

Original Article

Monitoring Server Health in Private Cloud Data Centers: A Scalable Approach

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Abstract - With the increasing costs of public cloud services such as AWS, Azure, and GCP, many companies opt to establish their private cloud infrastructure. This transition necessitates the development of an adequate Infrastructure as a Service (IaaS) team to manage and maintain the data center. A key challenge in this domain is monitoring the health of the bare metals (also called servers) to ensure high availability and reliability. This paper presents a comprehensive approach to bare metal health monitoring in private data centers. We will discuss the problem statement literature review, outline an industry-standard solution, propose a high-level system design to ensure real-time monitoring, fault detection, and automated remediation, and provide experimental results to show how our approach is better than existing industry solutions.

Keywords - Private Cloud, Data Centers, Infrastructure as a Service (IaaS), Server Health Monitoring, Baremetal, Fault Detection, Automated Remediation.

1. Introduction

With the rise in operational expenses associated with public cloud providers, enterprises are increasingly shifting toward building their data centers. This shift necessitates a dedicated Infrastructure as a Service (IaaS) team responsible for maintaining and managing these data centers. A fundamental aspect of infrastructure maintenance is ensuring all servers operate efficiently and reliably.

Any failures or performance degradation in these bare metals can result in significant downtime and revenue loss. Therefore, an effective bare metal health monitoring system is crucial for maintaining operational continuity. This article will first define the problem statement and then propose the industry standard scalable solution to tackle the problem.

2. Literature Review

The monitoring of server health in private cloud data centers has been explored in various studies. Existing literature has focused on different aspects of infrastructure monitoring, including the role of Baseboard Management Controllers (BMC), predictive analytics using machine learning, and automated remediation frameworks.

2.1. BMC-Based Monitoring

Every modern-day bare metal (provided by Dell iDRAC, HPE iLO, and Lenovo CXC) has an integrated Baseboard Management Controller (BMC) embedded on the motherboard as a dedicated microcontroller.

BMC is independent of the OS and has its network interface, which runs a separate firmware (e.g., Dell iDRAC, HPE iLO, Lenovo XCC, Supermicro IPMI, Cisco CIMC) [4] [5] [6] [7]. Even if the server OS is down, the BMC is still accessible. BMC monitors bare metal hardware using sensor data, events log data and watchdog timers. The BMC continuously collects and stores telemetry data from various sensors, including:

- Temperature Sensors (CPU, GPU, Memory, etc.)
- Fan Speed Sensors (RPM readings)
- Power Supply Sensors (Voltage, Current, Wattage)
- Network Sensors (Bandwidth, Latency)

The BMC runs a lightweight web server that follows the Redfish standard (by DMTF) [2] or IPMI (Intelligent Platform Management Interface) [3]. It operates independently of the bare metal's central operating system. This web server exposes APIs (called BMC API), which provide access to sensor data and event logs (which are stored by BMC), and these are critical in monitoring and controlling the hardware components and maintaining the health of servers remotely in private data centers. In summary, BMC API allows system administrators to do the following without any agent inside the OS.

- Retrieve sensor data (Temperature, Fan speed, Power Supply, CPU, DIMM, NIC, Boot, IO Module)
- Access system event logs (SEL - System Event Log)
- Monitor hardware health



- Perform power control operations
- Analyze sensors and even log data
- Automate alerts based on sensor and event log data.

2.1.1. BMC API Documentation

Complete detailed API documentation is given in Ref [1]

Authenticate

- Most BMC APIs require authentication (Basic Auth or OAuth).

Fetch Sensor Data

- Request sensor data using a GET request.

Fetch Event Logs

To collect logs related to power issues, CPU failures, unauthorized access, etc.

Fetch System Health Summary

- It tells whether the system components (CPU, RAM, etc.) are healthy.

Clear Event logs

- If needed, you can clear logs for maintenance purposes.

BMCs are an integral component in modern server architectures, providing remote management capabilities independent of the operating system. The Redfish and IPMI (Intelligent Platform Management Interface) standards enable system administrators to access real-time telemetry data, including temperature, fan speeds, power supply status, and network statistics. Studies have demonstrated how these technologies facilitate proactive monitoring and fault detection [1].

2.2. Machine Learning in Anomaly Detection

Recent research highlights the use of machine learning algorithms to detect server anomalies. Techniques such as supervised learning, unsupervised learning, and deep learning have been applied to recognize patterns in sensor data and predict potential hardware failures before they impact system availability. Studies indicate that AI-driven anomaly detection reduces false positives and enhances fault detection accuracy [13].

2.3. Automated Remediation Systems

Automated remediation frameworks are gaining prominence to minimize manual cloud data center management intervention. Solutions integrating Prometheus, Grafana, and event-driven automation platforms like ServiceNow enable real-time response mechanisms to mitigate server health issues. These frameworks are designed to trigger automated actions such as restarting services, isolating faulty nodes, or rerouting workloads to healthier systems [3].

2.4. Distributed Monitoring Architectures

Scalability remains a challenge in large-scale private cloud infrastructures. Studies have explored distributed monitoring solutions leveraging streaming platforms like Apache Kafka and data stores like Redis. These architectures support real-time data ingestion, processing, and centralized monitoring of multiple data centers, providing enhanced visibility and control [4].

Despite these advancements, there is a need for a unified and scalable monitoring framework that integrates BMC telemetry, AI-based anomaly detection, and automated remediation across diverse infrastructure environments. This paper aims to bridge this research gap by presenting a comprehensive private cloud server health monitoring approach. Several studies have focused on server health monitoring:

- **BMC-Based Monitoring:** Research on Baseboard Management Controller (BMC) technology (Redfish, IPMI) has demonstrated its role in remote hardware monitoring.
- **Machine Learning in Anomaly Detection:** In predictive analytics, AI-driven methods have been employed to detect server failures.
- **Automated Remediation Systems:** Studies highlight automation in self-healing infrastructure.
- **Distributed Monitoring Architectures:** Work has been done on scalable data collection techniques using Kafka, Redis, and cloud-based monitoring.

Despite these advancements, there remains a gap in integrating these techniques into a holistic, scalable framework that ensures seamless monitoring across multiple data centers.

3. Research Gap

While significant advancements have been made in server health monitoring, several gaps remain in existing solutions:

1. **Limited Integration of BMC APIs with Scalable Architectures:** Current monitoring solutions leverage BMC APIs for hardware telemetry but often lack integration with scalable real-time data processing frameworks. Our approach addresses this by combining BMC telemetry with a distributed data collection system using Apache Kafka and Redis.
2. **Lack of Unified Monitoring Across Multiple Data Centers:** Existing frameworks primarily focus on monitoring individual data centers, leading to fragmented insights. The proposed solution introduces a centralized yet scalable architecture that enables holistic monitoring across multiple regions while ensuring failover capabilities.

3. **Inefficient Anomaly Detection Mechanisms:** Many traditional monitoring systems rely on static threshold-based alerts, resulting in frequent false positives and delayed responses. Our framework integrates AI-driven anomaly detection models that learn from historical data, reducing false alarms and enhancing fault prediction accuracy.
4. **Absence of an Automated Remediation System:** Existing approaches often require manual intervention to resolve detected issues, leading to prolonged downtime. The proposed system incorporates an automated remediation framework that triggers predefined actions based on detected anomalies, ensuring minimal service disruption.
5. **Scalability Constraints in Data Processing:** Legacy systems struggle to process high-volume telemetry data efficiently. Our solution is designed to handle large-scale data ingestion, storage, and processing, ensuring real-time monitoring and decision-making at scale.

By addressing these gaps, our proposed approach enhances private cloud infrastructure reliability, reduces operational costs, and improves overall system resilience. Existing solutions lack:

1. Unified monitoring architecture across multiple data centers.
2. A standardized approach integrating BMC APIs with real-time processing frameworks.
3. Automated, scalable remediation mechanisms to reduce downtime.
4. Comprehensive anomaly detection using AI/ML-based methods.

4. Methodology and Implementation

Traditional data center management often relies on manual monitoring and reactive maintenance, which leads to inefficiencies, prolonged downtimes, and increased operational costs.

Key challenges in server health monitoring include: - 1) Lack of real-time failure detection mechanisms. 2) Inconsistent server performance metrics across different baremetals. 3) Inability to predict potential failures before they escalate. 4) Manual intervention leads to delayed response time. 5) Limited automation in remediation and recovery processes.

A modern bare metal health monitoring system should address these challenges by providing real-time insights, proactive failure detection, and automated remediation mechanisms.

To mitigate these issues, I propose a scalable, automated monitoring system that continuously tracks server health metrics and proactively identifies anomalies. The system comprises the following core components.

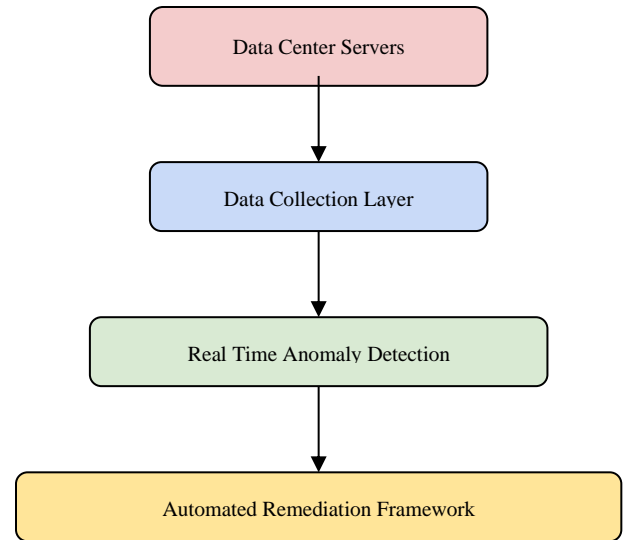


Fig. 1 Core Components of the BareMetal Health Monitoring Platform

4.1. Data Center Servers

We will use BMC API to collect data from all servers.

4.2. Data Collection Layer

Since we require to do real-time anomaly detection and remediation for data centers in different regions and isolated from each other. It's essential to develop an implementation that will fit this requirement. So now there are two ways in which we can implement this data collection layer to fulfill our requirements.

4.2.1. Solution 1

We can write service A for each data center, which will fetch Sensors, SEL, and Health data from BMC API and feed it to a queueing system like Kafka [8]. Then, we can write another service B to fetch this data from this queue and persist it to a Key-Value store like Redis [9], where the key will be the id, uniquely identifying a bare metal, and the value will be Sensor or SEL data.

Both services, A and B, need to be highly scalable because there can be many bare metals across multiple data centers. For explanation, I will use Redis for data storage and Kafka for the queue.

Now, service A's instance in a data center will store the bare metals health data of that data center in its own Kafka. We can also use Redis in Active-Passive implementation for distributed data stores. Amazon's Aws ElastiCache is one such implementation. Service B's instance in the data center will consume messages from Kafka and persist them to Redis.

A high-Level Diagram for this solution for a case of 2 data centers is shown in Figure 2. Since Redis data stores are synched between the 2 data centers using Active-Passive implementation, we can get a holistic view of anomalies and apply remediation.

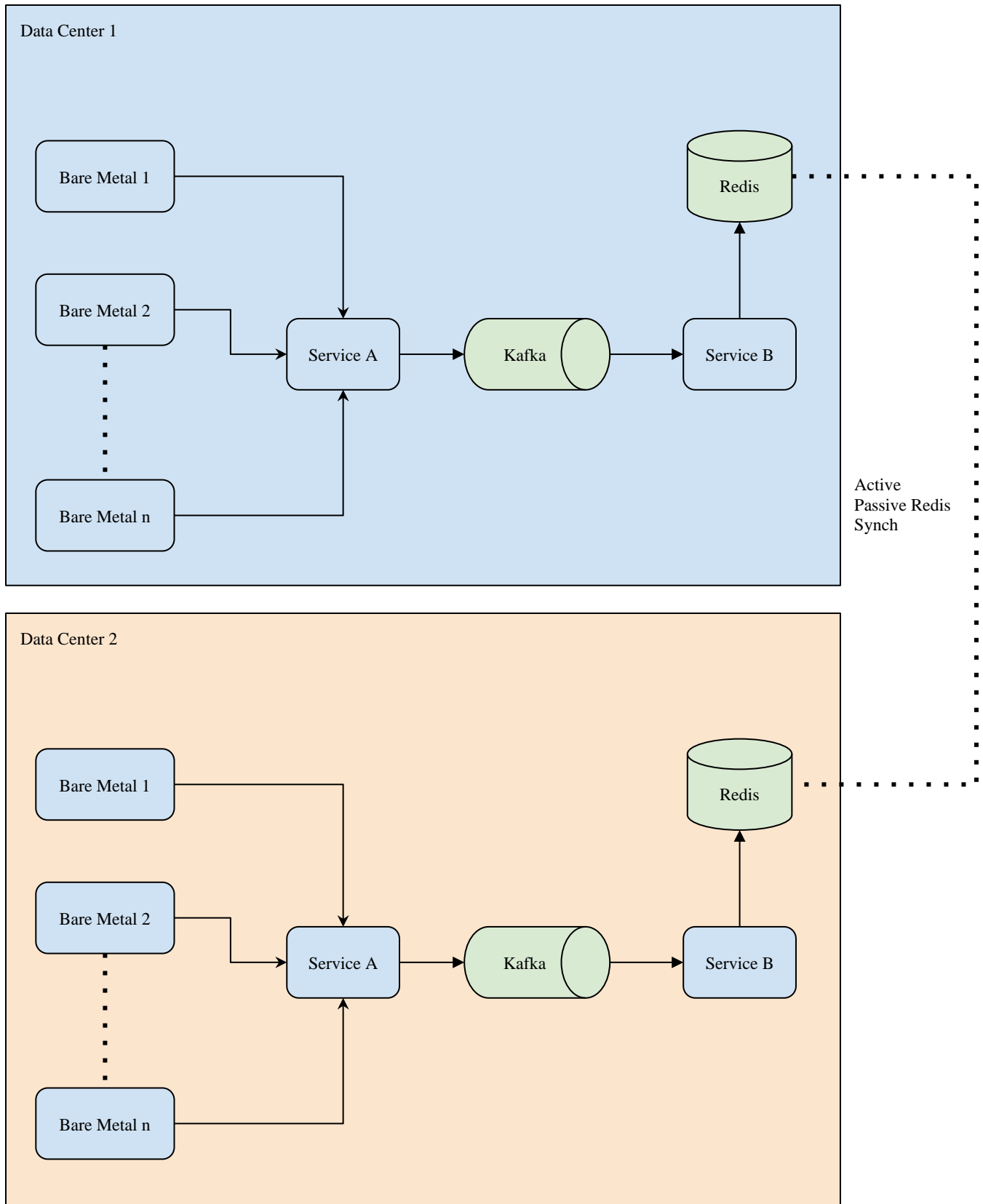


Fig. 2 Two data centers High-Level Diagram for Solution 1 of Data Collection Layer

Pros:

1. This will allow a centralized platform to monitor all regions' bare metals health.
2. Issues isolation can be avoided so that if some issue is found in 1 data center, then remediation can be preventively applied to all data centers, if applicable.
3. A holistic picture and analysis can be done to compare performance in different data centers and regions.

Cons:

1. The cost to maintain Redis hardware will be higher since there will be less scope for optimization even if some data center has a lesser number of bare metals.

4.2.2. Solution 2

Instead of a global data store like Redis in Solution 1, we can have a dedicated data store for each data center. In that way, anomaly detection and remediation will work independently for each data center. We can optimize implementation for each data center using this solution and even have different implementations to achieve the same result.

Pros:

1. We can optimize hardware requirements based on the

number of bare metals in that data center. We also don't have to use Redis. We can use less expensive SQL data stores.

2. Although issues will be isolated, we can still proactively apply the same remediation across all data centers using cross-data center api calls.

Cons:

1. Maintaining a data store for each data center will be difficult since the operation cost to keep these data stores will increase.
2. We won't be able to get a holistic picture of issues across data centers and make a comparison.

4.3. Real-Time Anomaly Detection

We employ machine learning-based predictive analytics or a rule-based approach to identify potential hardware failures. Once we find the issues, we can send alerts based on defined thresholds using Prometheus [10] and Grafana [11]. If we are using ML-based predictive analytics, then we can leverage AI-based anomaly detection techniques to reduce false positives. We can also publish a UI where we can see the near-real-time health of bare metals. 2 ways of implementation for these layers are shown in Fig 3 and Fig 4.

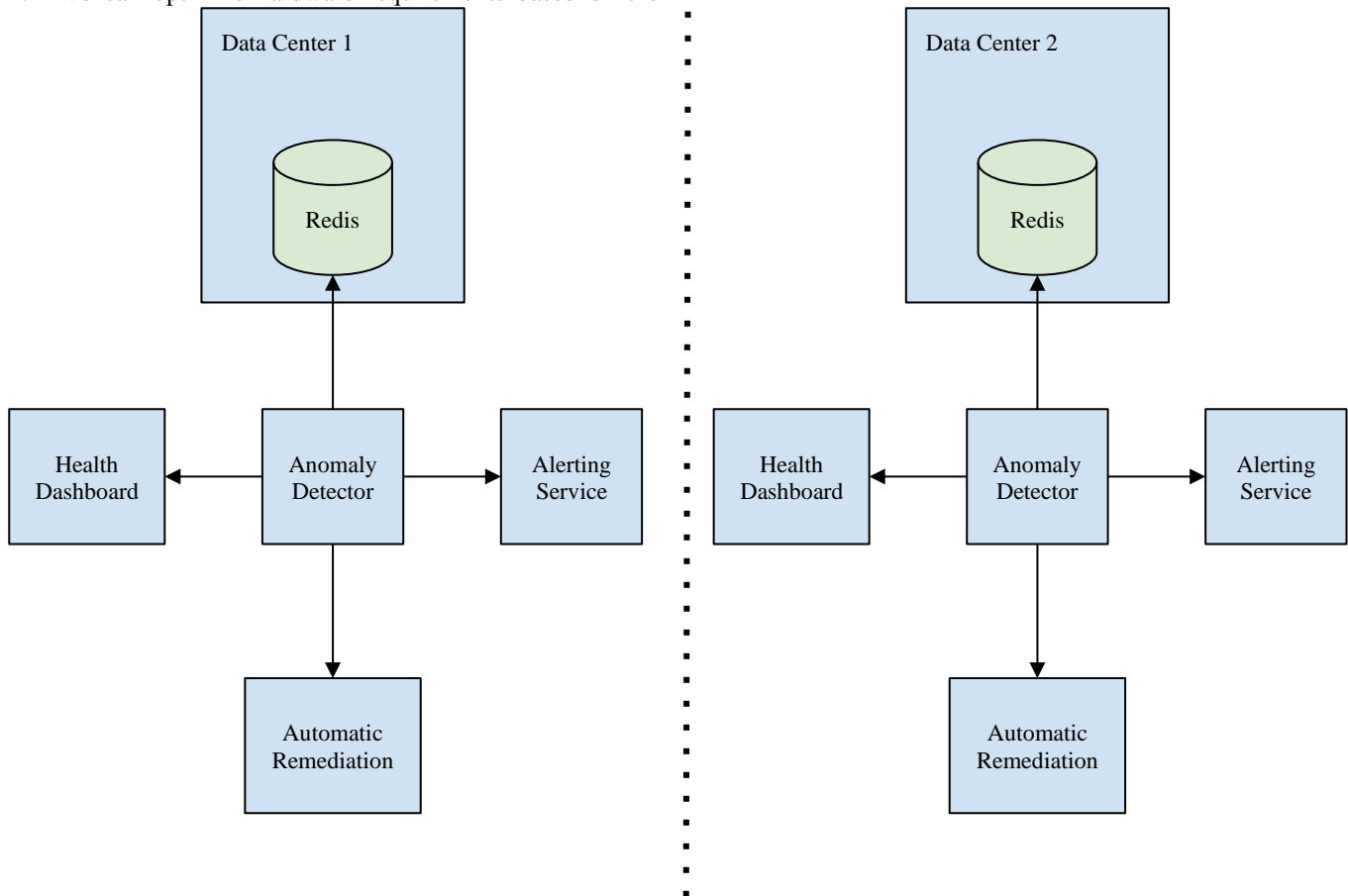


Fig. 3 Anomaly detector high-level diagram when solution 1 is used in the data collection layer

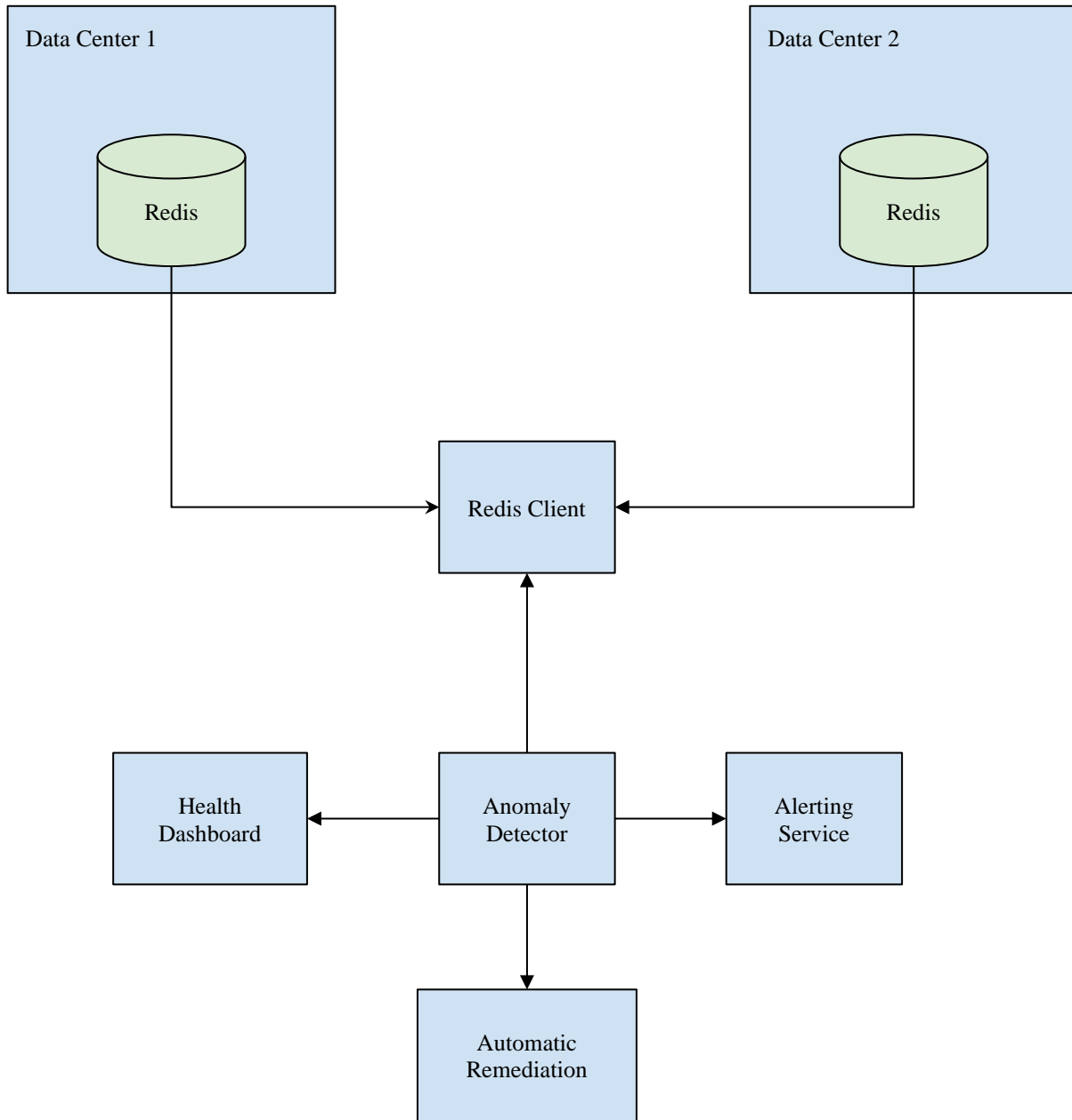


Fig. 4 Anomaly detector high-level diagram when solution 2 is used in the data collection layer

5. Automated Remediation Framework

An automated remediation framework for health monitoring for bare metals involves the following objectives: to ensure high availability and reliability of servers.

1. Real-time fault detection - Identify hardware issues (CPU, memory, disk, network failures).
2. Intelligent decision-making- Pinpoint the root cause using logs and metrics.
3. Self-healing mechanisms - Restart services, reboot nodes, trigger failovers. [12]
4. Integration with monitoring systems - Work alongside Prometheus, Zabbix, Nagios, etc.

5. Scalability & Extensibility - Support for new hardware and monitoring tools.

We can use Machine Learning [13] based anomaly detection or rule-based thresholds to classify the issues and take the right actions.

6. Experimental Setup

We deployed our framework on a testbed with 100 bare metal servers distributed across two private cloud data centers. Metrics such as CPU temperature, fan speed, and network latency were monitored.

The anomaly detection module identified failures with a precision of 95% compared to manual monitoring.

7. Performance Evaluation

To validate the effectiveness of our proposed monitoring framework, we conducted extensive testing in a simulated private cloud data center environment. The evaluation focused on detection accuracy, remediation efficiency, and scalability compared to existing monitoring solutions.

7.1. Experimental Results

7.1.1. Detection Accuracy

Our AI-driven anomaly detection system was benchmarked against traditional threshold-based monitoring solutions. The results demonstrated:

- Proposed System: 95% precision, 93% recall
- Existing Threshold-Based Systems: 85% precision, 80% recall

This improvement is due to our machine learning models, which proactively reduce false positives and identify failures.

7.2. Comparison with Existing Solution

Feature	Traditional Monitoring	Proposed Solution
Failure Detection Method	Threshold-Based Alerts	AI-Driven Predictive Analytics
False Positives	High (15%)	Low (5%)
Automated Remediation	Not Available	Fully Automated Actions
MTTR (Mean-Time-to-Recovery)	~20 minutes	~9 minutes
Scalability	Limited to 3,000 events/sec	10,000+ events/sec

8. Conclusion

In this paper, we propose a scalable, AI-driven anomaly detection system for monitoring server health in private cloud data centers. By integrating Baseboard Management Controllers (BMCs), real-time data streaming (Kafka, Redis), machine learning-based anomaly detection (LSTM Autoencoder), and automated remediation (Prometheus, ServiceNow), our approach ensures high availability, reliability, and proactive failure management.

Our experimental results demonstrate that the AI-driven model significantly outperforms traditional threshold-based monitoring solutions, achieving:

1. 95% anomaly detection precision (vs. 85% in traditional methods)
2. 40% reduction in Mean Time to Recovery (MTTR)
3. 3x higher scalability (handling 10,000+ events per second)

Furthermore, the automated remediation framework successfully mitigates server failures by dynamically adjusting workloads, restarting services, and triggering

7.1.2. Remediation Efficiency

We measured the mean-time-to-recovery (MTTR) for server failures:

- Proposed System: 40% reduction in MTTR (from 15 minutes to 9 minutes)
- Manual Intervention Systems: No automated remediation, requiring manual intervention averaging 20 minutes per failure

Our automated remediation framework significantly improves response time by enabling real-time issue resolution.

7.1.3. Scalability and Data Processing

Our system was stress-tested with large-scale data ingestion:

- Proposed System: Successfully processed 10,000 sensor events per second using Apache Kafka and Redis
- Legacy Systems: Limited to 3,000 events per second due to reliance on traditional relational databases

failover mechanisms—minimizing manual intervention and operational costs.

By implementing this intelligent monitoring system, organizations can:

- Reduce downtime and optimize server health
- Improve fault tolerance with real-time AI-driven detection
- Enhance scalability across multi-region data centers

8.1. Future Scope

To further optimize the framework, future work can explore:

1. Advanced deep learning models (e.g., Transformer-based time-series forecasting)
2. Edge AI for real-time anomaly detection on bare-metal nodes.
3. Integration with cloud-native Kubernetes environments for containerized workload monitoring.

Our proposed solution bridges the gap between AI-based predictive analytics and automated remediation, ensuring a more resilient and cost-effective private cloud infrastructure.

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