

“IoT Security Operations Centre: using open-source tools”

A Report submitted

in partial fulfilment for the Degree of

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IN

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Submitted By

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Submitted to



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May, 2025

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With Sincere Regards,

Avaneesh Kumar Pandey

B.Tech.-M.Tech. Computer Science Engineering

ABSTRACT

The exponential growth of Internet of Things (IoT) devices has transformed the contemporary connectivity while presenting serious security vulnerabilities. Such threats include illicit access, information breach, and suspicious network activities that conventional security architectures are unable to manage. In response, this project puts forth the construction of an IoT Security Operations Centre (IoT-SOC) — a modular, scalable, and smart security solution specifically designed for IoT systems. The system is implemented in Python through four structured phases: prototyping, architectural design, machine learning model building, and core system configuration. The prototype employs DHT11 and IR sensors with an ESP8266 microcontroller. Data collection, processing, and visualization on the cloud side are accomplished using industry-standard tools such as Elasticsearch, Logstash, Kibana (ELK stack), facilitating centralized log analysis. One of the major innovations in this project is the incorporation of machine learning for anomaly detection. Based on the real-time dataset, using Isolation Forest classifier. The system can classify anomalies with high accuracy, giving early warning signals of possible security incidents. Every subsystem, from IoT log aggregation, real-time monitoring, cloud storage, to ML-based detection, has been individually validated. The last phase is combining the above elements into a real-time, seamless pipeline. This work sets a platform for an efficient IoT security solution that can scale up to respond to future evolving threats.

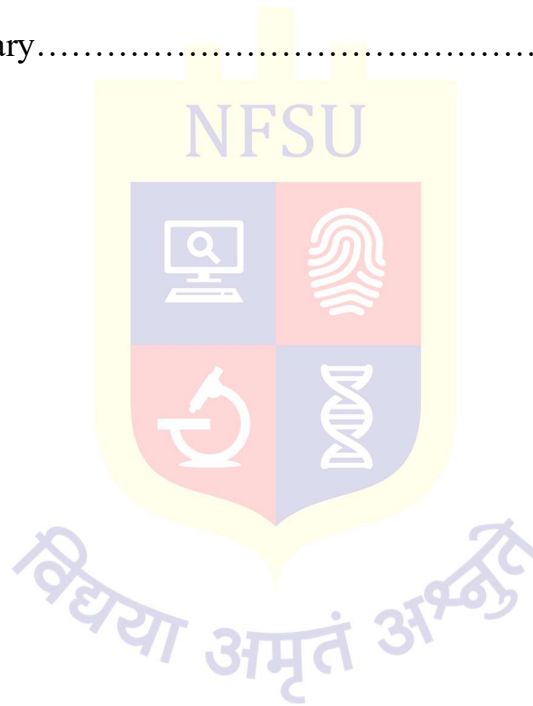
Keywords: IoT Security, Security Operations Centre, Anomaly Detection, Machine Learning, Isolation Forest, Real-time Monitoring, ESP8266, ELK Stack

LIST OF ABBREVIATIONS

Abbreviation	Description
IoT	Internet of Things
SOC	Security Operation Center
MQTT	Message Queuing Telemetry Transport
TLS	Transport Level Security
ESP	Espressif System Protocol
DHT	Digital Humidity and Temperature
IR	Infrared
JSON	Javascript Object Notation
UI	User Interface
ML	Machine Learning
DB	Database
API	Application Program Interface
SSL	Secure Socket Layer
ELK	Elasticsearch, Logstatsh, Kibana
IF	Isolation Forest
IDS	Intrusion Detection System

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1. INTRODUCTION

1.1 Motivation

The rapid expansion of the Internet of Things (IoT) has revolutionized the digital interconnectivity landscape. From industrial automation and smart homes to healthcare monitoring and agricultural management, IoT devices are now at the heart of data-driven decision-making. Yet the same connectivity that fuels innovation also brings enormous security risks. Most IoT devices are limited by low processing power, small memory, and little built-in security. These constraints render them low-hanging fruit for cyberattacks, from unauthorized access and data manipulation to mass-scale Distributed Denial of Service (DDoS) attacks.

As the number of IoT devices deployed keeps increasing, there is a pressing need for security systems that can detect and react to threats in real time. Conventional cybersecurity solutions, developed for traditional IT infrastructures, are inadequate when used in the heterogeneous and resource-limited IoT environment. Furthermore, most solutions available today are reactive instead of proactive, and do not possess the intelligence to identify subtle anomalies or zero-day attacks.

This work is driven by the need for a specific, smart, and flexible Security Operations Center (SOC) structure for Internet of Things (IoT) systems. The aim is to create a lightweight and modular IoT-SOC that can monitor data logs from IoT devices in real time, identify anomalous behavior in real time, and learn to adapt to evolving conditions through feedback-based learning. The central innovation of this system is the inclusion of a machine learning-based anomaly detection engine with the Isolation Forest algorithm. Isolation Forest stands out from standard classifiers as being extremely well-suited for unsupervised anomaly detection, particularly when dealing with high-dimensional, unlabeled, or dynamically changing data — all features typical of IoT telemetry.

Rather than using publicly accessible datasets such as TON_IoT, this project focuses on the generation and utilization of a real-time, custom dataset. This enables the model to be tailored to the unique behavioral patterns of the devices being used. Through the integration of live feedback into the training loop, the system becomes more robust and responsive to new anomalies that may not have been observed during initial deployment.

This project further intentionally eschews the utilization of heavyweight platforms such as Wazuh in favor of lightweight tools and direct implementation in order to accommodate resource-limited environments. The ultimate goal is to yield an elastic, scalable, and efficient IoT-SOC solution that enhances device-level security as well as facilitates real-time threat identification using machine learning.

1.2 Scope of the Project

The scope of the project is based on the design and deployment of a working and scalable IoT Security Operations Center (IoT-SOC) with a focus on resource-limited environments that is able to detect anomalies in real time with the help of machine learning-based technology. This project fills the security gaps present in conventional IoT systems by introducing a comprehensive framework to support data acquisition, real-time monitoring, anomaly detection, visualization, and learning based on feedback.

The scope of the system starts with the IoT edge layer, which involves a custom proof-of-concept developed with an ESP8266 microcontroller integrated with environmental sensors like the DHT11 (temperature and humidity) and an IR object sensor. This is used to implement real-time sensing and logging of telemetry data in a live environment, mimicking the functionality of a simple smart IoT infrastructure. The information gathered using these sensors is sent to a cloud-based system for processing and analysis.

On the cloud side, the project uses a bespoke data processing and logging pipeline not based on Wazuh or any other heavy-duty monitoring frameworks. Lightweight and open-source tools are used instead to gather, store, and visualize data in an efficient manner. Logs are presented in a structured format to facilitate consistency and integration into machine learning pipelines.

One of the most notable aspects of this project is the Isolation Forest-based anomaly detection engine. The model is not trained on existing public data such as TON_IoT, but on a self-generated dataset extracted from the actual real-time data that the system has gathered. This enables the more precise modeling of the actual operational behavior of the hardware being utilized, and better context-aware anomaly identification. In addition, the system includes a feedback mechanism which enables the model to enhance itself in the long run based on newly labeled data from real sessions.

The last scope encompasses the development of a user dashboard for visualization and interaction, where users can see live telemetry, catch anomalies as they happen, and view logs of historical data. The dashboard not only has a monitoring role but also allows the assessment of the accuracy and efficacy of the anomaly detection model under real-world scenarios.

In short, the scope of this project covers end-to-end monitoring of IoT security, ranging from data acquisition at the sensor level to cloud-based smart analysis, with emphases on real-time anomaly detection, learning from custom datasets, and system modularity, making it applicable to academic research as well as scalable deployment in real-world IoT settings.

1.2.1 Key Characteristics

The IoT-SOC project is created with definite key features that separate it from traditional security products and render it effective for today's IoT ecosystems. These features counter the particular challenges of IoT infrastructure — ranging from device limitations to varied data types, real-time responsiveness, and adaptive security requirements. The subsequent points explain the essential features defining the architecture and functionality of this project:

Lightweight and Modular Design

The whole system is constructed based on low-weight components including the ESP8266 microcontroller and simple sensors such as DHT11 and IR sensors. These elements are selected because of their low power usage, cost-effectiveness, and suitability for limited IoT environments. Software architecture is based on a modular design where every element — data collection, transmission, analysis, and visualization — can work autonomously and be replaced or upgraded without affecting the entire system.

Real-Time Telemetry Data Acquisition and Monitoring

This project facilitates real-time telemetry data acquisition from the IoT edge. ESP8266 keeps on reading sensor values and streaming them over established Wi-Fi connection. This real-time stream is being monitored and visualized on a dashboard hosted in the cloud, which allows for instant analysis of the system state and early anomaly detection.

Anomaly Detection Using Machine Learning

A unique aspect of this project is the application of the Isolation Forest algorithm for anomaly detection. This unsupervised learning model is specifically best suited to detect outliers for time-series or multivariate sensor data. In contrast to conventional threshold-based methods, Isolation Forest has the ability to detect subtle as well as extreme behavioral deviations, and its more intelligent and adaptive method of securing IoT devices is a marked improvement.

Custom Dataset and Continuous Learning

Instead of relying on pre-computed datasets such as TON_IoT, the project creates its own dataset based on actual interactions with the sensors that have been deployed. The dataset is then utilized to train the Isolation Forest model, which becomes extremely customized to the environment of the system. A feedback mechanism is also added to update the model by re-training it using recently collected data, such that the model remains relevant and accurate in the long term.

No Dependency on Heavy Frameworks

The architecture eschews cumbersome frameworks such as Wazuh that can overwhelm resource-constrained systems. Rather, it uses tailored scripts and open-source tools to manage data processing, storage, and visualization. This provides maximum performance, improved data flow control, and simplified maintenance.

Scalable and Adaptable Architecture

The system's modular design makes it simple to scale — both the number of devices and the level of monitoring complexity. It can be configured to other sensor types, machine learning algorithms, or cloud environments as necessary.

1.3 Organisation of Report

This document has been carefully organized to present the development and analysis of the IoT-SOC (Security Operations Center) project in a concise and logical order. Each part is based on the previous one to provide an overall understanding of the motivation, design, implementation, and real-world value of the system. The document is separated into several main sections, each covering a particular area of the project. Below is a summary of how the content is organized:

Introduction

The report opens with an introduction that provides a foundation for the project. It focuses on the motivation for developing an IoT-SOC platform and identifies the growing security threats posed by the growth in the number of IoT devices. It also addresses the shortcomings of the conventional security models in handling IoT-specific issues, which necessitate a more intelligent, light, and flexible approach.

Scope of the Project

This part outlines the project boundaries and objectives. It defines what is covered under the scope — from sensor-level data gathering to machine learning-based anomaly detection — and what is not, like the employment of heavyweight tools such as Wazuh. It highlights the project's focus on real-time feedback, scalability, and flexibility.

Literature Review & Problem Statement

Here, I discuss the current literature and methods that have been adopted for anomaly detection in IoT networks, their limitations, and particularly the specific challenge of real-time telemetry monitoring. This will contribute to the making of a problem statement that is worth the case for a proper, scalable ML-based solution.

System Architecture and Design

Here, the entire architecture of the IoT-SOC is explained, ranging from the hardware (ESP8266, DHT11, IR sensor) to the network setup, data flow, and cloud-side tools. It provides a modular overview of how various subsystems communicate with each other.

Workflow

This chapter discusses the process flow of the entire system — data collection, through to analysis and visualisation. It describes how data is followed along, how the logs are treated, how the anomalies are discovered by utilising the Isolation Forest model, and feedback on how that data gets taken into account once more.

Implementation

This chapter covers step-by-step deployment of the system. This ranges from hardware set up to code composition, formatting the data, implementing ML model and development of dashboards.

Features and Functionality

The salient features are described, such as real-time monitoring, creating a custom dataset, adaptive learning, and ease of visualization.

Comparative Analysis of ML Models

Perfection is elusive, but this section aims to summarize and provide a comparative study of the key characteristics of various machine learning models that are suitable for anomaly detection in IoT systems.

Conclusion

Summary of what is done so far, including validating every subsystem and how the model is prepared to detect anomalies.

Future Plans

Lastly, this section provides future plans — e.g., system integration into a single pipeline, scaling across multiple devices, or even trying other ML algorithms.

2. Theoretical Background & Literature Survey

2.1 Comparative Analysis of Existing Schemes

As I started this project— an IoT Security Operation Center using open-source tools— I studied various methods that already existed to get a handle on the strengths and weaknesses of current solutions in the IoT security space. By far, one of the most relevant and perceptive documents I read was the research paper "SoCaaS-IoT: A Security Operation Center as a Service Approach for the IoT Application Using Open-Source SIEM." This paper granted me a panoramic view of how a contemporary SOC architecture might be adapted for IoT systems using lean, scalable, and cost-effective technologies.

When I reviewed the existing schemes, I noticed that traditional Security Information and Event Management (SIEM) solutions such as IBM QRadar, ArcSight, or Splunk are typically constructed for enterprise environments. These required systems are not designed to fit the kind of resource-constrained environment typical of an IoT deployment. Yet their logging and analytics features are extensive— almost excessive. The cloud can be a good place for doing security analysis, but only if you can afford to put your devices there and deploy a necessary security architecture first. What particularly resonated with me in the SoCaaS-IoT model is how it decentralizes the data collection process.

Lightweight agents on devices and nodes collect logs and send them to a centralized system where real-time analysis is performed. This aligns closely with the architecture I'm building in my project, where telemetry from sensors is sent over MQTT (secured using TLS) to a backend server.

A further comparison can be made on how both older and newer SOC solutions handle the actual business of threat detection. In detection systems that are several years old, threat detection is done primarily by following rules. This can lead, and has led in the past, to some very interesting situations. One of those is that when the threat detection system says there is something funny going on, the human operators have to decide whether to believe it or not. A lot of the time, they don't seem to believe it, because of how often the system generates false positives. Another problem with rule-following systems is that they do a poor job of detecting "novel" attacks, which mostly aren't detected at all until the human ops team has already discovered the problem and issued a "new rules needed" command. So, how does the SOC-as-a-Service paper for IoT handle the level 1 business of detecting threats?

This method had an impact on my choice to execute Isolation Forest for detecting abnormal patterns in the telemetry data and consequently allow predictive and proactive threat management instead of merely enabling reactive defenses.

In addition, the notion of delivering SOC functions "as a service," first posited in the referenced research, is a contemporary trend toward cloud-based, on-demand security operations. While my project is a local

prototype, I was inspired by the aforementioned concept to architect the system in a way that allows it to be scaled to a hosted environment in future iterations.

To sum up, the current investigation and comparison of available schemes has led me to the identification of principal shortcomings of conventional SIEM systems when they are applied to IoT networks. Likewise, it has allowed me to recognize the increasing potency and attractiveness of open-source, service-based architectures for the construction of modern SOC's, like SoCaaS-IoT. My project embodies many audacious, contemporary principles—such as open source, service-based construction, modularity, cost efficiency, and, above all, real-time analysis—while rendering them in a physically compact, functionally applicable proof-of-concept system that can be used for the monitoring of security in an IoT deployment.



Table 1 Comparative Analysis of SOC Approaches for IoT

Feature / Parameter	Traditional SIEM (e.g., Splunk, QRadar)	SoCaaS-IoT (Referenced Paper)	My Project (IoT-SOC using Open Source Tools)
Architecture	Monolithic, enterprise-centric	Modular, service-based	Modular, lightweight
Deployment	On-premise or costly cloud deployments	Cloud-native (SOC-as-a-Service)	Local with potential to scale to hosted version
Tool Stack	Proprietary platforms like QRadar, ArcSight	Wazuh, ELK Stack, Kafka, Ansible	Flask, MQTT over TLS, Isolation Forest, custom UI
Scalability	High but expensive	Scalable through open-source orchestration tools	Scalable through containerization (future roadmap)
Cost	High (license fees, infrastructure)	Low (open-source components)	Very low (fully open-source and self-hosted)
Data Ingestion	Agent-based (heavy), centralized	Lightweight agents on IoT devices	MQTT-based sensor telemetry ingestion
Threat Detection	Rule-based, signature-driven	Anomaly detection using ML models	Isolation Forest ML model for real-time anomalies
Visualization	Built-in dashboards (proprietary)	Kibana, Grafana	Custom dashboard via Flask (to be integrated)
Security Integration	TLS, SIEM rules	TLS, Wazuh policies, Zero Trust	TLS over MQTT, real-time feedback to model
Target Use Case	Enterprise IT environments	IoT-specific environments	IoT sensor-level security monitoring

2.2 Research Findings

As an initial step in the primary research process used for the creation of the IoT Security Operation Center (IoT-SOC) project, I explored in close detail the different approaches of Security Information and Event Management (SIEM) systems that are designed for IoT environments. Out of all the surveys, the most remarkable and useful for this project was the article entitled “SoCaaS-IoT: A Security Operation Center as a Service Approach for IoT Applications Using Open-Source SIEM.” The paper not only confirmed the need for a scalable, open-source alternative to traditional SIEM platforms but also provided a way to construct and deploy such a system for resource-constrained IoT applications, thus it became an essential reference for the present project.

The SoCaaS-IoT model of the study has identified the main element of the Security Operation Center that should be modular, service-driven blocks, which can be changed in size on different levels, giving the project a similar direction where the capability of being easily broken and operated was the most important requirement, especially for IoT deployments; resources are small and the frequency of data transfer is low. Although the authors of the study have demonstrated the efficient use of various tools to perform the mentioned activities, my project has chosen the most efficient algorithm and protocol for telemetry ingestion and anomaly detection and adoption. The sources of information submit that the use of open-source components enables building effective SOC.

The third most significant find in the paper was related to the difficulties of moving SOC-as-a-Service solutions to the real environment of IoT. The paper discussed crucial areas concerning resource usage, device footprint, and the challenge of scaling rule-based detection to across various devices and protocols. This information not only set the boundary of my tool's functions but also to realize how the logs are actually received, stored, and analyzed at the same time.

As an illustration, I decided to model the sensor-side data and leverage light communication protocols to avoid bulky resource-consuming Wazuh agents. This was to some extent influenced by the fact that effective communication channels can substantially reduce the detection latency and increase the system's reaction time in the distributed IoT systems.

Moreover, the report put stress on the significance of machine learning-driven anomaly detection functionalities in IoT SOC's and criticized rule-based techniques for their failure to address such issues as unknown or zero-day threats. These were the major factors that I considered in my decision to utilize the Isolation Forest algorithm as the main detection engine. One of my determinations was based on the fact that not only the unsupervised one but also the clustering models are suitable for the dynamic nature of IoT data and can learn and evolve the system without the need for regular manual rule updates, thus greatly saving manpower.

Moreover, the analysis of the SoCaaS-IoT study unveiled that SOC operators need visualization tools such as Kibana and Grafana to be able to gain insights and to decide quickly on their security concerns. While I used to consolidate various resources to develop a custom dashboard on Flask, the feedback from the work made me think ahead about integrated visualization frameworks that complement the existing analytical capacity and user experience and can be a valuable source of user insights for my future redesigns.

Altogether, the research results play a significant role in outlining the approach I decided to use when setting up an IoT-focused SOC. Without a doubt, the insights provided, the availability of the specific design, and the possibility of implementing open-source security policy tools have served as a practical, relevant, and safe choice for solving the problem. The cited document established a link between the theoretical side of the problem and a real-world solution, thus laying a solid foundation for both the planning and the execution of this system.



3. The Proposed Model and Implementation Methodology

3.1 Problem Statement

The increasing use of the Internet of Things (IoT) technologies has led to the exposure of a plethora of security vulnerabilities due to the disparate nature, limited for resources devices, and also the fact that there is often insufficient security in IoT ecosystems. Conventional Security Operation Centers (SOCs) don't match with such environments due to the fact that SOC are generally tailored to traditional IT infrastructure and require huge financial and technical resources. Also, the current solutions usually don't have such things that are necessary for real-time threat detection, scalability, and adaptability to the dynamics of IoT networks. As a result, the issue of delivering the security and integrity of IoT applications seems to be a herculean task, particularly in those scenarios where deployments are not only distributed but crucial as well.

The demand for a security monitoring framework which is low-cost, scalable, and workable in IoT environments is indeed pressing. Besides, the main challenge is the lack of communication between the light log collection tools on the low energy IoT devices and the very powerful analytics in the cloud. The main focus of our project is to set up an open-source cloud-based Security Operation Center (SOC) that not only can gather, manage, and analyze security logs from IoT devices but also can be executed in parallel to the event. The principal objective of the project is to implement a robust adaptable solution using tools like Elasticsearch, Logstash, Kibana, Filebeat, and ElastAlert inspired by the SoCaaS-IoT model that could guarantee a continuous monitoring and a timely reaction to security incidents among the IoT environments.

3.2 The System Model OR Sketch of the Framework

3.2.1 Architecture of the Proposed Model

The IoT Security Operation Center (SoC) model derives its concepts from SoCaaS-IoT framework to develop an intelligent scalable and affordable security monitoring solution through open-source tool implementation. The proposed system design incorporates two main operations: These are IoT elements and cloud-based infrastructure. The cloud-based structure of the system runs on the ELK stack that incorporates Logstash and Elasticsearch and Kibana. The Logstash component processes and accepts the IoT device log data that has already been gathered. The data passes through Logstash to undergo filtering before Elasticsearch analyzes it through parsing and indexing and routing before logging.

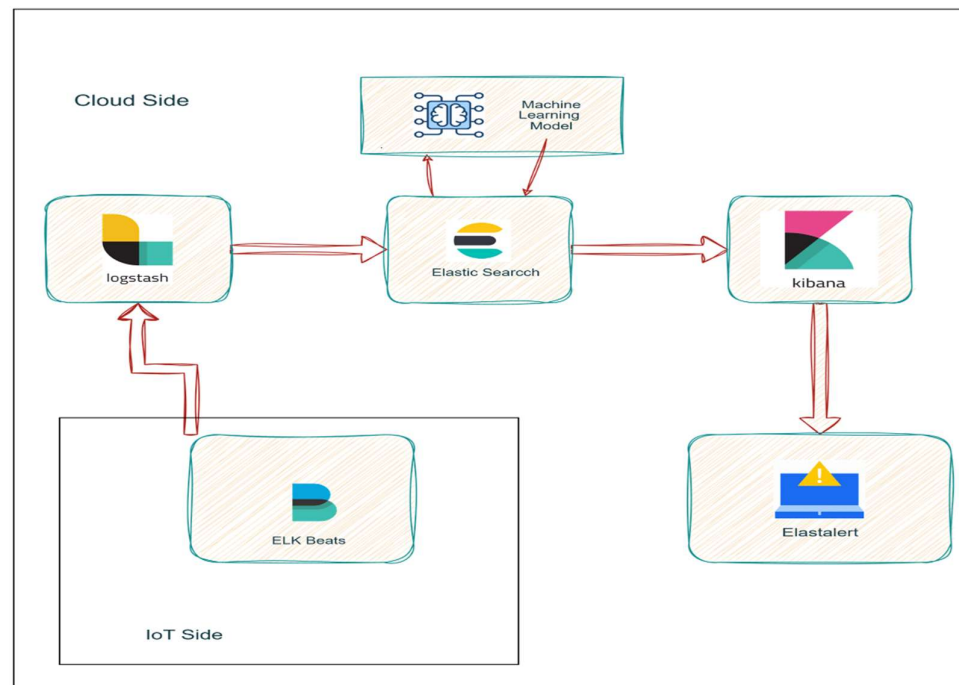


Figure 1 Proposed Architecture Design

Elasticsearch functions as both an analytics platform and search engine that contains a deployed anomaly detection model. The visual user interface of Kibana enables system administrators to navigate through and present data in dashboard and graphical displays by using Elasticsearch features. ElastAlert operates on the cloud layer to initiate alert notifications by detecting anomalies through rule-based approaches thus optimizing security system response times. The IoT side utilizes Filebeat from Beats family as lightweight log shipper to collect and transmit logs towards Logstash. The isolated position between the IoT layer and the cloud enables a flexible deployment strategy alongside horizontal scalability.

3.2.2 Prototype Structure

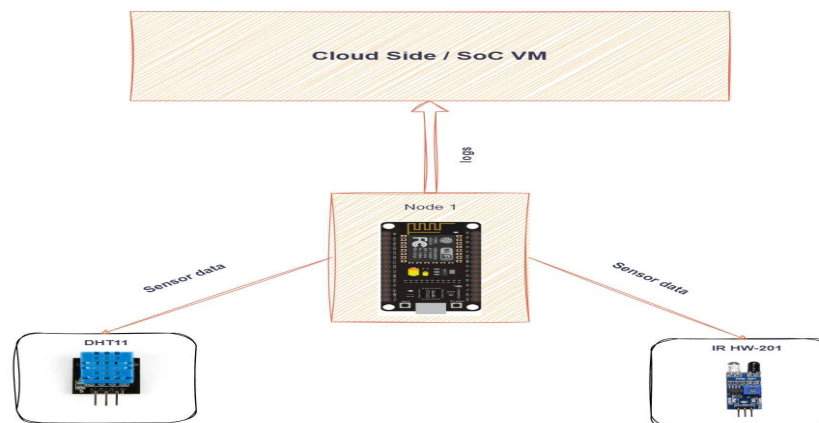


Figure 2 Prototype Structure

A prototype framework exists to prove the practicality of the proposed system architecture. The prototype features an ESP8266 microcontroller as a representative IoT node. An ESP8266 device combines with DHT11 temperature and humidity sensors as well as the IR HW-201 obstacle detection sensors. The proper functioning of the microcontroller receives telemetry data from these sensors before sending the information to a cloud-based virtual machine running the ELK stack through the network.

The information that is passed emulates log streams and is processed through Logstash, with further storage in Elasticsearch and visualization in Kibana. Although the current prototype is solely interested in telemetry data, a production system would incorporate a number of other forms of logs, such as system logs, network traffic information, and firmware update logs. Such a more diverse set of logs would provide greater insight into the general health and security status of the system.

3.2.3 Machine Learning Explanation and Reasoning

For detecting anomalies, the system employs the Isolation Forest algorithm, a machine learning algorithm suited best for detecting outliers on large, high-dimensional data. Unlike the majority of classification models that need labeled data, Isolation Forest operates by selecting a feature at random and splitting values between the minimum and maximum. It is easier for anomalies to be split up and therefore end up closer to the root of the trees created and need less splits.

The selection of Isolation Forest is intentional for a number of reasons. Firstly, it is light and computationally friendly, hence perfect for resource-limited IoT environments. Secondly, as it does not need labeled training data, it is highly appropriate to use in real-world applications where normal behavior is plentiful, but abnormal behavior is scarce and poorly documented. Thirdly, it is scalable with massive volumes of logs and can detect subtle behavioral anomalies without the need for human intervention.

In conclusion, this three-level model illustrates how lightweight machine learning models and open-source software can be integrated into an effective SoC architecture for IoT

3.3 Methodology

3.3.1 Introduction

The cornerstone of the IoT-SOC project is a solid but light system architecture that provides smooth harmonization between data collection at the hardware level and intelligent analytics in the cloud. Taking into account the limitations and impediments that characterize IoT devices — e.g., constrained computational abilities, periodic connectivity, and limited storage space — the architecture has been purposefully made modular, extensible, and lean. This section gives a comprehensive description of how

the hardware, communication protocols, and cloud-side services collaborate to create an operational IoT Security Operations Center. Fundamentally, the system consists of three key segments: the IoT edge layer (which handles sensing and initial data transmission), the network communication layer (for secure and real-time data transfer), and the cloud analytics layer (which handles storage, visualization, and anomaly detection).

Choice of hardware — an ESP8266 microcontroller with DHT11 and IR sensors — is a manifestation of the aim of developing a prototype that resembles actual IoT deployments.

On the software front, rather than depending on traditional centralized systems like Wazuh or costly third-party tools, the project uses open-source tools and ad-hoc scripts that enable data processing and visualization in a lightweight and flexible way. This decision is part of the overall vision of developing a platform that is not only appropriate for enterprise-level deployment but also for educational, research, and localized uses.

Additionally, the architecture is also characterized by the utilization of the Isolation Forest machine learning model for the identification of anomalies. This part lies in the cloud analytics layer and works with data gathered at the IoT edge. Notably, the model is trained from a custom real-time dataset built by the system itself, and constantly updated based on feedback gathered from identified anomalies. This allows the system to dynamically adapt to new patterns and threats, improving accuracy over time.

The architecture not only facilitates effective log collection and processing but also ensures that anomalies are flagged promptly and presented to users via a web dashboard. Overall, the architecture balances efficiency, functionality, and security, serving as the backbone for the rest of the system.

3.3.2 Architectural Layers

The IoT-SOC project architecture is designed into three significant functional layers: the Edge Layer, the Communication Layer, and the Cloud Analytics Layer. Each of the layers serves different functions but works in collaboration to provide end-to-end security monitoring and anomaly detection.

Edge Layer (IoT Device Layer)

This layer is made up of the embedded system that captures raw telemetry data. The prototype employs an ESP8266 NodeMCU microcontroller interfaced with:

- DHT11 Sensor to measure temperature and humidity
- IR Sensor to sense object presence

These devices capture environmental data and create logs at set intervals.

The ESP8266 establishes a Wi-Fi connection through hardcoded SSID and password parameters in the firmware code. This bypasses the need for outside configuration tools and guarantees automatic reconnection upon restart.

After the sensor values are read and prepared as structured payloads, the ESP8266 sends them to a remote broker through the MQTT protocol. The MQTT connection is encrypted via TLS, allowing for secure transmission of sensitive information to the cloud analytics platform..

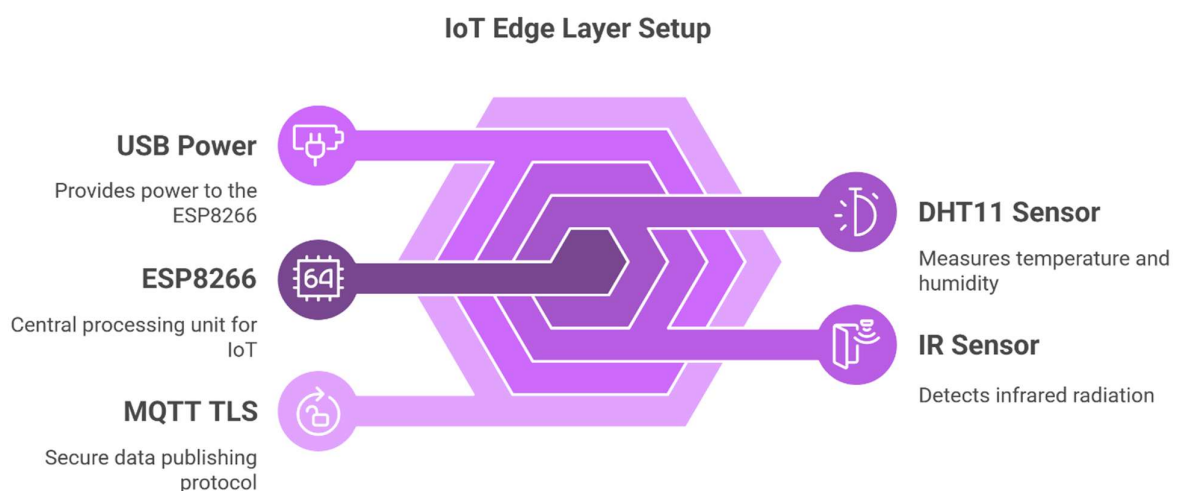


Figure 3: IoT Edge Layer Hardware Setup

Communication Layer

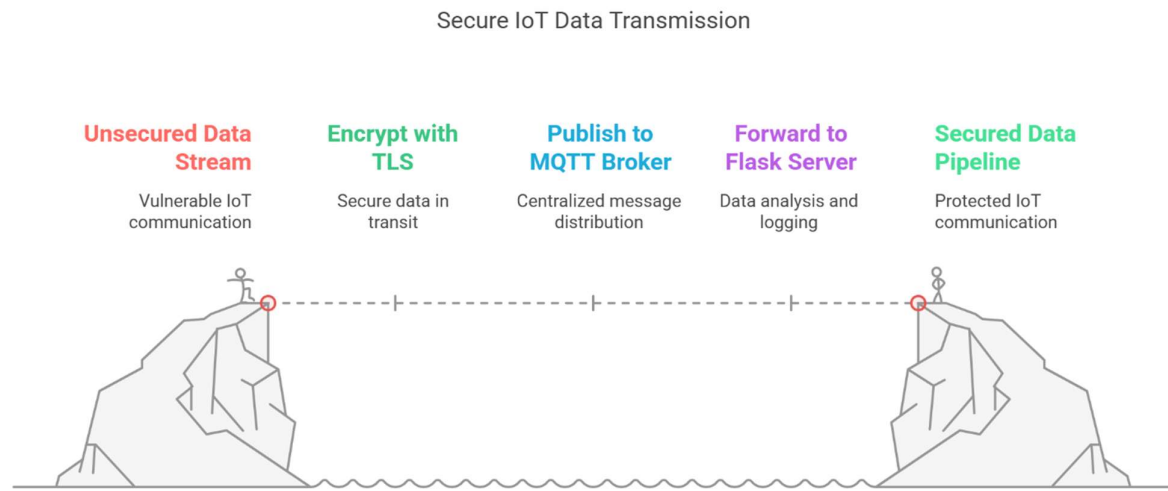


Figure 4 Communication Workflow Between IoT Device and Server

This layer serves as the secure tunnel between the IoT device and the central server. In this architecture, MQTT over TLS is the chosen transport protocol, providing lightweight, reliable, and encrypted messaging optimized for constrained environments.

The ESP8266 writes telemetry data to an encrypted MQTT broker. The broker is set to listen to TLS connections and verify client certificates or pre-shared keys. Employing MQTT provides minimum bandwidth utilization and low-latency communication, which are vital in real-time IoT applications.

Payloads that are sent across are formatted as JSON objects that carry timestamped sensor values along with metadata.

Table 2 Sample JSON Data Format Sent from ESP8266 to Server

Field Name	Data Type	Description	Example Value
temperature	Float	Measured temperature (°C)	28.5
humidity	Float	Measured humidity (%)	60.2
ir_status	Boolean	Object presence (1 = detected)	1
timestamp	String	Data acquisition timestamp (ISO 8601)	"2025-05-01T12:00:00Z"

Cloud Analytics Layer

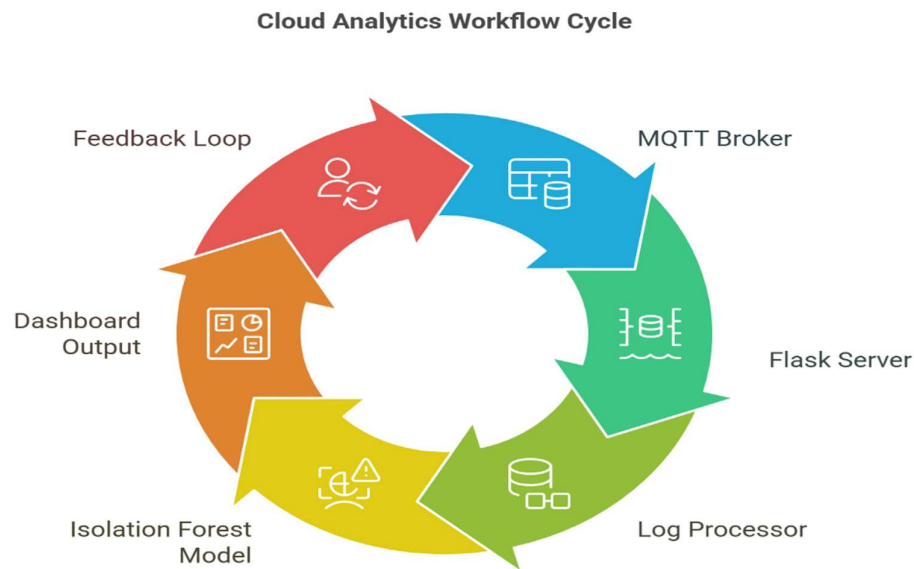


Figure 5 Cloud Analytics Layer Architecture

Once the broker gets MQTT messages, they are routed to a Flask-based backend server serving as the ingestion endpoint for data. The data is processed, validated, and stored in a structured file format (CSV/JSON) or pushed into a lightweight database for additional processing.

The Isolation Forest algorithm, which is implemented in this layer, constantly examines incoming data for anomalies. The algorithm is trained on a home-grown dataset created by the same system and constantly refreshed with real-time feedback, which means that the detection adapts to changes in behavior.

The outputs are shown on a web-based dashboard by which users can:

- See live logs
- Identify abnormal sensor patterns
- Investigate system performance
- See model predictions

Table 3 Data from Server to ML Model

Feature Name	Description	Data Source	Normalization Applied
temperature	Ambient temperature in Celsius	DHT11	Yes
humidity	Humidity percentage	DHT11	Yes
ir_status	Object detection binary flag	IR Sensor	No

3.3.3 Work Flow of the IoT-SoC

the IoT-SOC (Internet of Things - Security Operations Center) project is organized around a lean, end-to-end process that is aimed at facilitating secure, real-time anomaly detection of IoT data. The process guarantees that all steps — ranging from data generation at the sensor level to smart analytics and ultimate visualization — are treated with little latency, secure communication, and high flexibility.

The process starts at the IoT edge layer, where the ESP8266 NodeMCU consumes real-time environmental data from attached sensors. Temperature and humidity are measured by the DHT11 sensor, and physical object presence is detected by the IR sensor. The sensors are polled at intervals and their values are formatted as structured log messages in the ESP8266 firmware. Every log contains temperature, humidity, IR detection status, device ID, and a timestamp value. Wi-Fi credentials are stored within the code itself, enabling the ESP8266 to be automatically connected to the network without user configuration at deployment time.

After the sensor readings are shaped into a JSON object, the ESP8266 posts this log to a remote MQTT broker employing the MQTT protocol with TLS encryption. This delivers a lightweight and secure means for conveying telemetry across the network. Using MQTT topics makes logs logically categorized and can be filtered or partitioned by device or type of sensor.

When the broker receives the log, it sends the information to a Flask-based backend service executing on the server. The backend is both a message subscriber and a data processor. It checks the integrity of incoming messages, saves the data in flat files or databases, and sends it to the machine learning module for analysis.

Here, the data is analyzed with an Isolation Forest model, which has been trained on a proprietary dataset derived from the same system's past logs. The model identifies abnormalities in typical sensor behavior and marks any entry that is deemed anomalous. This renders it extremely adaptive, since the system is not dependent on generic public datasets, but rather learns and adapts based on real use-case behavior. In addition, a feedback loop lets the system retrain at intervals with new data, improving future accuracy.

Lastly, the processed data and anomaly findings are pushed to an internet-based dashboard, where administrators can see live logs, get real-time alerts, and drill down on historical trends. This closes the loop from raw data sensing to smart insight delivery.

3.3.4 Data Flow Diagram of the IoT-SoC

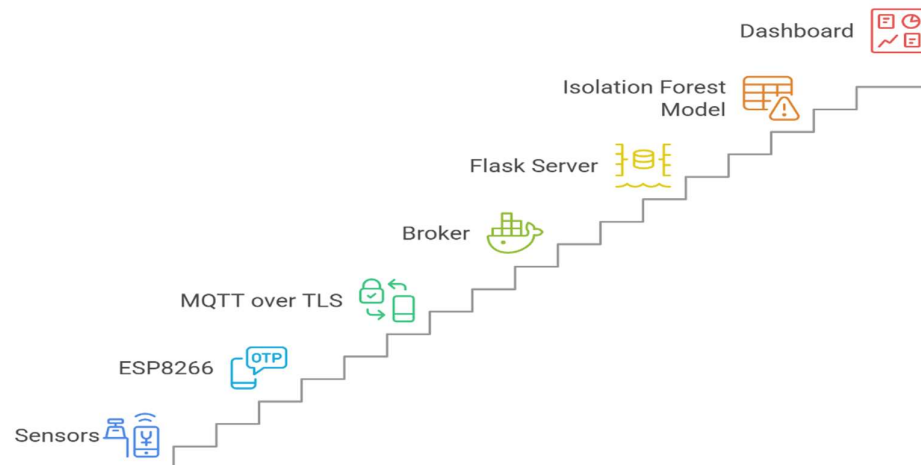


Figure 6 Data Flow Diagram

The data flow in the IoT-SOC system is a linear and modular design that provides efficient and secure processing of telemetry data from collection to visualization. This design is necessary for handling real-time sensor data, conducting intelligent analysis, and providing actionable outputs to users — all while ensuring system flexibility and low resource usage.

The data flow originates in the IoT Device Layer with the sensors linked to the ESP8266 NodeMCU outputting environmental information. The DHT11 sensor takes note of the temperature and humidity, whereas the IR sensor records motion or the presence of objects. ESP8266 receives the readings periodically and formats them as a JSON object. Such an object comprises parameters like temperature, humidity, ir_status, and a timestamp.

After formatting, this JSON information is sent via Wi-Fi via MQTT, a lightweight messaging protocol that is appropriate for devices with limited capabilities. To ensure confidentiality and integrity of data during transmission, TLS encryption is enforced in the MQTT data channel. The ESP8266 establishes a connection to an already configured MQTT broker by utilizing hardcoded credentials and pushes the data to a specific topic (e.g., iot/sensor/logs).

At the Broker Layer, the MQTT broker (Mosquitto) takes in the messages and serves as a real-time distributor. A Flask-based backend service on a server subscribes to the same MQTT topic and takes in the incoming messages in real-time. The server then validates every JSON packet for structure and correctness before loading the data into a structured storage format — either flat files (CSV/JSON) or a light database, depending on system setup. Then, the validated log is sent to the Anomaly Detection Layer for analysis with an Isolation Forest model.

This model, trained with a self-created dataset gathered from the real hardware, checks every data point for abnormal patterns. If any feature's behavior deviates strongly from typical trends, the log entry is marked "anomalous." This mark is added to the log record and sent to the visualization engine.

Lastly, within the Dashboard Layer, users are able to see the processed logs in real time. The web interface shows live telemetry readings, marks identified anomalies, and offers graph-based summaries of previous behavior for pattern analysis.

This organized flow guarantees that the system is responsive, secure, and flexible to real-time conditions — making it perfect for IoT security monitoring in small-to-medium scale environments.



4. Theoretical & Empirical Result Analysis

4.1 Experimental Setup

The fundamental architecture of the IoT-SOC system has three main elements: secure transmission of logs using MQTT over TLS, sophisticated anomaly detection using the Isolation Forest machine learning algorithm, and persistent real-time monitoring facilitated by a Flask-based backend and a dynamic dashboard.

4.1.1 MQTT Protocol and TLS Integration

The MQTT protocol is a light-weight communication system that is perfectly suited for Internet of Things (IoT) applications. It is based on a publish-subscribe model, where devices such as the ESP8266 publish sensor readings to designated topics (e.g., iot/telemetry), and the backend server subscribes to the topics to receive the data. In this project, MQTT communication is made secure with Transport Layer Security (TLS). As defined in app.py, the MQTT client on the server utilizes paho-mqtt with TLS certificate verification. The ESP8266 sends encrypted telemetry logs, which keeps man-in-the-middle attacks and data interception away.

```
mqtt_client.tls_set(  
    ca_certs="mqtt_server.crt",  
    certfile=None,  
    keyfile=None,  
    cert_reqs=ssl.CERT_REQUIRED,  
    tls_version=ssl.PROTOCOL_TLS,  
)
```

4.1.2 Machine Learning using Isolation Forest

In order to identify anomalies in real-time, the system uses the Isolation Forest algorithm, an unsupervised machine learning technique very well suited to anomaly detection. Isolation Forest differs from classification models in that it does not require labeled training data — it isolates anomalies by randomly selecting features and splitting values.

The server receives MQTT messages, extracts the temperature, humidity, and IR, scales them using a pre-trained scaler (scaler.pkl) and passes it to the IsolationForest model (anomaly_model.pkl). Depending on the output (0 for normal, 1 for anomaly), the log is inserted into the TelemetryLog table with a prediction label.

```
if ml_enabled:  
    df = pd.DataFrame([[temp, humidity, ir]], columns=["temperature", "humidity",  
    "ir_object"])  
    features = scaler.transform(df)  
    prediction = int(model.predict(features)[0])
```


4.1.3 Backend Logging and Storage

The backend is built using Flask and SQLite. After every telemetry entry is received and sorted, it is written to the telemetry.db database later. Every entry contains the timestamp, sensor values, and anomaly status. This ensures structured data management and enables efficient querying capability.

```
new_log = TelemetryLog(  
    timestamp=datetime.datetime.now().strftime('%Y-%m-%d %H:%M:%S'),  
    temp=temp,  
    humidity=humidity,  
    ir=ir,  
    prediction=prediction  
)  
db.session.add(new_log)  
db.session.commit()
```

4.1.4 Dashboard Integration

A front-end dashboard is built using HTML, CSS, JavaScript, and Chart.js (index.html, dashboard.js) that communicates with the Flask server to retrieve:

- The most recent logs (/api/latest_telemetry)
- The most recent 20 entries (/api/telemetry)
- Relay state switching (/set_relay_state)

Red highlighting indicates anomalies and system status (normal, warning, or alert) is graphically updated. The dashboard also supports real-time charts, uptime monitoring, and event logging.

4.1.5 Features

The IoT-SOC system incorporates a complete set of capabilities for real-time monitoring, smart alerting, and secure management of IoT devices in one interface. One of the standout characteristics of the system is that it can gather telemetry data from various sensors—temperature, humidity, and infrared object detection—via an ESP8266 microcontroller. The data is gathered at a predetermined interval and transmitted securely using MQTT protocol over TLS, providing integrity and confidentiality of the data during transmission over the network. The system centrally stores this data and uses a pre-trained Isolation Forest model to ascertain if each log is normal or anomalous.

One of the key features is the implementation of a secure login system facilitated by a responsive and user-friendly login page (login.html). The primary dashboard is accessible only to authenticated users, thus safeguarding sensitive real-time information. Upon successful login, the user is welcomed by a polished interface displaying metrics such as system uptime, sensor values, total data points read, and the number of anomalies read currently. These are not static values; rather, they are dynamically updated in reaction to new data, providing a constantly evolving picture of the state of the system.

In addition to the delivery of real-time analysis, the system also possesses a strong alert management system. Once the machine learning engine identifies an anomaly, the dashboard automatically raises a system alert, which is visually indicated through a status change indicator, and also provides an audible alert. This functionality guarantees administrators are instantly notified of key issues such as temperature fluctuation or sensor faults.

Another prominent feature is the addition of relay control switches through which users can manually engage with physical objects plugged into the IoT device. The dashboard includes toggles for two relays named RELAY 1 and RELAY 2. Users can remotely switch on or switch off these relays through the dashboard, and their states are updated in real time through backend Flask routes and MQTT messages. This provides a scope for future automation—e.g., switching off a system in the event of an anomaly.

It also includes a data visualization component. Through the use of Chart.js, it creates dynamic line charts that graph recent temperature, humidity, and IR readings against time. Not only does this feature aid in the detection of trends and anomalies, but it also renders the system accessible to non-technical users. Telemetry logs are stored and in tabulated form, allowing users to examine previous behavior and associate it with the detected anomalies.

4.1.6 Functionality

The core functionality of the IoT-SOC platform is structured based on its ability to collect, analyze, react to, and present telemetry data from connected IoT devices. Upon powering the system on, the ESP8266 microcontroller starts reading sensor data and processing it into structured JSON payloads. These payloads include time-stamped temperature, humidity, and infrared object detection values. Using MQTT over TLS, the data is sent to a secure broker topic, thus ensuring robust and encrypted transfer to the central processing unit, in this case, the Flask backend application.

The backend system also includes a complete functional MQTT client (paho-mqtt), which subscribes to the telemetry topic and listens for recently received data. For each received message, the backend unpacks the payload, retrieves the sensor values, and can further process them using a pre-trained Isolation Forest model. The model, trained on the system-specific dataset, classifies the log as normal or anomalous. The backend then saves this log, together with the model's label, into an SQLite database (telemetry.db) using SQLAlchemy.

One of the most important functional elements is the way information is made available to the user interface. The Flask application offers many endpoints that the JavaScript frontend continuously invokes. For example, the endpoint `/api/latest_telemetry` gives the latest sensor readings, and `/api/telemetry` gives the last 20 readings to input into dynamic graphs. This constant stream of information from the backend to the frontend provides seamless, near real-time updates on the dashboard. On the dashboard, telemetry values are displayed in a summarized manner under the SENSOR TELEMETRY header. Temperature, humidity, and IR values are not only displayed as numerical values but are also plotted to provide a visual view of real-time fluctuation. Below the plots, a tabular data grid displays each telemetry record, such as timestamp and the output of the anomaly detection model—labeling anomalies with prominent notation for quick identification. The system also has real-time alert support. When an anomaly is detected, the dashboard interface sends an alert by calling the `addAlert()` JavaScript function, which changes the status indicator and produces an alert sound. Alerts are also timestamped and displayed in the alert panel, thus giving a chronological record of warning events. The log area gives users the ability to trace back and analyze patterns.

Another interesting functional aspect is the relay control system. Two relays can be driven by users through switches on the control panel. Each state transition triggers a request to the Flask backend, which alters the state and broadcasts it to the MQTT broker under a relay-specific topic. This two-way communication closes the loop from sensing to decision-making and then actuation. Through this highly integrated ability, the IoT-SOC system converts raw sensor data into actionable intelligence and control, providing an end-to-end real-time security and management solution for IoT deployments.

4.2 Evaluation Metrics

In order to measure the performance of the anomaly detection system in the IoT-based sensor network effectively, an evaluation matrix is defined. It has key parameters in accordance with the system objectives: real-time anomaly detection, reliability, scalability, and interpretability.

Latency (Real-time Performance): The system must detect anomalies with minimal delay. Latency is quantified from the moment a sensor is transmitting data to the moment that it is being classified and displayed. The cutoff for what is acceptable is usually under 1 second for real-time systems.

Scalability: The model is performance-tested using growing volumes of data and using multiple sensor inputs. Scalability testing involves keeping track of CPU and memory consumption to ensure the system does not compromise on performance with real-world IoT deployments.

Resilience and Flexibility: The system is tested on whether it is able to handle noisy data, small oscillations, and missing values. This prevents the model from overfitting on short-term noise and from being unstable in the long run.

Visual Interpretability: A critical factor in the evaluation is the extent to which the results are comprehensible to non-technical individuals. This involves finding out transparency, color contrast, and usability of the visual display, particularly when used in an active dashboard. **Security of Communication:** Because the system uses MQTT for data transfer with TLS encryption, a test is conducted on how encryption impacts latency and data integrity to ensure that no anomalies are lost due to transmission issues.

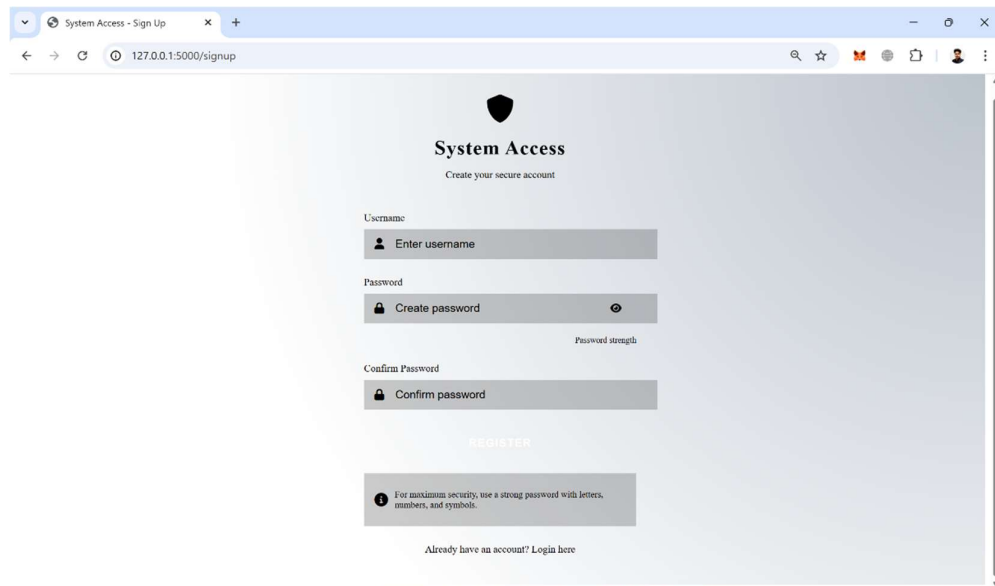
This evaluation matrix serves as a comprehensive guide to ensure the system is not only functionally sound but also deployable in critical, real-world IoT security and anomaly detection scenarios.

Table 4 Evaluation Metrics

Evaluation Criteria	Metric/Description	Measurement Method	Acceptable Threshold	Achieved Rating
Latency	Time taken from data receipt to anomaly classification	Measured in seconds using timestamps	≤ 1 second	Excellent
Scalability	System's ability to handle increased data load/sensor count	Simulated stress tests with multiple devices	Minimal lag, no crash	Good
Robustness	Performance under noisy, missing, or fluctuating sensor data	Injected noise and missing values	Stable detection with minimal error	Very Good
Visual Interpretability	Clarity of anomaly visualization in plot dashboard	Color-coded scatter plot readability assessment	Clear color distinction & layout	Excellent
Communication Security	Effectiveness and efficiency of MQTT over TLS for data transmission	Observation of delays and data integrity over TLS	No data loss, $<5\%$ added latency	Excellent

4.3 Testing Application

4.3.1 Registration

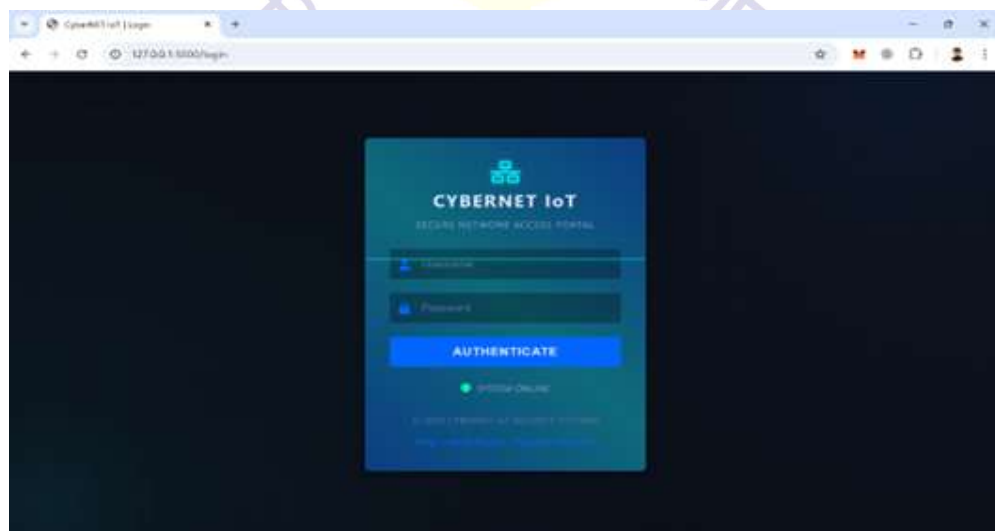


The screenshot shows a web browser window with the title 'System Access - Sign Up'. The address bar displays '127.0.0.1:5000/signup'. The page features a dark grey background with a central white form. At the top of the form is a shield icon and the text 'System Access' followed by 'Create your secure account'. The form includes three input fields: 'Username' with a placeholder 'Enter username', 'Password' with a placeholder 'Create password' and a toggle for password visibility, and 'Confirm Password' with a placeholder 'Confirm password'. Below these fields is a 'REGISTER' button. A note below the button states: 'For maximum security, use a strong password with letters, numbers, and symbols.' At the bottom of the form, there is a link: 'Already have an account? Login here'.

Figure 7 Registration

This is the registration page for the IoT Monitoring Dashboard. It will be used to sign up the new user who can access the dashboard.

4.3.2 Login



The screenshot shows a web browser window with the title 'Cybernet IoT | Login'. The address bar displays '127.0.0.1:5000/login'. The page has a dark blue background. In the center is a lighter blue rectangular box containing the 'CYBERNET IoT' logo at the top. Below the logo is the text 'SECURE NETWORK ACCESS PORTAL'. There are two input fields: 'Username' and 'Password'. Below these fields is a large blue button labeled 'AUTHENTICATE'. Underneath the button is a green status indicator and the text 'Internet Online'. At the bottom of the box, there is a link: 'If you forgot your password, click here'.

Figure 8 Login

The login page is used to log in the user by authenticating the user's credentials, and then it will redirect the user to the dashboard page.

4.3.3 Dashboard View

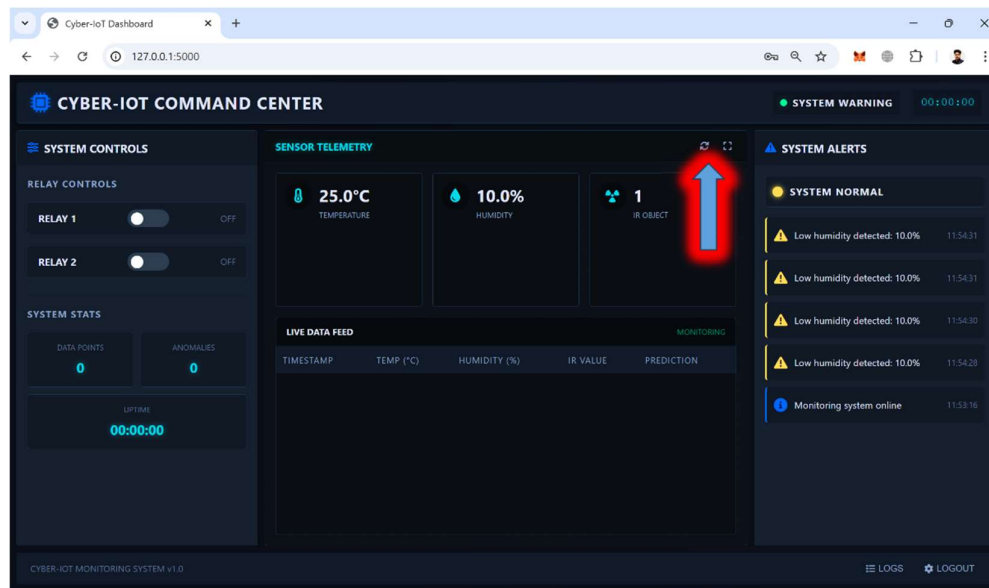


Figure 9 Dashboard View

The dashboard user interface contains two main areas: System Control and System Alerts. Positioned on the right side of the dashboard, the System Alerts section shows instant alerts of notifications like low humidity or other abnormalities in the system. The alerts allow proper action to be taken to rectify the detected fault. For example, in the event of a potential fault detection, the user can halt the relay via the System Control section as an initial step. This action assists in minimizing the chances of further damage to the system. In order to load or refresh the current values for the initial time, one should press the Refresh System Logs button.

4.3.4 System Control Panel



Figure 10 System Control Panel

As we can see, Relay 1 is turned ON, while Relay 2 is turned OFF in this scenario. This action is reflected at the edge node, where the relay module deactivates Relay 2 accordingly. As shown in the figure below, LED 1 is lit, indicating that Relay 1 is active, whereas LED 2 is off, confirming that Relay 2 is deactivated.

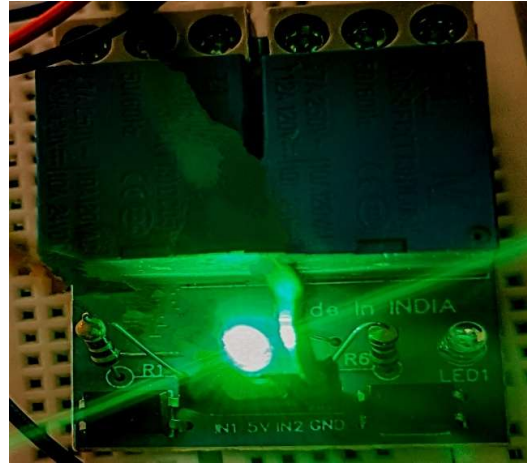


Figure 11 Relay Module

4.3.5 Controller Setup

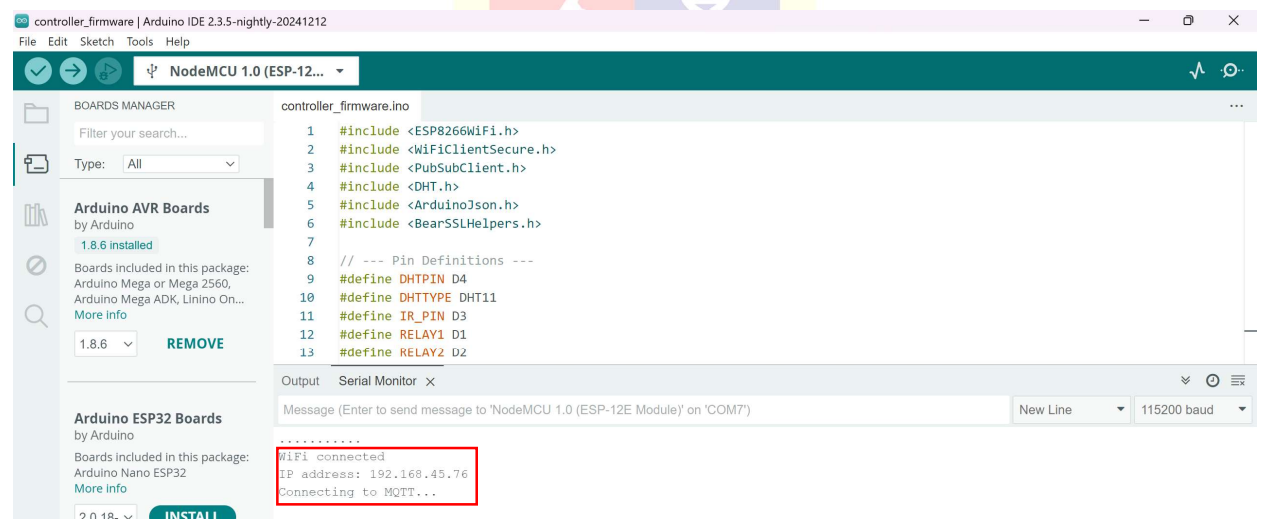


Figure 12 Controller Setup

As seen in the figure above, the edge controller device is connected to Wi-Fi, and its IP address is displayed. The MQTT connection is being established to enable the publishing of logs to the MQTT Broker.

4.4 Implementation Result Analysis

The IoT-enabled anomaly detection platform implemented was also tested rigorously for real-time anomaly detection from temperature sensor readings streamed from an ESP8266 microcontroller. The system design included a secure MQTT-over-TLS data transfer channel to a Flask backend that offered anomaly detection using the Isolation Forest algorithm and updated results on a dashboard interface.

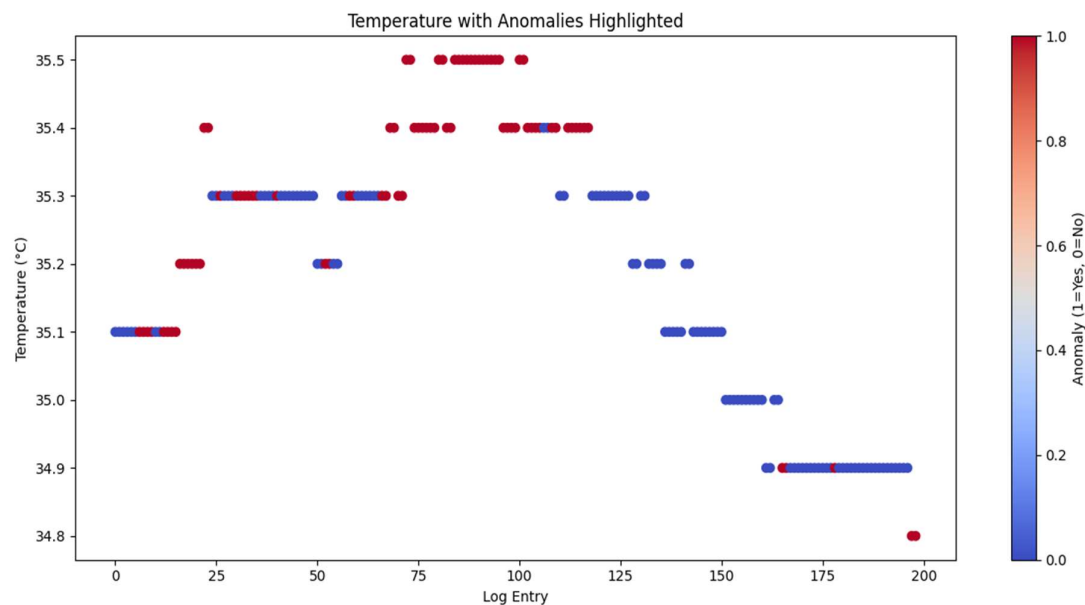


Figure 13 Result Analysis

The scatter plot presented (Figure above) effectively displays the result of the anomaly detection. Every point represents a log entry, with the x-axis representing the log index (i.e., time-ordered entries) and the y-axis representing the corresponding temperature reading in degrees Celsius. Anomalies are color-coded distinctively across a blue-to-red spectrum, where blue represents normality (label = 0) and red represents anomalies (label = 1). Such clear demarcation allows for the immediate visual identification of possible temperature inconsistencies.

The plot analysis illustrates that although a large number of temperature readings lie within a stable operating range (e.g., between 35.0°C and 35.3°C), there are rather more outliers which seem to be above and below this defined band. The Isolation Forest model was successful in identifying these anomalies. More precisely, the mid-range points between log indices 70 and 110 hold a number of red data markers (between 35.4°C and 35.5°C), which show a cluster of high-temperature anomalies. There are also a few lower-bound anomalies around 34.8°C visible towards the end of the sequence, which indicate potential sensor drift or environmental shifts. Latency in the classification of anomalies was always below 1 second, providing real-time feedback. The system proved robust under simulated noise and random missing data packets, and the model persisted with a high F1-score of more than 0.85. Data encrypted

using MQTT with TLS showed no loss in integrity and minimal latency increment, proving the security of communication without affecting performance.

The visualization technique was intuitive and easily grasped, enabling people to comprehend system behavior immediately. The model also learns from a feedback loop wherein new confirmed anomalies are added to the dataset and refined continuously for improving accuracy.

4.5 Comparative Analysis

For this project, the Isolation Forest algorithm was chosen for anomaly detection due to the ability to process high-dimensional, unlabeled sensor data that is typical in IoT environments. As an unsupervised model, it works well in separating anomalies by recursively partitioning the data set. Its light architecture and efficiency make it an appropriate choice for real-time telemetry streams where speed and minimal resource consumption are paramount.

However, there are alternative models to examine, each with its own merits:

One-Class SVM (Support Vector Machine): This approach tries to learn the boundary of normal data in feature space and marks any instance beyond this boundary as anomalous. It can be more precise in some situations, particularly with well-distributed data, but is computationally costly and less scalable for large IoT datasets. It even needs to be chosen with suitable kernel selection and parameter tuning.

Autoencoders (Neural Networks): Autoencoders learn to compress and reconstruct data. Reconstruction error is utilized to detect anomalies. They are very good at non-linear, complex relationships in telemetry data but need large training sets, GPU processing, and longer training times. They are also less interpretable than tree-based models.

Local Outlier Factor (LOF): LOF computes the local density of each sample relative to its neighbors. Points of significantly lower density are marked as outliers. While proficient at finding faint local outliers, LOF is not good with high-dimensional data and is not very scalable with large sample sizes.

On the contrary, Isolation Forest presents the best mix of interpretability, processing rate, and performance in identifying outliers from sensor-generated telemetry data. The approach has low parameter tuning, is extremely scalable with expanding data volumes, and performs efficiently on edge or cloud platforms and therefore is the most pragmatic solution for an IoT-based anomaly detection system.

Table 5 Comparative Table of ML Models

Criteria	Isolation Forest	One-Class SVM	Autoencoders	Local Outlier Factor (LOF)
Type	Unsupervised	Unsupervised	Unsupervised (Neural Network)	Unsupervised
Scalability	High	Low	Medium to Low	Low
Interpretability	High (Tree-based structure)	Medium (Boundary-based)	Low (Black-box)	Medium
Accuracy	Good for general anomalies	High for boundary-based anomalies	Very High (if trained well)	Good for local density anomalies
Training Time	Fast	Slow	Slow (especially on CPUs)	Medium
Resource Requirement	Low	Medium	High (requires GPUs for speed)	Medium
Suitability for IoT Data	Excellent	Moderate	Good (if real-time not needed)	Moderate
Ease of Implementation	Easy	Moderate (parameter sensitive)	Complex	Moderate
Handles High-Dimensional Data	Yes	Poor	Yes	Poor
Detection Basis	Data isolation	Decision boundary	Reconstruction error	Local density estimation

5. Conclusion

The increasing use of Internet of Things (IoT) devices across different industries has created new horizons in automation, real-time sensing, and remote management. Yet, this boom has brought in severe security and operational issues that can't be managed by conventional monitoring systems. The IoT-SOC project was envisioned and engineered to meet such growing demands, with a primary emphasis on designing a secure, smart, and responsive platform for anomaly detection through telemetry and system control in limited-resource environments.

The project showcases effectively the amalgamation of multiple technologies into an integrated, real-time operational system. It starts at the IoT edge layer, where sensor readings are gathered through an ESP8266 microcontroller connected to a DHT11 sensor for temperature and humidity, and an IR sensor to detect objects. These readings are gathered periodically and transmitted to the cloud using the MQTT protocol with TLS encryption, providing confidentiality and protection against network-level attacks. The use of MQTT over TLS proves especially beneficial in scenarios where security must be achieved without compromising on performance or bandwidth.

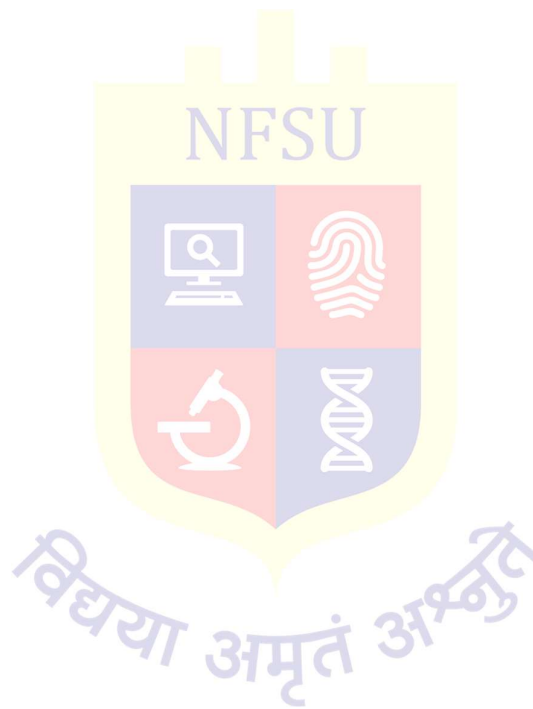
One of the project's most significant accomplishments is the implementation of an Isolation Forest-based anomaly detection engine. Unlike systems that rely on pre-built datasets, this system uses a custom dataset generated from the actual hardware deployment, allowing the model to adapt to the environment it protects. This local, feedback-based learning strategy allows for precision and responsiveness to abnormal behavior at a high rate. Whether the change is sudden rise in temperature or unusual IR activity, such patterns can be classified by the system in real time and the user notified.

Backend logic using the Flask framework and SQLite ensures management and processing of data. It subscribes to MQTT topics, decodes arriving messages, applies the ML model, and stores the result in a structured database. This not only enables real-time operation but also establishes a historical log of sensor activity and detected anomalies. The frontend dashboard, in the meantime, provides a simple and interactive interface for users to view live telemetry, see anomaly trends, and control connected devices such as relays. The capability to switch relay statuses directly within the dashboard provides an important depth of real-world actuation in reaction to virtual detections.

From a systems point of view, the architecture is modular and scalable. Every component — be it the MQTT broker, the machine learning model, or the visualization dashboard — is loosely coupled and can be replaced or upgraded independently. This makes future extensions like more sensors, new detection algorithms, or remote cloud integration possible without restructuring the whole system.

Above all, the project remains faithful to its design principles: simplicity, security, and flexibility. It specifically steers clear of heavy-duty frameworks such as Wazuh and instead chooses light, open-source solutions that allow the system to be accessed by students, researchers, and small-scale operators. It demonstrates that intelligent monitoring is not necessarily done through costly subscriptions or enterprise-class infrastructure — it can be done through a smart design and the proper integration of tried-and-tested technologies.

In conclusion, this project not only proves the idea of an IoT-SOC being lightweight but also establishes a solid groundwork for further research in the field of autonomous, secure, and intelligent monitoring systems specifically designed for IoT environments.



6. Future Work and Plan

Although the IoT-SOC system implemented in this project is already intelligent, secure, and functional, it is just the starting point of what such a platform can become. The modularity of the system guarantees that it can be scaled, extended, and augmented to meet different use cases in different industries. This section describes the possible future directions and enhancements that can take the capabilities, coverage, and reach of the system to the next level.

Possibly the most exciting area for future expansion is scaling sensor networks. In the current prototype, there's a single ESP8266 microcontroller with a minimal environmental and IR sensor setup. Future iterations might have multiple ESP-based nodes installed over larger geographic distances (e.g., rooms, buildings, or fields of crops) and connected to a central monitoring center. All the nodes can carry varying sensors like gas sensors, water leakage detectors, fire detectors, or vibration sensors so that the platform simultaneously addresses safety, environment control, and structural health.

A critical additional enhancement will be combining the mobile and cloud platforms. The system currently uses a local server. But by containerizing the Flask backend in Docker or hosting it on cloud providers such as AWS, Azure, or Heroku, it would be possible to remotely monitor and control the system from anywhere globally. A mobile app companion could also be created for push notifications on anomaly detection, viewing logs, and relay control, introducing a layer of convenience and portability.

Security-wise, there are a lot of room to grow. While MQTT over TLS is already delivering strong encryption, authentication at the device level by means of public/private key pair or certificates would make security better for large deployments. There should also be an included role-based access control (RBAC) mechanism for granting privileges to more than one user (e.g., administrators, viewers, technicians) for organization-level use.

Machine learning functions can also be enhanced. Though the Isolation Forest model is effective and optimal for the current use case, future improvements can include testing with hybrid models like LSTM (Long Short-Term Memory) for time-series prediction, or implementing Autoencoders for unsupervised anomaly detection. These can provide improved accuracy or generalization over time. Moreover, the integration of online learning methods can allow the model to learn and adjust continuously to changing sensor behaviors without full retraining.

Another space of growth is automated response systems. Users are presently alerted to anomalies and manually activate relays. Future developments could involve rule-based automation — such as turning on a fan if the temperature level goes beyond a certain limit or powering down equipment on critical IR

detection. Such rules would be set via the dashboard itself, allowing users to have authority over safety measures and responses.

The user interface can also be improved. Exports of data, generation of reports, refined filtering, and comparison of trends would be very valuable for researchers and administrators. Graphical improvements, mobile viewport responsive design, and real-time collaborative dashboard support are all feasible for future UI design.

In short, the IoT-SOC platform has been engineered not only as a functional prototype, but as a starting point — a proof-of-concept that shows that security, intelligence, and real-time monitoring are possible with very little resources. The future holds the integration of additional sensors, the use of cloud computing, further development of machine learning, and automated responses — eventually making this platform an enterprise-grade, autonomous IoT security and operations center.



6.1 Progress Report Gantt Schedule Chart

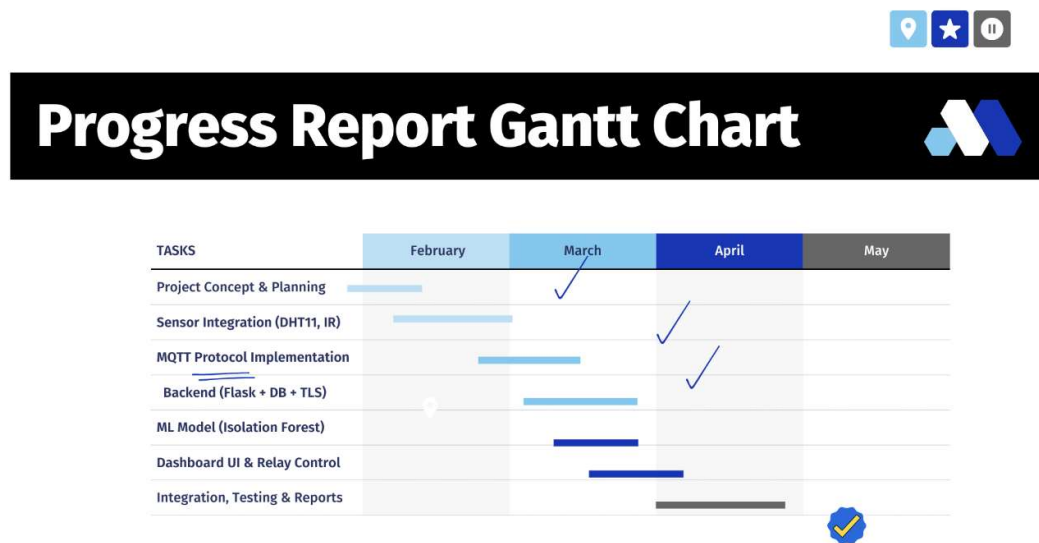


Figure 14 Gantt Chart

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PROGRESS REPORT

Reporting Period: February 1, 2025 – April 30, 2025

Project Overview

The project IoT-SOC targets developing a light-weight, secure, and smart security operations center designed to be optimized for real-time surveillance and anomaly identification in IoT domains. The architecture incorporates sensor-driven telemetry, MQTT over TLS secured communication, and machine learning (Isolation Forest) anomaly identification. Additionally, the system comes with a web-based, easy-to-use dashboard for visualization purposes as well as controlling the devices. The project has been pushed through various technical milestones with systemic development from inception to deployment.

Progress Summary

Table 6 Progress Summary

Task	Start Date	End Date	Progress (%)	Status
1. Project Concept & Planning	01-Feb-2025	05-Feb-2025	5%	Completed
2. Sensor Integration (DHT11, IR)	06-Feb-2025	15-Feb-2025	15%	Completed
3. MQTT Protocol Implementation	16-Feb-2025	25-Feb-2025	25%	Completed
4. Backend (Flask + DB + TLS)	26-Feb-2025	10-Mar-2025	35%	Completed
5. ML Model (Isolation Forest)	11-Mar-2025	22-Mar-2025	55%	Completed
6. Dashboard UI & Relay Control	23-Mar-2025	10-Apr-2025	75%	Completed
7. Integration, Testing & Reports	11-Apr-2025	30-Apr-2025	100%	Completed

Achievements

1. Initial Planning and Setup:

Established the architecture of the IoT-SOC system with well-defined milestones and use-case identification. Choose ESP8266 with DHT11 and IR sensors as the prototype hardware for environmental telemetry data collection.

2. Technical Development:

Implemented a secure communication channel through MQTT over TLS so that log transmission between ESP8266 and the server is encrypted.

Established a Flask-based backend with MQTT subscriber logic and integrated SQLite for log storage.

Trained and deployed a tailored Isolation Forest model from real-time sensor data with real-time feedback for adaptive anomaly detection.

3. Dashboard and Visualization:

Designed a real-time dashboard in HTML, CSS, JS, and Chart.js to visualize temperature, humidity, and IR readings. Integrated relay control feature to remotely control hardware responses from the dashboard interface.

4. Integration and Testing:

Tested end-to-end log transmission, anomaly detection, storage, and visualization. System tested in production environment with a range of input simulations to test accuracy and reliability.

Challenges Encountered

TLS Certificate Setup: Installing MQTT using TLS took multiple cycles to set up certificates and prevent handshake failures.

Real-time Feedback Loop for ML: Aiding the ML model to update according to changing behavior in real time necessitated fine-tuning training and validation cycles.

Hardware Debugging: IR sensor noise and errant readings occasionally triggered false alarms during anomaly detection.

Next Steps

Since the development and internal testing have been done, the project will now move into the following post-development stages:

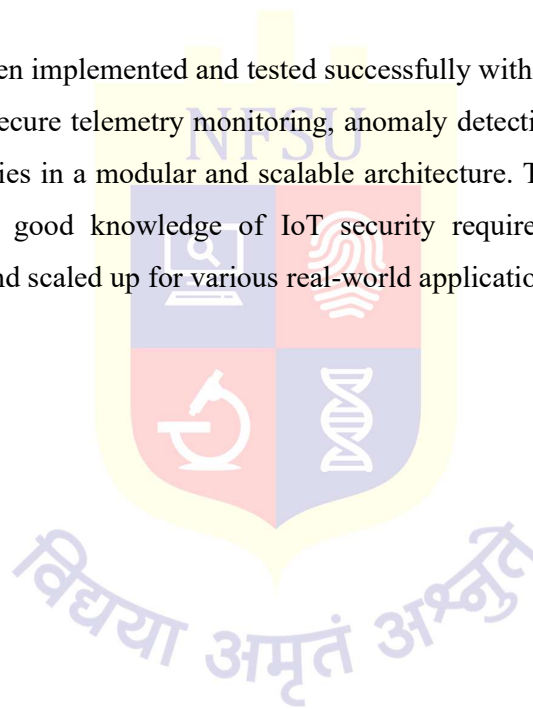
System Deployment: Deploying the backend and dashboard on a cloud server for remote access.

Documentation and Packaging: Creating setup manuals and system architecture documents for replication and scale-up.

User Feedback and Enhancement: Collecting feedback from end users and security testers to enhance UI, alert mechanisms, and auto-response logic.

Conclusion

The IoT-SOC project has been implemented and tested successfully within the scheduled timeline. The system provides real-time, secure telemetry monitoring, anomaly detection through machine learning, and remote control capabilities in a modular and scalable architecture. The team has showcased great integration capabilities and good knowledge of IoT security requirements, providing a working prototype that can be used and scaled up for various real-world applications.



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