Driving intelligent IoT monitoring and control through cloud computing and machine learning

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Abstract. At present, cloud computing and the Internet of Things are closely integrated. IoT devices gather data through sensors and transmit it to the cloud for storage, processing, and analysis. This synergy enables efficient data management and in-depth analysis, facilitating real-time monitoring and predictive maintenance. This article explores leveraging cloud computing and machine learning for intelligent IoT monitoring and control. Edge computing, a distributed architecture, decentralizes data processing from the cloud to reduce latency and improve efficiency. This combination enhances security and drives the development of intelligent systems.

Keywords: Internet of Things, Cloud Computing, Edge Computing, Real-time Information and Analytics.

1. Introduction

The origins of iot monitoring and control technology can be traced back to the 1980s, when remote monitoring and control systems began to appear in the field of industrial automation. With the development of computer and communication technology, people began to try to connect sensors and actuators with the network to achieve remote monitoring and control. [1] In 1999, an MIT study first proposed the concept of the "Internet of Things," meaning that objects can be connected and communicated with each other through a network, enabling information sharing and intelligent control. Since then, Internet of Things monitoring and control technology has gradually become a research hotspot in industry, agriculture, health and other fields.[2] In recent years, with the continuous maturity

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of Internet of Things technology and driven by relevant national policies, a large number of innovative applications in the Internet of Things industry have been rapidly developed. From the explosive growth of consumer smart homes and smart items to the continuous innovation of enterprise in intelligent manufacturing, intelligent transportation, public safety and medical fields, the market size of the entire Internet of Things is expanding rapidly. However, the ensuing problem is that more and more Internet of Things information security incidents are frequent.

2. Related work

2.1. Application of edge computing in iot monitoring and control

Edge computing (also known as Edge computing) is a distributed computing architecture that moves the processing of applications, data, and services from the central node of the network to the logical edge nodes of the network. The "edge" is defined as any compute and network resource along the path between [3] the data source and the cloud data center. The basic principle of edge computing is that the computation should occur in close proximity to the data source for processing. In many cases, edge computing is more efficient than cloud computing for some computing services. By moving critical data processing functions to the edge of the network or near the source of the data, edge computing can help connected devices maintain the same level of efficiency even when the network connection is poor.

2.2. Application Research and Practical Cases

In the dynamic landscape of IoT monitoring and control, the convergence of machine learning techniques has emerged as a catalyst for transformative innovation. Here, we explore the dual facets of application research and practical cases, showcasing the symbiotic relationship between machine learning and intelligent IoT systems:

(1) Data Analysis and Predictive Maintenance

Machine learning algorithms empower IoT systems to extract actionable insights from vast datasets, enabling advanced data analysis. Key techniques include:

$$\sum i = 1k \sum x \in S_i \backslash\backslash x - ui \backslash\backslash \frac{2}{2} \tag{1}$$

Anomaly Detection: $p(x)<\epsilon$

Research demonstrates the efficacy of these algorithms in identifying patterns and anomalies, optimizing system performance, and facilitating predictive maintenance strategies.

(2) Energy Optimization and Fault Detection:

Machine learning enhances energy optimization efforts by analyzing consumption patterns and dynamically adjusting resource allocation in IoT-enabled systems. Key formulas include:

$$\check{y}=f(x) \tag{2}$$

(3) Resource Allocation:

$$\sum \frac{n}{i=1} \omega_i x_i \tag{3}$$

Real-time fault detection and diagnosis benefit from machine learning algorithms, ensuring system reliability and uptime through prompt remedial actions.

3. Application research and practical cases

3.1. Data Analysis and Predictive Maintenance

Machine learning can make real-time predictions. Through the Internet of Things and clustering algorithms, we can monitor and optimize production processes to ensure the safety of workers in dangerous areas. For example, consider the production process of a chemical plant. Data collected using iot sensors, such as temperature, pressure, and chemical concentrations, can be fed into a clustering algorithm for analysis. [4] By clustering historical and current data, potential production risks can be predicted and timely measures can be taken to avoid accidents. The combination of iot and clustering algorithms helps to achieve effective risk management. Clustering algorithms can use past data to predict a risk and automatically react to that risk.

3.2. Introduction to Experimental Framework: IoT and Clustering Algorithms

To validate the effectiveness of machine learning algorithms in IoT environments, experimental frameworks are essential. In this section, we introduce the experimental setup focusing on IoT and clustering algorithms. Machine learning relies on data, which spans various types, including numerical, visual, or textual data such as sensor data, images, or textual records. This section outlines the data collection and preparation process for training machine learning models in our experimental setup.

3.3. Energy Optimization and Fault Detection

In the Internet of Things (IoT) environment, real-time fault detection and diagnosis is a key component to ensuring system reliability and continuous operation. [5] This data includes equipment status, sensor readings, environmental conditions, and more. Machine learning algorithms are applied to this data to identify abnormal patterns and potential signals of failure. Troubleshooting typically involves the following key steps: 1) Feature extraction and selection: Fault related features are extracted from the monitored data. 2) Pattern recognition and classification: Machine learning algorithms are used to analyze and classify the extracted features to identify different types of failure modes. [6] 3) Fault location and reasoning: Based on the identified fault mode, infer the possible fault location and cause. 4) Corrective actions and feedback: Take appropriate corrective actions based on the diagnosis result, such as repairing the device, replacing parts, or adjusting the system configuration. In summary, by harnessing the power of connected devices, advanced analytics, and machine learning, businesses can achieve unprecedented levels of efficiency, productivity, and competitiveness in today's dynamic market landscape.

4. Experiment methodology and results

4.1. IoTEnsemble: Machine learning-based iot attack detection

Based on the clustering results, it can profile the traffic pattern of each device behavior separately, thus effectively reducing the dependence on the generalization of a single model.[7] In the experimental phase, the researchers examined a 57.1 gigabyte iot traffic dataset spanning nine months and a rich malicious traffic dataset. The results show that IoTEnsemble can detect multiple botnet malware and cyberattacks more effectively than existing solutions in today's intelligent and functional iot environments. Compared to other methods, IoTEnsemble demonstrated higher accuracy and recall rates in this case, as well as better F1 values. As a result, IoTEnsemble has shown significant advantages in detecting malicious behavior based on common protocols, providing a reliable solution for countering cybersecurity threats.

4.2. Traffic activities implement clustering

The ultimate goal of the activity clustering method proposed in this paper is to aggregate the traffic used for the same activity so that each sub-model in the integrated model learns the traffic model of a single activity. The algorithm needs to meet three design goals: 1) [8] good interpretability, which can be understood by network administrators; 2) as little prior knowledge as possible, such as the number of protocols or activities used by the device; 3) Appropriate clustering granularity to ensure the correctness of clustering while using as few clusters as possible.

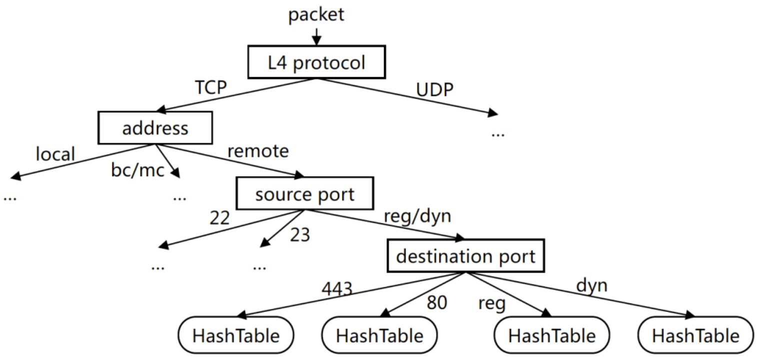


Figure 1. Activity clustering based on tree structure; bc/mc

An Internet of Things behavior clustering method based on tree structure is proposed (as shown in Figure 1). First, a packet from the bidirectional stream quintuple f=(device-IP, dst-domain/IP, src-port, dst-port, protocol) is initially clustered using four-level rules:

- L4 protocol: TCP or UDP;
- Address: dst-domain/IP is a resolved domain name, remote IP address, local IP address, or broadcast/multicast address;
- src-port: a system port number or a registered port or dynamic port number range;
- dst-port: indicates a system port number, registered port number range or dynamic port number range.

Since the iot device is generally on the client side, the source port number is often not helpful for clustering (unless it is a system port such as 22, 23 for SSH, Telnet), but the destination port in the registered port number range can still represent some common iot services, such as SSDP (1900), STUN (3478), etc. At the end of the tree structure, each leaf node contains a hash table, whose key value IS a bidirectional stream quintuple f, whose value is an incremental statistical structure IS=(Nin, Nout, Tin, Tout, S), where [9]N represents the number of packets, Trepresents the sum of packet arrival intervals, in and out represent the direction, and so on. S represents the set of package sizes. No matter how many packets a stream has, this structure can be maintained at a constant level of storage complexity.

4.3. Model construction

IoTEnsemble has two detection stages:

1. Rule matching: Using active key values can quickly filter out highly abnormal traffic, such as connections with unknown domain names and unknown protocols;

2. Integrated model: Learn traffic patterns for each activity and detect abnormal traffic by identifying deviations from normal patterns.

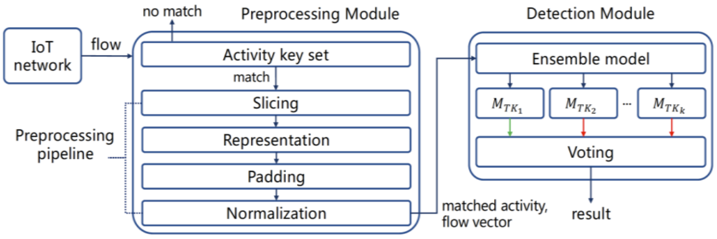


Figure 2. IoTEnsemble overall architecture

Figure 2 shows the overall structure of IoTEnsemble. The pre-processing module first receives iot traffic and uses a quintuple to match the set of active key values obtained through the clustering tree. Since the clustering tree algorithm results in an abstract plan (such as domain names containing wildcards, "reg/dyn" port number ranges, etc.), the matching is a fuzzy matching process, which reduces the possibility of false positives. [10] The pipeline includes four steps: segmentation, characterization, filling and normalization, and finally a sequence feature vector is constructed using the IP packet length and arrival time interval of the first r packets of a quintuple.

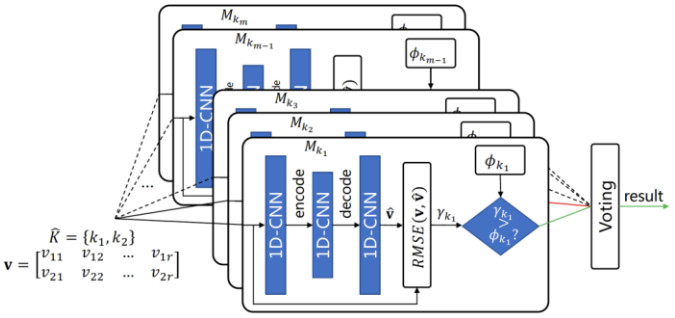
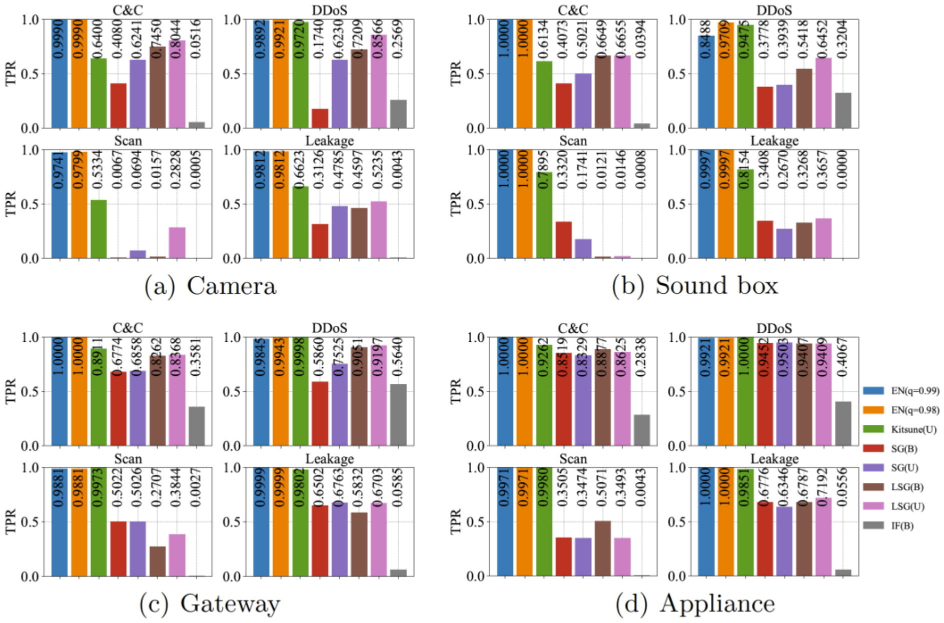

M_{k_m}
$M_{k_{m-1}}$
$\phi_{k_{m-1}}$
M_{k_3}
M_{k_2}
M_{k_1}
ϕ_{k_1}
1D-CNN
encode
1D-CNN
decode
1D-CNN
$\hat{\mathbf{v}}$
$RMSE(\mathbf{v}, \hat{\mathbf{v}})$
γ_{k_1}
$\gamma_{k_1} \overset{?}{>} \phi_{k_1}$
Voting
result
...
$\hat{K} = \{k_1, k_2\}$
$\mathbf{v} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1r} \\ v_{21} & v_{22} & \cdots & v_{2r} \end{bmatrix}$

Figure 3. Detection module based on ensemble learning

The detection module consists of multiple unsupervised learning submodels, each learning traffic patterns independently (Figure 3). Benefits include no need for malicious traffic during training and the ability to detect zero-day attacks. Submodels employ 1D convolutional neural network autoencoders to learn data representation implicitly. During detection, higher reconstruction errors indicate non-conforming data, triggering detection.

4.4. Verification result

Six existing NADS were used as baselines to compare the abnormal traffic detection capabilities of the IoTEnsemble framework, including Kitsune, the SOTA solution published in NDSS. IoTEnsemble achieves better detection effect than other schemes for most attack categories. In contrast, Kitsune's performance on some of the more complex devices, such as cameras and audio, became significantly worse, while IoTEnsemble's detection ability was barely affected.



(a) Camera

(b) Sound box

(c) Gateway

(d) Appliance

Figure 4. Comparison of IoTEnsemble and five baseline NADS

It can be seen from the results in FIG.4 that in machine learn-based iot fault detection, malware can evolve to use common protocols such as [11] HTTP to disguise its C&C channel. The experimental results show that IoTEnsemble achieves leading detection against multiple attacks regardless of the amount of activity in the iot network. This may be attributed to IoTEnsemble's integrated model and active clustering algorithm, which are able to more effectively capture the characteristics and patterns of different attack behaviors, thus improving the accuracy and comprehensiveness of detection.

5. Conclusion

To sum up, this experiment adopts advanced machine learning algorithm and network security technology, designs an anomaly detection system based on IoTEnsemble framework, and verifies it in a real IoT environment. The experimental results show that IoTEnsemble has significant performance advantages in detecting a variety of network attacks and malicious activities, showing higher detection accuracy and robustness compared to existing schemes. This achievement is not only of great significance for improving the level of IoT network security, but also provides useful reference and reference for the research and practice in related fields. From the point of view that iot and cloud computing continue to generate large amounts of data, this paper discusses the application of edge computing as a distributed computing architecture, and the role of machine learning in data analysis and fault detection. By combining iot with edge computing, latency can be reduced, efficiency improved, and security enhanced, thereby driving the development of intelligent systems.

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