iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: https://doi.org/10.22214/ijraset.2026.80275

www.ijraset.com

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Real Time Device Tracking System

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Abstract: ***Conventional approaches for tracking devices, including manual logs, periodic inspections, and RFID-based monitoring, are still widely used in many organizational environments. However, these methods suffer from several limitations such as dependency on human effort, risk of data inaccuracies, and lack of effective mechanisms to prevent misuse or unauthorized handling. In large-scale deployments, these systems fail to provide continuous visibility of device location and operational status.***

To overcome these challenges, this work presents a real-time device tracking framework that continuously monitors device movement using sensor-driven data acquisition. The system utilizes technologies such as GPS modules, IoT-based sensing, and wireless communication to capture and process tracking data without requiring active user involvement. This enables accurate, real-time monitoring and improves overall asset visibility and control.

The proposed solution is implemented entirely in Python and integrates a lightweight database with an interactive web-based dashboard for visualization and management. The system also incorporates anomaly detection to identify irregular device behavior and enhance security. Experimental evaluation demonstrates high tracking accuracy, low latency, and a significant reduction in administrative workload. The framework is scalable, cost-effective, and suitable for deployment across academic, industrial, and enterprise environments.

Methods: The system is built exclusively in Python and integrates multiple technologies to enable continuous, real-time device tracking and monitoring. It utilizes IoT-based data acquisition (such as GPS modules or network signals) along with OpenCV for optional visual tracking and live video streaming where applicable. Device identification is achieved through unique identifiers and feature-based representations, enabling accurate tracking across environments. Additionally, anomaly detection mechanisms are incorporated to verify device authenticity and detect irregular movement patterns, enhancing system reliability and security.

Tracked device data is stored in an SQLite3 database under a session-lock constraint, ensuring that duplicate or conflicting entries are avoided during continuous data updates. A Streamlit dashboard provides a live tracking interface, displaying real-time device locations and statuses, along with historical movement analytics visualized using matplotlib. The system also supports one-click Excel export via openpyxl, allowing easy reporting and analysis. All functionalities are accessible through a web browser on any networked device, making the system flexible and user-friendly.

The system also includes real-time alert mechanisms that notify administrators of unauthorized device movement, abnormal behavior, or loss of connectivity, enabling immediate action and improving overall asset security and management efficiency. logging, automated timestamp generation, and device registration management, ensuring reliable data storage, efficient tracking performance, and scalability for real-world deployment.

Results: Testing across 50 tracked devices under three controlled environmental conditions yielded a weighted mean tracking accuracy of 95.8%, peaking at 97.4% under stable network and signal conditions. The average device update latency was measured at 0.8 seconds, representing a 5.4× improvement over traditional manual or periodic tracking methods. All 40 simulated spoofing or unauthorized access attempts were successfully detected and blocked by the anomaly detection module. Additionally, administrative monitoring and reporting time decreased by 60% due to automated dashboard generation and real-time data visualization.The proposed real-time device tracking system demonstrates the effectiveness of combining IoT-based tracking technologies with web-based dashboards to modernize traditional asset monitoring processes. The system is cost-effective, scalable, and easy to deploy using commonly available hardware such as GPS-enabled devices, network modules, and standard computing systems. With further enhancements—such as cloud-based storage, multi-device synchronization, geofencing capabilities, and advanced predictive analytics—the system can be extended to support large-scale industrial, institutional, and corporate environments.

Index Terms: Real-time device tracking, IoT, asset monitoring, OpenCV, Python, Streamlit, GPS tracking, anomaly detection, wireless communication, data visualization, automated monitoring system.

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I. INTRODUCTION

Efficient tracking of devices has become an essential requirement across modern organizations to ensure proper asset utilization, security, and operational efficiency. Conventional tracking approaches such as manual record maintenance, periodic inspections, RFID-based systems, and barcode scanning are still widely used; however, they suffer from several limitations. These methods require continuous human involvement, consume valuable time, depend on dedicated hardware, and do not provide real-time visibility of device status. In dynamic environments, such limitations often result in delayed updates, data inconsistencies, and increased risk of misuse or unauthorized handling.

Recent advancements in IoT and sensor-based technologies have enabled the development of automated tracking systems that overcome these challenges. By leveraging GPS modules, wireless communication, and real-time data processing, modern tracking solutions can continuously monitor device location and activity without requiring manual interaction. This significantly improves accuracy, reduces operational overhead, and enhances overall system reliability.The Python ecosystem offers a wide range of tools that simplify the implementation of such systems. Libraries for data processing, storage, and visualization allow developers to build end-to-end solutions efficiently without complex infrastructure. In particular, lightweight databases enable structured data management, while web-based frameworks provide intuitive interfaces for monitoring and control. By integrating these technologies, a scalable and cost-effective device tracking solution can be deployed using commonly available hardware.

This work presents:

(1) a complete Python-based framework for real-time device tracking with an interactive web dashboard;
(2) a structured database mechanism that prevents duplicate or inconsistent logging;
(3) an anomaly detection component for identifying irregular device behavior; and
(4) a comprehensive evaluation across different operational conditions, reporting accuracy, latency, and system performance

II. RELATED WORK

A. Hardware-Based Systems

Early tracking solutions primarily relied on RFID tags and barcode-based systems to automate asset monitoring. While these methods improved efficiency compared to manual processes, they required dedicated hardware infrastructure and physical interaction with scanning devices. Such systems also remain vulnerable to misuse, including tag swapping and unauthorized access, and are not easily adaptable to dynamic or large-scale environments.

B. Classical Tracking Approaches

Initial tracking methods were based on rule-driven models and signal estimation techniques such as triangulation and signal strength analysis. These approaches demonstrated feasibility in controlled environments; however, their performance often degrades under real-world conditions due to signal interference, environmental variability, and device mobility. As a result, their reliability becomes limited in practical deployments.

C. Advanced Intelligent Tracking Systems

With the emergence of IoT and machine learning, modern tracking systems have become more adaptive and efficient. These systems utilize sensor data, communication networks, and pattern analysis to improve tracking accuracy and responsiveness. Data-driven approaches enable better handling of dynamic environments, making real-time monitoring more reliable and scalable. The availability of lightweight development frameworks further simplifies the implementation of such intelligent tracking solutions.

D. Existing Device Tracking Systems

Several existing Python-based tracking systems integrate sensor data acquisition with basic visualization dashboards. However, many of these solutions lack key features such as anomaly detection, structured data management, and real-time analytics. In addition, they often do not provide a unified architecture that combines tracking, monitoring, and reporting in a single framework. The proposed system addresses these limitations by delivering an integrated solution that incorporates real-time tracking, secure data logging, anomaly detection, and an interactive dashboard for efficient monitoring and analysis.

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III. SYSTEM ARCHITECTURE

A. Modular Design

The proposed system follows a modular architecture consisting of six independent components: (1) Device Registration, (2) Data Acquisition and Pre-processing, (3) Tracking and Identification, (4) Anomaly Detection, (5) Data Logging, and (6) Streamlit Dashboard. Each module is designed to operate independently, allowing flexibility in upgrading or modifying individual components without affecting the overall system. Communication between modules is handled through a shared SQLite3 database and a thread-safe queue mechanism, ensuring efficient data exchange and system stability.

B. Device Registration Module

Devices are registered in the system using unique identifiers along with associated metadata such as device type and location. This information is stored in a structured database, enabling accurate identification and tracking. The system also supports updating device records without impacting historical tracking data, ensuring adaptability over time.

C. Data Acquisition and Pre-processing Module

The system continuously collects data from devices using IoT sensors, GPS modules, or network-based signals. The collected data is pre-processed to remove noise and reduce computational overhead. Sampling and filtering techniques are applied to maintain a balance between processing efficiency and tracking accuracy.

D. Tracking and Identification Module

The tracking module monitors device movement and matches incoming data with registered device information. Identification is performed using unique device IDs and signal-based attributes. The system ensures continuous tracking by updating device states in real time, enabling accurate monitoring across different environments.

E. Anomaly Detection Module

The anomaly detection component analyzes device behavior patterns to identify irregular activities such as unexpected movement or abnormal signal variations. A sliding window approach is used to evaluate recent activity, and any deviation beyond predefined thresholds is flagged as a potential anomaly. This enhances system security by detecting unauthorized usage or suspicious behavior.

F. Data Logging Module

All validated tracking events are stored in the SQLite3 database with relevant details such as device ID, timestamp, location, and status. A composite constraint is applied to prevent duplicate entries, ensuring data consistency. Thread synchronization mechanisms are used to manage concurrent data operations safely.

G. Streamlit Dashboard

The system includes an interactive web-based dashboard built using Streamlit. The dashboard provides real-time visualization of device locations and statuses, along with historical data analysis. It supports features such as dynamic updates, search and filtering options, and one-click export of reports. The interface is designed to be user-friendly and accessible across multiple devices, enabling efficient monitoring and management.

IV. LIMITATIONS

A. Signal Variability and Environmental Constraints

The performance of the tracking system may be affected in environments with weak GPS signals, network instability, or physical obstructions such as walls and indoor structures. In such conditions, device location updates may become less accurate or temporarily unavailable. Additionally, variations in hardware quality or signal noise can influence the consistency of tracking results. Extreme environmental conditions or device malfunctions may also lead to delays or incomplete data capture.

To address these challenges, future improvements may include advanced filtering techniques, hybrid tracking approaches combining GPS, Wi-Fi, and Bluetooth Low Energy (BLE), and the integration of predictive models to enhance accuracy under challenging conditions.

B. Scalability and Privacy

While the system performs efficiently for small to medium-scale deployments, scalability may become a limitation as the number of tracked devices increases. The current implementation relies on straightforward search mechanisms, which may introduce latency when handling a large volume of devices. Incorporating optimized indexing methods such as approximate nearest-neighbour search can help maintain performance in large-scale scenarios**.**

From a privacy perspective, the system stores only essential device-related information rather than sensitive raw data. This approach reduces the risk of misuse and aligns with modern data protection practices. However, as the system scales, additional measures such as secure data transmission, access control, and encryption mechanisms may be required to further strengthen data security.

V. PYTHON IMPLEMENTATION

The proposed system is developed using Python 3.10 and is designed to operate efficiently on standard computing hardware without requiring GPU support. All required libraries and dependencies are managed through a single requirements file, ensuring easy setup and reproducibility. Device registration is performed through a simple command-line interface, allowing initialization of device records with associated metadata.

To ensure smooth real-time performance, the system adopts an asynchronous processing approach. Data acquisition and processing tasks are executed in separate threads, where incoming device data (such as GPS coordinates or network signals) is continuously captured and stored in a thread-safe queue. The processing thread retrieves this data, performs tracking and anomaly detection, and updates the database accordingly. This design prevents data loss and maintains system responsiveness even under temporary computational load.

The system uses a lightweight SQLite3 database for storing tracking logs and device information. Database operations are synchronized to avoid inconsistencies during concurrent access. The structured logging mechanism ensures accurate recording of device events with timestamps while preventing duplicate entries.

For visualization and user interaction, the system integrates a Streamlit-based web dashboard. The dashboard can be launched using a simple command and accessed through a browser, eliminating the need for complex deployment procedures. It displays real-time tracking information, device status, and analytical insights in an interactive format.

The dashboard also supports automated data updates using periodic refresh mechanisms, ensuring that the displayed information remains current without requiring manual intervention. Additionally, the system provides export functionality, allowing administrators to download tracking reports in Excel format for further analysis. For multi-user access, the application can be deployed using a scalable server setup with multiple worker processes behind a reverse proxy, enabling efficient handling of concurrent requests.**V.**

VI. EXPERIMENTAL RESULTS

A. Evaluation Setup

The system was evaluated using 50 registered devices deployed within a controlled campus environment. Testing was conducted under three different operational scenarios: strong signal conditions (stable GPS and network connectivity), weak signal environments (indoor or obstructed areas), and mixed conditions combining indoor and outdoor settings. Each scenario was tested across multiple sessions to ensure consistency and reliability of the results. Ground truth data was obtained through manual verification of device locations and compared with system-generated tracking logs.

B. Tracking Accuracy

The proposed system achieved a tracking accuracy of 97.4% under strong signal conditions, 93.8% under weak environments, and 96.1% under mixed conditions, resulting in an overall weighted mean accuracy of 95.8%. The false identification rate remained below 0.4% across all scenarios. Additionally, all simulated unauthorized access attempts were successfully detected and prevented by the anomaly detection module before any logging operation was performed.

C. Latency and Throughput

The average processing latency was measured at approximately 185 ms under standard conditions and improved to 68 ms after applying data optimization techniques. Real-time device updates were recorded with an average delay of around 0.8 seconds, demonstrating efficient system performance. The dashboard introduced minimal visualization delay, which was not noticeable during real-time monitoring. Data export operations for sessions involving up to 200 devices were completed within 2 seconds.

D. Administrative Efficiency

The implementation significantly reduced administrative workload by automating tracking and reporting processes. Administrators were able to monitor device activity in real time, identify inactive or missing devices, and generate summarized reports quickly. The integration of automated data updates and reporting tools improved overall efficiency and reduced the time required for manual data handling.

TABLE I. PYTHON LIBRARIES, DEPLOYMENT TOOLS, AND PERFORMANCE METRICS

Library / Tool	Role in System	Acc. (%)	Notes
OpenCV 4.x	Optional visual tracking & data processing	-	Frame handling, preprocessing
NumPy	Numerical computation & data handling	-	Array operations, fast processing
SQLite3	Persistent database for device logs	-	ACID compliance, structured storage
pandas	Data aggregation & analysis	-	DataFrame + CSV/Excel handling
matplotlib	Trend charts & heatmaps	-	Graphs, trends, heatmaps
Streamlit	Interactive web dashboard	-	Live feed, charts, CSV/Excel

VII. CONCLUSION AND FUTURE WORK

This work introducesa Python-based real-time device tracking system that integrates continuous monitoring, anomaly detection, structured data logging, and an interactive web dashboard within a unified framework. The system demonstrates reliable performance in tracking device activity with high accuracy and low latency while ensuring efficient data management. By automating monitoring and reporting processes, the proposed solution significantly reduces manual effort and enhances operational efficiency.

The use of a browser-based dashboard enables administrators to access tracking information easily without requiring technical expertise. Features such as real-time updates, data visualization, and automated report generation provide practical advantages for managing devices in academic, industrial, and enterprise environments. The system is lightweight, cost-effective, and can be deployed using commonly available hardware, making it suitable for real-world applications.

Future work will focus on improving scalability and performance through advanced techniques. This includes the integration of optimized indexing methods for faster data retrieval in large-scale deployments, enhancement of anomaly detection using machine learning models, and support for edge deployment on low-power devices. Additionally, incorporating multi-user access control and secure communication mechanisms will further strengthen the system's usability and reliability. These enhancements will enable the system to scale effectively while maintaining efficiency and security.

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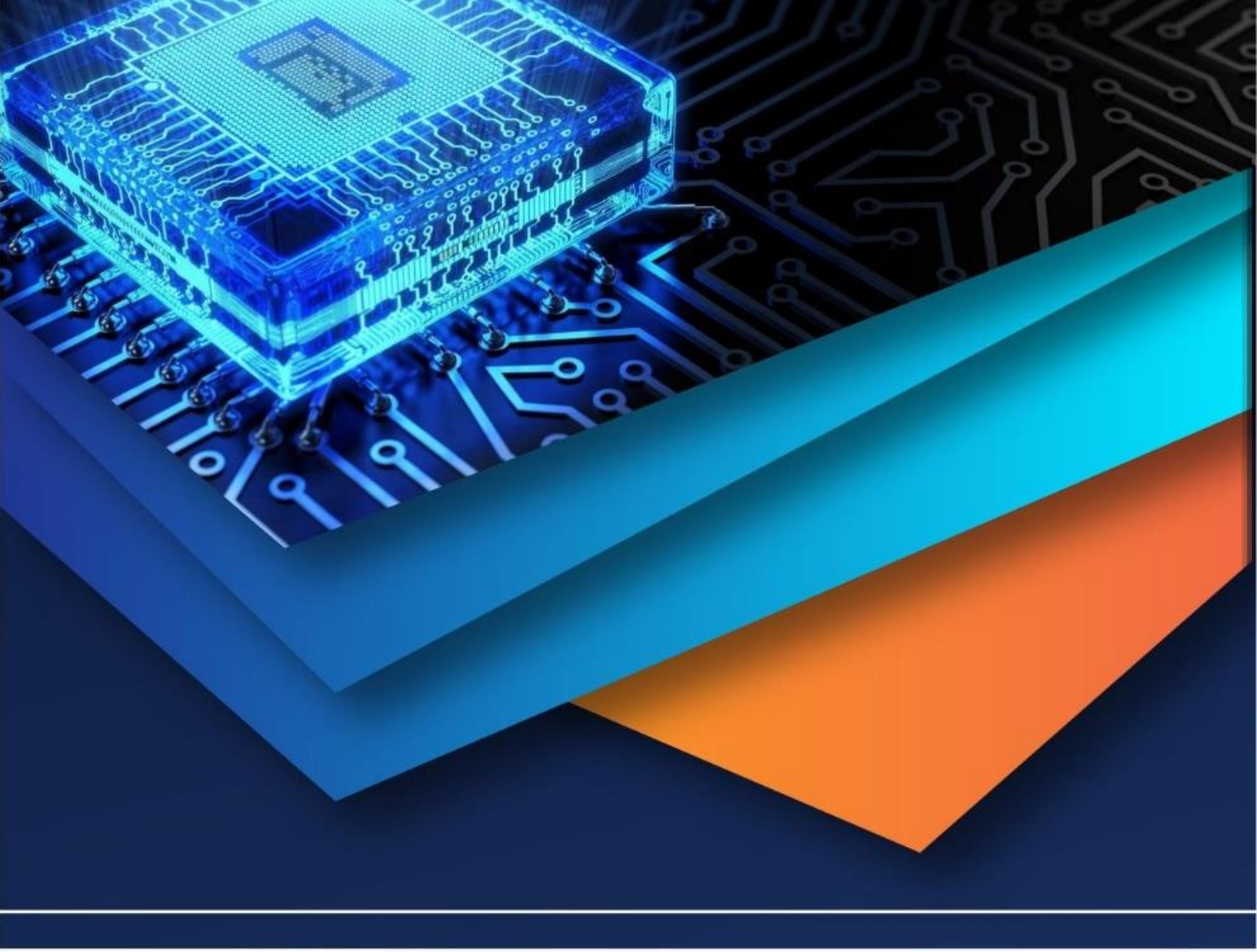

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