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Optimized Isolation Forest based Docker Container Anomaly Monitoring System

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***Abstract*— This paper presents an enhanced anomaly detection system for Docker containers, leveraging an improved version of the Isolation Forest algorithm. Due to the highly dynamic and ephemeral nature of containerized environments, traditional monitoring approaches often fall short in identifying issues such as performance degradation, security breaches, and inefficient resource usage. Docker containers are widely adopted for deploying scalable applications in isolated environments, but their complexity makes consistent and accurate monitoring a challenge. To address this, our approach integrates hyperparameter tuning and optimized feature selection into the Isolation Forest model, significantly improving its ability to detect abnormal behavior. We evaluate the system using real-world Docker container data, and the results demonstrate superior performance compared to conventional methods. The proposed solution effectively identifies both known and previously unseen anomalies in real-time, without relying on labeled datasets.**

***Index Terms*— Anomaly monitoring, Docker container, Log analysis, Isolation forest.**

I. INTRODUCTION

With cloud computing becoming more accessible, Docker containers are widely adopted for their fast deployment capabilities, especially by companies like Amazon, IBM, and Oracle. However, as container usage increases, so do concerns around security and stability. Notable incidents, such as outages in Amazon's cloud infrastructure, highlight the need for effective anomaly detection to maintain service reliability.Traditional rule-based or statistical methods often fall short in detecting subtle issues in complex, multi-container environments. Density-based techniques like LOF and ABOD offer better results but can be computationally heavy at scale. Existing monitoring tools such as Nagios and cAdvisor use fixed intervals, which either increase overhead or delay detection.

To address these challenges, this study proposes an optimized Isolation Forest-based system for Docker container anomaly detection. It passively monitors multi-dimensional resource metrics and assigns importance weights based on workload types. The system adapts monitoring intervals in real-time and uses anomaly scores to trigger root cause analysis via container logs.

Key contributions include:

- A dynamic anomaly detection system tailored for Docker containers.
- A weighted Isolation Forest model that improves detection by considering workload-specific metrics.
- Experimental validation in simulated and AWS environments to assess detection accuracy and system responsiveness.

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II. Related Work

Traditional monitoring tools like Nagios [8], Zabbix, and Ganglia [6] are effective for static systems but lack adaptability for dynamic containerized environments. Container-specific tools such as cAdvisor [13] and Anand et al.'s framework [12] enable lightweight monitoring but fall short in persistent data storage and advanced anomaly detection. Statistical [9], entropy-based [22], deep learning [23, 24, 25], distance-based [26, 27], and density-based methods like LOF [10] offer partial solutions but struggle with high-dimensional data and scalability. Isolation Forest (iForest) [20] stands out for its efficiency in such contexts but assumes equal feature importance, which limits accuracy in diverse workloads. Recent research [16, 18] focuses on orchestration and scaling, with limited emphasis on real-time anomaly detection or automated fault diagnosis. This highlights a gap for integrated solutions that support workload-aware feature optimization, adaptive monitoring, and log-based root-cause analysis.

III. Proposed Methodology

A. System Architecture

The system includes four primary modules in Figure 1 below—Monitoring Agent, Monitoring Data Storage, Anomaly Detection, and Anomaly Analysis. Each host runs a lightweight monitoring agent that collects resource usage, which is stored in a time-limited InfluxDB instance and analyzed using an Isolation Forest algorithm. Detected anomalies are further examined through log analysis.

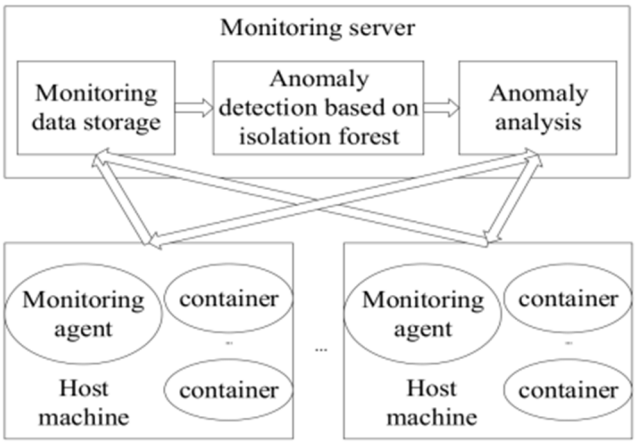

Figure 1: System Architecture

B. Monitoring Agent

The agent is composed of functional modules for:

- Real-time resource metric collection (CPU, memory, I/O, network).
- Data formatting and mirroring aggregation.
- Container lifecycle tracking via Docker API.
- Adaptive monitoring period adjustment based on anomaly sensitivity.
- Container queue management and prioritization.
- Log collection and data transmission.

C. Monitoring Data Storage

Utilizes InfluxDB to store container metrics and metadata. Data is retained for one hour and monitored through a control table. If 100 data rows are collected for a container, they're sent in JSON format to the anomaly detection module for analysis.

D. Anomaly Detection (iForest Optimization)

A modified Isolation Forest algorithm is used to detect anomalies:

- Assigns dynamic weights to resource metrics based on container behavior.
- Adjusts feature selection bias to focus on active resources.
- Tracks isolation features across trees to identify the root resource causing anomalies

$$M = \begin{cases} 0, & (\sum_{i=1}^{p} N_i = 0) \\ W_0 + \frac{\sum_{i=1}^{p} f(N_i - \epsilon)}{p} \end{cases} \quad (3)$$

Algorithm 1 Weighted random algorithm

Input: M_1, M_2, M_3, M_4 ///M_1 is CPU weight, M_2 is Memory weight, M_3 is IO weight, M_4 is Network weight.

Output: i ///A feature among the four features (CPU usage rate, Memory usage rate, IO rate, Network usage rate).

1: $M_{all} = M_1 + M_2 + M_3 + M_4$
2: $R = Random() * M_{all}$
3: **for** $i = 4, R > 0, i = i - 1$ **do**
4: $\quad R = R - M_i$
5: **endfor**
6: return i

E. Monitoring Period Adjustment

Based on the container's anomaly score:

- If the score is within a warning range, monitoring frequency is increased.
- If the score returns to normal, the monitoring period is reset.

$$f = \frac{d + p}{2}$$

F. Anomaly Analysis

- Log Preprocessing: Filters out noise and irrelevant logs[27] (e.g., HTTP access logs, escape sequences).
- Log Analysis: Uses a rule-based system and Apriori algorithm to detect known and unknown patterns. New patterns are added to the rule base for continuous improvement[28].

IV. Results and Discussion

Experiments were conducted in both simulated and real-world cloud setups. The real-world test used Amazon EC2 instances (t3.medium and t3.small) with Ubuntu 16.04 and Docker 18.03.1-ce. Two representative containerized applications from CloudSuite—Memcached and Web Search—were used, with Mutilate and Faban generating realistic workloads.

To evaluate system effectiveness, four types of faults were injected: CPU overload, memory leaks, disk I/O spikes, and network congestion. These were simulated using stress loops, heap allocations, FIO, and bandwidth throttling.

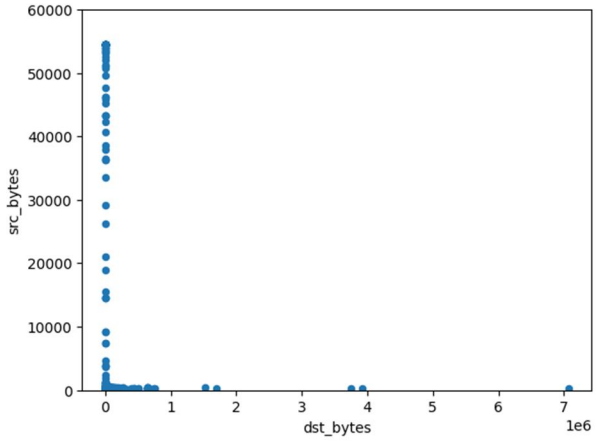

Figure 2: Scatter Plot of src_bytes vs dst_bytes

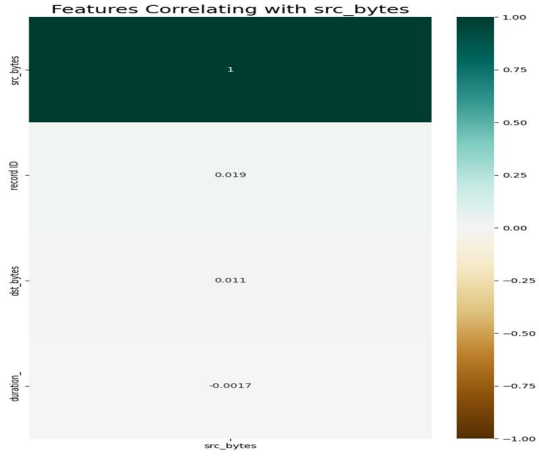

Figure 3: A Scatter Plot of src_bytes vs dst_bytes

```
# calculates the suspected share of outliers in the dataset
num_of_suspected_outliers = df[df['src_bytes'] > (median_src_b + std_dst_b)].count()
estimte_contamination = num_of_suspected_outliers / total_smaples
estimte_contamination = estimte_contamination.iloc[0]
print(estimte_contamination)
n_estimators = 50
data = df[["duration_", "src_bytes","dst_bytes"]]

# trains the model
model = IsolationForest(contamination = estimte_contamination, n_estimators = n_estimators)
model.fit(data)
```

```
0.003950598044181244
IsolationForest(contamination=0.003950598044181244, n_estimators=50)
```

Figure 4: Isolation Forest Model Initialization

	precision	recall	f1-score	support
0	1.00	1.00	1.00	255648
1	0.05	0.01	0.02	1022
accuracy			0.99	256670
macro avg	0.52	0.51	0.51	256670
weighted avg	0.99	0.99	0.99	256670

```
TN:  255372
FP:  276
FN:  1008
TP:  14
TP+FN:  1022
TN+FP:  255648
Accuracy: 0.9949974675653563
```

Figure 5: Model Performance Metrics

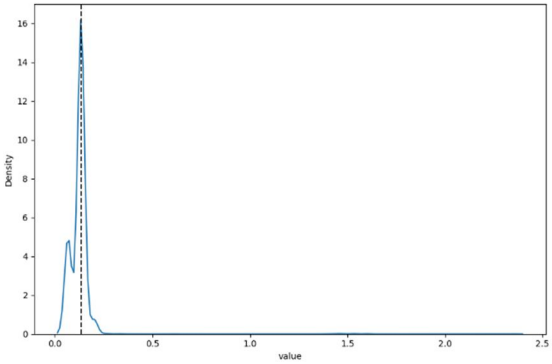

Figure 6: Distribution of Anomaly Scores from Isolation Forest

The optimized Isolation Forest (iForest) algorithm was compared against the baseline iForest and Local Outlier Factor (LOF). Results showed:

- Higher accuracy and lower false alarms for optimized iForest.
- Better detection of subtle anomalies (e.g., 60–80% CPU web attacks) versus standard models.
- Clear fault localization, based on feature isolation frequency.

Example case studies showed that optimized iForest could:

- Correctly detect real anomalies like CPU spikes and network issues.
- Ignore normal workload fluctuations.
- Identify root causes via log correlation.

Performance tuning revealed:

- 100 isolation trees gave the best balance between accuracy and computation time.
- Dynamic monitoring intervals reduced detection delays by 13.5%, without increasing system load

IV. Conclusions

This paper presents an online anomaly detection approach for containers that leverages an enhanced Isolation Forest algorithm to analyze multidimensional resource data. By assigning tailored weights to different resource metrics and adjusting feature selection to reflect the specific behavior of containerized applications, the method improves detection precision. The system also adapts the monitoring interval based on the severity of anomalies, helping to minimize response delays. Furthermore, it incorporates log analysis to pinpoint the underlying causes of unusual behavior. Tests conducted on both virtual and physical cloud environments confirm that the proposed method effectively detects abnormal container activity without degrading system performance.

References

[1] A. Anwar, M. Mohamed, V. Tarasov, M. Littley, L. Rup- precht, Y. Cheng, N. Zhao, D. Skourtis, A. S. Warke, H. Ludwig, D. Hildebrand, and A. R. Butt, "Improving docker registry design based on production workload analysis," in 16th USENIX Conference on File and Storage Technologies (FAST 18). Oakland, CA: USENIX Associa- tion, 2018, pp. 265–278.

[2] "Amazons container strategy examined," https://www. informationweek.com/cloud/infrastructure- as- a- service /amazons- container- strategy- examined/a/d- id/1317515.

[3] "IBM containers on bluemix," https://www.ibm.com/bl ogs/bluemix/2015/06/ibm- containers- on- bluemix/.

[4] "Munz docker occs," http://www.oracle.com/technetwo rk/articles/cloudcomp/munz- docker- occs- 3585210.html.

[5] "Amazons cloud service partial outage affects certain websites," http://www.dailymail.co.uk/sciencetech/arti cle-4268850/Amazons- cloud- service- partial- outage- affects- certain- websites.html.
[6] M. L. Massie, B. N. Chun, and D. E. Culler, "The ganglia distributed monitoring system: design, implementation, and experience," Parallel Computing, vol. 30, no. 7, pp. 817– 840, 2004.
[7] "Introduction to Zabbix," http://tim.kehres.com/.
[8] "Nagios: The industry standard in it infrastructure monitoring," https://hops://www.n- agios.org/.
[9] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detec- tion: A survey," ACM Computing Surveys, vol. 41, no. 3, pp.1–58, 2009.
[10] M. M. Breunig, H. P. Kriegel, and R. T. Ng, "LOF: iden-tifying density-based local outliers," in ACM SIGMOD International Conference on Management of Data, 2000, pp. 93–104.
[11] H. P. Kriegel, M. S. Hubert, and A. Zimek, "Angle- based outlier detection in high-dimensional data," in ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2008, pp. 444–452.
[12] S. A. K, J. A. K, and K. A, "Resource monitoring of docker containers," International Journal of Advance Engineering and Research Development, vol. 3, no. 2, pp. 146–149, 2016.
[13] "Google.cAdvisor," https://github.com/google/cadvis or.
[14] N. Naik, "Building a virtual system of systems using docker swarm in multiple clouds," in IEEE International Symposium on Systems Engineering, 2016, pp. 1–3.
[15] S. Mcdaniel, S. Herbein, and M. Taufer, "A two-tiered approach to I/O quality of service in docker containers," IEEE/ACM Transactions on Networking, vol. 6, no. 1, pp. 42– 55, 2015.
[16] G. M. Tihfon, J. Kim, and K. J. Kim, A New Virtualized Environment for Application Deployment Based on Docker and AWS. Springer Singapore, 2016.
[17] R. Liu, R. Liu, R. Liu, A. C. Arpaci-Dusseau, and R. H. Arpaci-Dusseau, "Slacker: fast distribution with lazy dock- er containers," in Usenix Conference on File and Storage Technologies, 2016, pp. 181–195.
[18] N. Nguyen and D. Bein, "Distributed MPI cluster with docker swarm mode," in Computing and Communication Workshop and Conference, 2017, pp. 1–7.
[19] S. Julian, M. Shuey, and S. Cook, "Containers in research: Initial experiences with lightweight infrastructure," in XSEDE16 Conference on Diversity, Big Data, and Science at Scale, 2016, p. 25.
[20] F. T. Liu, M. T. Kai, and Z. H. Zhou, "Isolation forest," in Eighth IEEE International Conference on Data Mining, 2009, pp. 413–422.
[21] N. L. D. Khoa and S. Chawla, Robust Outlier Detection Using Commute Time and Eigenspace Embedding. Springer Berlin Heidelberg, 2010.
[22] M. Jiang, M. A. Munawar, T. Reidemeister, and P. A. S. Ward, "Efficient fault detection and diagnosis in complex software systems with information-theoretic monitoring," IEEE Transactions on Dependable and Secure Computing, vol. 8, no. 4, pp. 510–522, 2011.
[23] Sahane, P., Shelke, S., et.al. "Identification of Spoofing URLs Using Hybrid Algorithms", Smart Trends in Computing and Communications. SMART, Lecture Notes in Networks and Systems, vol 645. Springer, 2023, pp: 283-290.
[24] Wandile, N., Bhonde, A., Garje, A., Chavan, P., & Bhangale, P. Blockchain-based Integration of Social Media and Music for Enhanced Privacy and Trust in a Decentralized Ecosystem. Grenze International Journal of Engineering & Technology (GIJET), 10, 2024.
[25] Kedar, S., Dhawale, S., Vaibhav, W., Kadam, P., Wani, S., & Ingale, P. Privacy preserving data mining. International Journal of Advanced Research in Computer and Communication Engineering, 2(4), 2013.
[26] S. Ramaswamy, R. Rastogi, and K. Shim, "Efficient algo- rithms for mining outliers from large data sets," in ACM SIGMOD International Conference on Management of Data, 2000, pp. 427–438.
[27] F. Angiulli, S. Basta, and C. Pizzuti, "Distance-based de- tection and prediction of outliers," IEEE Transactions on Knowledge and Data Engineering, pp. 145–160, 2006.