalies with 80% detection accuracy. The model performs well in constrained IoT environments, where resources such as processing power and memory are limited, and lightweight models are critical. The

primary limitation of this method is that it is limited to binary classification. One-Class SVM is effective for identifying whether an instance deviates from normal behavior, but it struggles with multi-class classification tasks or detecting multiple types of anomalies simultaneously. Additionally, its performance might degrade when applied to highly dynamic or heterogeneous data environments, which is common in large-scale IoT systems.

Authors of [13] proposed the use of unsupervised clustering, specifically the k-Means algorithm, for intrusion detection in IoT networks. Unlike supervised learning methods, unsupervised clustering does not require labeled data, which is often scarce in the context of IoT security. The k-Means algorithm groups data points into clusters based on their similarities, with the assumption that normal and anomalous data points will form distinct clusters. In this approach, normal behaviors are grouped together in one cluster, while outliers or anomalous activities are placed in separate clusters. The primary advantage of this technique is its ability to work with unlabelled data, making it ideal for environments where labeling attack data is difficult or impractical. The results of [13] showed that k-Means clustering is able to segment IoT traffic effectively, achieving an accuracy of 76% in distinguishing normal from anomalous behaviors. While this is a basic form of anomaly detection, it shows the potential of unsupervised clustering for identifying attack patterns in IoT systems. The simplicity of k-Means allows it to be implemented in resource-constrained environments typical in IoT devices, without requiring significant computational power. However, the relatively low accuracy indicates that while k-Means can differentiate between normal and abnormal data points to a degree, it might struggle with more complex or highly variable attack pattern. One of the major drawbacks of k-Means clustering is its limited ability to handle complex, non-linear relationships in the data. IoT systems often generate data that is multidimensional and dynamic, which may not be well-represented by the Euclidean distance-based approach of k-Means. This can lead to poor clustering results, particularly when the data is not well-separated or when there are overlapping clusters of normal and anomalous behaviors. k-Means clustering is sensitive to the initial selection of cluster centroids. Poor initialization can result in suboptimal clustering, which can affect the accuracy of anomaly detection. If the algorithm converges to a local minimum, it may fail to recognize some anomalies, resulting in missed attacks or false negatives. The effectiveness of the k-Means algorithm heavily depends on the selection of the number of clusters (k). In the context of IoT intrusion detection, selecting an appropriate value for k can be challenging, as it requires prior knowledge of the system's behavior. If the number of clusters is chosen incorrectly, the algorithm may either overfit or underfit the data, leading to poor detection performance. As IoT systems scale with more devices and traffic, the complexity of data grows, which might limit the effectiveness of k-Means clustering. In large IoT networks, the clusters may become increasingly difficult to distinguish, and the algorithm may struggle to maintain its performance across multiple, highly variable data points. k-Means clustering provides a useful foundation for unsupervised anomaly detection in IoT systems, particularly in environments where labeled attack data is unavailable. The approach offers a simple and computationally inexpensive solution, with the potential for real-time intrusion detection. However, the method's effectiveness is limited by its inability to handle complex data patterns, sensitivity to initialization, and challenges in selecting the optimal number of clusters. With an accuracy of 76%, k-Means may not be sufficient for detecting sophisticated or evolving attacks in large-scale, dynamic IoT environments. This highlights the need for more advanced clustering or hybrid methods that can better handle the complexity and scale of IoT data.

Authors of [15] apply Bayesian Networks for probabilistic anomaly detection in IoT systems. Bayesian Networks are a type of probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph. This method is especially useful in scenarios where uncertainty and probabilistic relationships between variables are important. It allows for more interpretable models, as it can provide insights into how various system components interact and contribute to anomaly detection. The use of Bayesian Networks in this study provides interpretable results, with 83% accuracy in detecting anomalies. This approach is particularly valuable in IoT systems where understanding the reasoning behind decisions is crucial. The probabilistic nature of the model allows it to manage uncertainty, making it well-suited for dynamic environments where IoT data is often noisy and incomplete. One significant limitation is that Bayesian Networks may face scalability issues. As the number of IoT devices and the complexity of the relationships between them increase, the size of the Bayesian Network grows exponentially, making it computationally expensive. Furthermore, the inference process in large networks can become slow, which may limit its applicability in real-time systems or large-scale deployments. Additionally, Bayesian Networks might not be as effective in handling complex, high-dimensional data without careful feature engineering. The comparative analysis of existing anomaly detection methods is given in Fig.2.

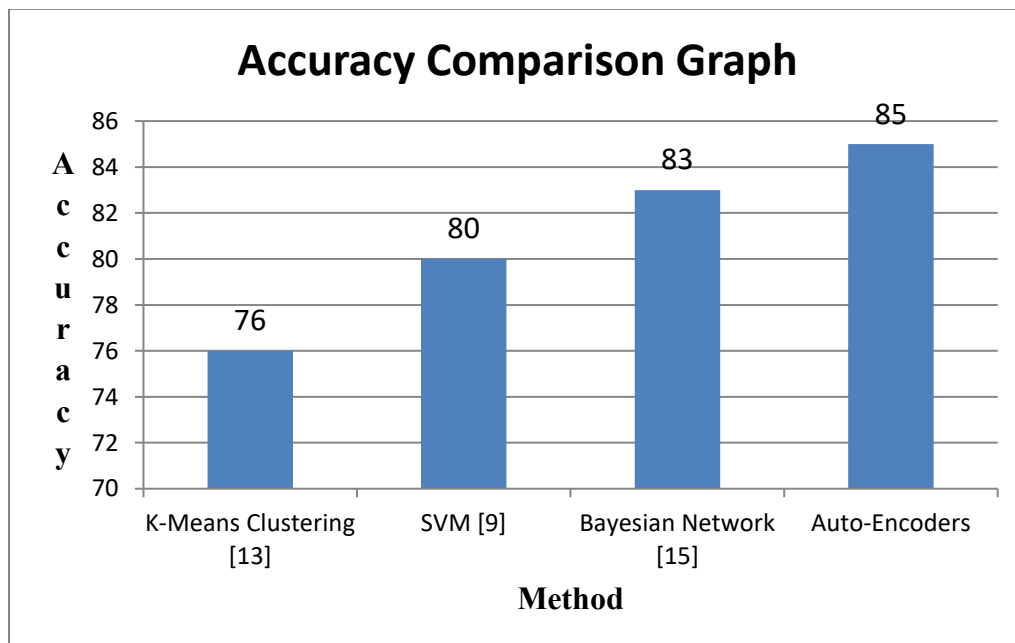


Fig.2 Comparative analysis of existing anomaly detection methods

## V. Conclusion

This research presents a novel framework integrating deep learning-based anomaly detection with blockchain-enabled trust mechanisms to enhance the security and data integrity of IoT systems. The proposed model effectively combines autoencoders for real-time anomaly detection with blockchain's immutability and decentralized trust. Achieving an accuracy of 85%, this approach lays the groundwork for future research in scalable, efficient, and secure IoT ecosystems. Future work will focus on improving model scalability, reducing energy consumption, and addressing interpretability challenges in DL models.

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