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AI-SLMS: An AI-Integrated Framework for Predictive Maintenance, Intelligent Scheduling, and Access Control in University Laboratory Management Systems

Bingcan Wang*, Jin Zhang
School of Design, Jiangsu Open University, Nanjing 210036, Jiangsu, China
E-mail: wangbc@jsou.edu.cn, zhangjin@jsou.edu.cn
*Corresponding author

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In recent years, a smart, safe, and efficient way to run university labs has become increasingly popular. Traditional management systems rely on manual processes that are error-prone, slow, and offer limited adaptability. To address these challenges, this study proposes a Smart Laboratory Management System (AI-SLMS) that optimizes operations, improves safety, and enhances the user experience in academic labs. AI-SLMS integrates predictive maintenance, intelligent scheduling, and secure access control using machine learning and the Internet of Things (IoT). The system employs Random Forest and Logistic Regression models, trained on integrated datasets (Kaggle Predictive Maintenance and TON_IoT), to anticipate equipment failures. For resource allocation, an intelligent scheduling module utilizes genetic algorithms for optimization. The system also enforces role-based access through RFID and biometric authentication. Experimental validation over three months in a university setting demonstrated significant improvements across key metrics: a 71.2% reduction in equipment downtime, a 78.7% decrease in scheduling conflicts, a 53.5% improvement in resource utilization, and 98.3% authentication accuracy. In conclusion, AI-SLMS offers a scalable and intelligent framework that significantly enhances the efficiency, security, and responsiveness of university laboratory management systems.

Povzetek: Študija predstavlja pametni sistem AI-SLMS, ki z uporabo umetne inteligence in IoT bistveno izboljša učinkovitost, varnost in upravljanje univerzitetnih laboratorijev.

1 Introduction

University labs are needed more than ever as higher education faces increasing challenges. Laboratories provide hands-on learning, experimentation, and ideation. This applies especially to science, technology, and engineering. Despite this, colleges struggle to operate laboratories effectively. Real-time monitoring is lacking, resources are wasted, costly equipment is abused, safety requirements are neglected, and lab sessions must be scheduled manually [1]. Traditional systems that require human monitoring and manual job execution are inefficient, error-prone, and prone to loss. Lab staff may be unable to focus on creative problem-solving and research if paperwork distracts them. Disconnected hardware, sensors, and computers make decisions harder. These systemic difficulties need a fast, inventive, and scalable solution. This technique streamlines lab operations and provides real-time data to administrators, students, and professors [2].

Several automated and semi-automated methods improve lab administration. For inventory tracking, experiment control, and asset performance monitoring, LIMS and CMMS software have helped businesses. Most of these systems are rule-based and inflexible [3]. They seldom employ pattern recognition, decision-making, or predictive analytics [4]. IoT-based devices monitor temperature, humidity, and occupancy, as in labs [5]. Despite automation, they work autonomously and do not perform cognitive processing of the collected data. Some organizations run on spreadsheets, while others utilize simple web tools that require human changes [6]. These technologies are good for storing fundamental data, but they can't solve problems, foresee maintenance needs, intelligently allocate resources, or assure energy efficiency [7]. This implies there is little data on how to construct cutting-edge AI-SLMS. Using sensor data, cognitive algorithms, and cloud platforms, this system can optimize itself in real time and give a comprehensive operational solution [8].

To solve this, our work will create and improve an AI-powered Smart Laboratory Management System. The proposed system combines machine learning algorithms with sensor-based data to monitor lab operations, forecast maintenance schedules, and maximize equipment use. This study intends to achieve three primary goals:

- Creating an architecture driven by artificial intelligence can enable real-time laboratory monitoring, predictive maintenance, and intelligent scheduling using data from Internet of Things sensors and historical logs.
- To maximize resource use using data-driven decision-making processes, limit downtime of laboratory equipment, and minimize human interference in laboratory operations.
- Three measures that can be assessed by contrasting the system with normal laboratory administration procedures are operating efficiency, system responsiveness, and user satisfaction. This assessment will take place in a university setting [9].

The study proposes a new AI-based system and demonstrates its value by applying it in a real-world environment, yielding measurable outcomes [10]. Integrating artificial intelligence and the Internet of Things—a powerful yet largely uncharted frontier in laboratory management—can transform how institutions manage their vital infrastructure.

The goal of this study is to develop and deploy AI-SLMS. This modular laboratory management system combines intelligent scheduling, predictive maintenance, and secure access control, leveraging IoT and artificial intelligence technologies. The system is compared to more modern intelligent baseline systems and tested in an actual university setting to gauge gains in resource usage, operational effectiveness, and user satisfaction.

This study addresses three critical gaps in existing laboratory management systems: (a) the absence of an integrated architecture that unifies predictive maintenance, intelligent scheduling, and secure access control; (b) the lack of AI-driven decision-making that can dynamically respond to real-time IoT sensor data; and (c) the limited adaptability and scalability of current systems across diverse institutional environments. Accordingly, the following research questions guide this study: How effectively can AI-SLMS predict and prevent equipment failures compared to traditional maintenance approaches? Can an AI-based scheduling algorithm significantly reduce booking conflicts and enhance resource utilization in academic laboratories? Does a dual-factor authentication mechanism improve access security without compromising operational efficiency? From these, the study hypothesizes that (i) First, AI-SLMS reduces equipment downtime by over 50% over prior systems. At least 60% less disagreement will result from clever scheduling. Finally, the hybrid RFID-biometric module will authenticate over 95%. This project aims to make university labs safer, more efficient, and more scalable. We will build a modular framework for intelligent laboratory management, add AI, and test it on real-world datasets (Kaggle Predictive Maintenance and TON_IoT).

2 Literature review

Laboratory administration has recently changed to accommodate more sophisticated, efficient processes driven by technological developments. Traditional laboratory management systems [11] have struggled with limited real-time monitoring, inefficient resource use, and delayed decision-making. Often, these systems relied on human record-keeping and used paper-based methods. Given these constraints, researchers are investigating modern digital technologies such as cloud computing, the IoT, and artificial intelligence to enhance laboratory management and operations.

Many scholarly studies have looked at how artificial intelligence techniques affect laboratory management. Predictive maintenance, which employs ML models to forecast when equipment might fail, has generated much excitement. This increases laboratory operational efficiency and helps reduce downtime [12]. Zhang et al. [13] proposed data-driven algorithms for predictive maintenance of lab equipment in a 2018 paper. Using sensor data, these models would forecast when items would break and when to begin preventative maintenance. Kumar et al. (2017) also enhanced the dependability and accuracy of failure forecasts [14] by including deep learning methods into their predictive maintenance system.

Systems based on artificial intelligence (AI) also handle smart scheduling, another vital aspect of laboratory management. Many previous systems underutilized or overbooked laboratory resources since effective scheduling was difficult. Zhang and Xie [15] created a smart scheduling approach for lab resources using reinforcement learning. This approach was designed to maximize the efficient use of existing equipment while reducing the conflicts that result. Liu et al. [16] investigated an approach combining optimization strategies with machine learning to enhance real-time scheduling of laboratory resources. The outcome was a happier user base and a more effective scheduling system. Research by Chen et al. [17] indicates that AI systems can adapt in real time to evolving conditions. This study developed a real-time scheduling system using multi-agent reinforcement learning to effectively control laboratory resources.

Academic articles on methods for controlling and monitoring systems—including those employing Internet of Things devices in laboratories—have also generated considerable debate. Among the environmental elements Chen et al. [18] tracked using Internet of Things sensors in their lab were humidity, temperature, and air quality. The collected data was used to ensure the safety of the laboratory environment and the optimal operation of the equipment. Li et al. [19] expanded on this concept and conducted more studies linking laboratory inventory control systems to the Internet of Things. Their solution tracked equipment use and stocks using an IoT sensor network. The system could ensure a continuous supply of all materials and supervise restocking.

Although the current study has faults, much territory remains to explore. Intelligent scheduling and predictive maintenance are well-studied, but integrating them into laboratory management systems for real-time monitoring, automated resource allocation, and safety compliance is unexplored. Some methods struggle to accommodate different research centers and institutions. Few articles address data-driven decision-making in relation to cloud computing, AI, the IoT, and other topics.

This paper introduces an AI-SLMS (Smart Laboratory Management System) that uses smart scheduling, predictive maintenance, and utilization trend analysis to solve these problems. Inventory tracking, real-time monitoring, and safety compliance may be automated using sensor data and cloud computing. We'll respond thoroughly as this is a lab management issue. Data-driven decision-making may enhance academic lab operations and funding allocation. Our versatile and scalable method provides a robust foundation for institutions and addresses contemporary challenges.

Even with recent improvements, the scope of current systems is frequently still constrained. For example, machine learning (ML)-based predictive maintenance models [12][13] have demonstrated efficacy in predicting equipment failures; however, they are not connected with real-time data processing or scheduling. In a similar vein, intelligent scheduling techniques such as MARL frameworks [17] and RL-Based SA [15] provide dynamic job allocation but lack secure access and predictive maintenance. Environmental sensing is enabled by IoT-based monitoring technologies [18][19], though these typically lack cloud-based synchronization and analytical intelligence. It is frequently challenging to scale these compartmentalized systems across various institutional configurations.

To review the current state of the art and highlight the research need, Table 1 briefly summarizes the major approaches, datasets, and findings from prominent relevant works. The research shows that current systems lack a holistic architecture, regardless of how effectively they execute real-time scheduling or predictive maintenance. As shown in the table, there is little research that blends predictive maintenance, intelligent scheduling, and secure access control into a single framework or uses both real-world and benchmark datasets for assessment. This fragmented scenario underscores the suggested AI-SLMS as a modular yet integrated solution to address all these interrelated concerns. Table 1 presents a comparative summary of Related Work in Smart Laboratory Management.

Table 1: Comparative summary of related works in smart laboratory management

Reference	Primary Focus	Core Methodology	Dataset(s) Used	Key Performance Metrics
Zhang et al. (2018) [13]	Predictive Maintenance	Data-driven ML Models	Synthetic sensor data	Failure prediction accuracy
Kumar et al. (2017) [14]	Predictive Maintenance	Deep Learning	Historical equipment logs	Model Accuracy, Recall
Zhang & Xie (2019) [15]	Intelligent Scheduling	Reinforcement Learning (RL)	Simulated booking requests	Resource Utilization, Conflict Rate
Chen et al. (2021) [17]	Real-time Scheduling	Multi-Agent RL (MARL)	Laboratory resource logs	Scheduling Efficiency, Response Time
Chen et al. (2020) [18]	Environmental Monitoring	IoT-based Sensing	IoT sensor data (Temp, Humidity)	Data Accuracy, System Uptime
Li et al. (2019) [19]	Inventory Management	IoT & Sensor Networks	RFID and usage logs	Inventory Accuracy, Restocking Time

On the other hand, the suggested AI-SLMS integrates cloud-based monitoring, intelligent scheduling, predictive maintenance, and access control into a single, modular architecture. This integrated design provides a strong solution for contemporary academic laboratory contexts by filling important gaps in automation, interoperability, and operational efficiency.

3 Proposed Method of AI-based smart laboratory management system (AI-SLMS)

Artificial intelligence (AI) and automation technologies are built into our modern Smart Laboratory Management System (SLMS). This will help older laboratory management systems address recurring problems. This system's primary goal has been to increase academic laboratories' operational efficiency by simplifying maintenance chores, maximizing equipment scheduling, strengthening safety policies, and encouraging resource use. This system's application has met this objective. This system's implementation has facilitated the attainment of this objective. Historically, traditional systems have frequently relied on manual processes that are labor-intensive, error-prone, and unable to respond to real-time data dynamically. Manual processes are time-consuming and error-prone; therefore, this is the case. The AI-SLMS has thus enabled the implementation of a scalable, automated method for laboratory operations. Including innovative modules such as predictive maintenance, intelligent scheduling, access control, and pattern analysis has enabled this work to be completed successfully.

3.1 System architecture

The architecture of the Smart Laboratory Management System includes several separate modules that perform distinct functional tasks. These modules are intended to be linked together and perform their tasks. The system uses a modular design to ensure scalability, maintainability, and extensibility across various laboratory configurations. Every module runs in an integrated manner, interacting with a centralized data processing system and cloud storage infrastructure, thereby fulfilling the specific function for which it was designed.

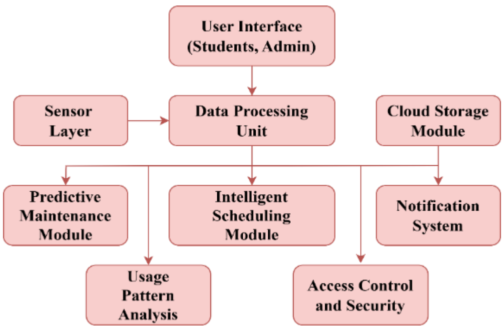

Figure 1: System architecture of AI-based smart laboratory management system

Figure 1 shows the interaction between the AI-SLMS's hardware and software components and depicts its overall architecture. The User Interface (UI) is at the top of the hierarchy. Its goal is to enable natural, straightforward communication with a broad range of stakeholders, including students, teachers, lab managers, and administrators. User interfaces make it easier to submit access requests, view maintenance alerts in real time, and reserve equipment.

Below the User Interface, the Sensor Layer consists of many Internet of Things sensors distributed throughout the lab. Amongst other important factors, these sensors monitor temperature, humidity, air quality, equipment use, and access logs. The Data Processing Unit receives real-time sensor data. Using advanced artificial intelligence technologies, this unit generates the most efficient schedules, predicts failures, and performs trend analysis.

The Cloud Storage Module stores all sensor data, user logs, access credentials, and historical maintenance records persistently and securely. This layer allows remote data access and synchronization across multiple laboratory sites. Ultimately, the Notification System delivers timely alerts, reminders, and reports to users and system administrators responsible for specific systems, leveraging insights from AI modules. It improves operational continuity, compliance with safety regulations, and job awareness. The pseudocode below summarizes the proposed integrated Smart Laboratory Management System (AI-SLMS) workflow. Predictive maintenance, intelligent scheduling, usage pattern analysis, access control, and system optimization are the main components of this system. The pseudocode has been split into two modules. Module 1 focuses on operational intelligence — predicting equipment failures, allocating resources optimally, and identifying usage trends. It leverages historical and real-time data to ensure the laboratory operates efficiently, reduces downtime, and improves equipment utilization.

Module 2 ensures secure access to laboratory facilities by verifying user credentials through RFID and biometric authentication. It enforces role-based permissions, granting entry only to authorized personnel, thus safeguarding sensitive equipment, experiments, and data. This module also fine-tunes system models for better performance, compares smart and traditional lab metrics to quantify improvements, and communicates results to stakeholders via email, SMS, or app notifications, ensuring transparency and informed decision-making.

3.2 Predictive maintenance module

A predictive maintenance module has been created to minimize laboratory downtime and prevent equipment malfunctions. This module has relied on historical maintenance records and real-time sensor data to train a machine learning model. The model has recommended preventive maintenance actions to be done before the predicted failure of a piece of equipment.

First, the procedure calls for collecting sensor data on the machine's vibrations, temperature, usage duration, and other relevant parameters. The data is then cleaned and normalized to remove any noise. Historical data labeled with binary outcomes—either "healthy" or "faulty"—has been used to train a supervised machine learning model, such as a Random Forest or a Logistic Regression model.

```
Pseudocode: Smart Laboratory Management System (AI-SLMS)
Module 1: (Core Lab Intelligence)
INPUT: sensorData, bookingRequests, usageLogs, accessRequests, systemModels
OUTPUT: optimizedOperations, comparisonReport

Load historicalData, realTimeData, and userRequests
cleanData ← Preprocess(sensorData)
model ← TrainModel(cleanData)
maintenanceList ← { item | model.predict(item) > threshold }
schedule ← ∅
for each request in bookingRequests do
    for each resource in Resources do
        for each timeSlot in TimeSlots do
            if resource available and no conflict then
                Assign(request, resource, timeSlot)
                Add assignment to schedule; break
            end if
        end for
    end for
    if the request is not assigned then Mark as Deferred
end for
clusters ← KMeans(Preprocess(usageLogs), k)
Generate optimizedOperations and comparisonReport
return optimizedOperations, comparisonReport
```

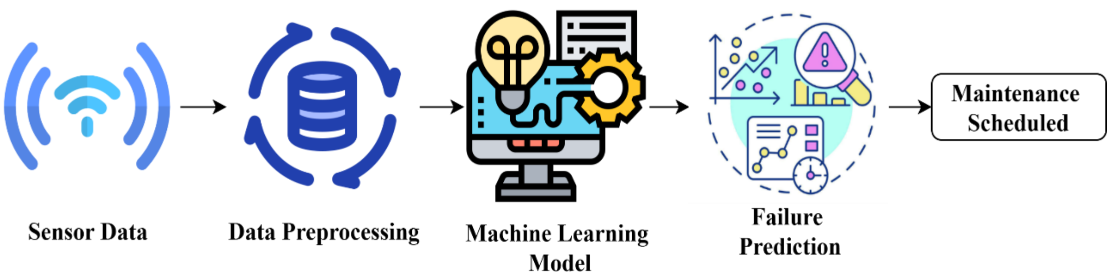

Figure 2: Predictive maintenance module

Figure 2 shows the design of the Predictive Maintenance Module. This module trains machine learning models using real-time sensor data and historical maintenance records. This enables prompt execution of maintenance interventions and early identification of potential equipment failures. The model calculates the failure probability, indicated by the formula $\boldsymbol{P(y = 1 \mid X)}$, with $\boldsymbol{X}$ being the feature vector and $\boldsymbol{y}$ the label. This likelihood has been estimated using logistic regression-based calculations in Equation (1).

$$P(y = 1 \mid X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}} \quad (1)$$

Users will be informed of required maintenance if this opportunity exceeds a specified threshold. The system always has the most current information and tracks the maintenance schedule. This predictive approach has helped reduce unplanned downtime and extend equipment life, improving overall operations.

To forecast the condition of lab equipment, the AI-SLMS's predictive maintenance module uses two supervised machine learning models: Random Forest and Logistic Regression. To ensure a robust ensemble effect, the Random Forest classifier was configured with 100 decision trees (n_estimators = 100). The Gini impurity was used as the splitting criterion to assess node purity, and a maximum depth of 10 was selected to balance model complexity and overfitting. To increase diversity and resilience, the bootstrap option was enabled, enabling the model to construct each tree on distinct subsets of the data.

Module 2: Security & Access Control, Optimization & Reporting

Input: accessRequests, models, oldSys, userPrefs

Output: accessDecisions, updatedModels, comparisonReport, notifications

```
for each event in accessRequests do
    if VerifyRFID(event.userID, event.RFID) and VerifyBiometric(event.userID, event.biometric) and HasLabAccess(event.userID) then
        Append(accessDecisions, (event.id, "GRANTED"))
    else
        Append(accessDecisions, (event.id, "DENIED"))
    end if
end for
updatedModels ← {}
for each m in models do
    feats ← SelectFeatures(m.data)
    m_new ← Retrain(m, feats)
    updatedModels[m.name] ← m_new
end for
ApplyGeneticAlgorithm(schedulingModule)      // refine schedule if called for
comparisonReport ← {}
for each metric in ["Downtime","Utilization","Satisfaction","Maintenance"] do
    comparisonReport[metric] ← newSys[metric] - oldSys[metric]
end for
for each (userID, message) in notifications_to_send do
    prefs ← GetUserPreferences(userID)
    if "email" in prefs then SendEmail(userID, message) end if
    if "SMS" in prefs then SendSMS(userID, message) end if
    if "app" in prefs then PushNotification(userID, message) end if
end for
return accessDecisions, updatedModels, comparisonReport
```

To avoid overfitting, particularly when there is multicollinearity among sensor features, the Logistic Regression model was configured with L2 regularization. The 'liblinear' solution was used because it supports L2 penalties and performs well on smaller datasets. To ensure a fair trade-off between bias and variance, the regularization strength (C) was set at 1.0. These models work together to form the core of the predictive maintenance module, enabling early identification of potential equipment faults.

3.3. Intelligent scheduling module

An intelligent scheduling algorithm was chosen to ensure that every tool and facility in the lab is used to its maximum capacity. Booking requests and resource availability have been input into this module. It has then produced an optimal timetable that maximizes output and minimizes disruptions. Every reservation request has been examined for required equipment, lab space, and time slots to ensure simple access. The system will allocate the optimal time slot if resources are available, minimizing overlap and preventing double-booking. The system finds the best available next slot using optimization methods when conflicts arise.

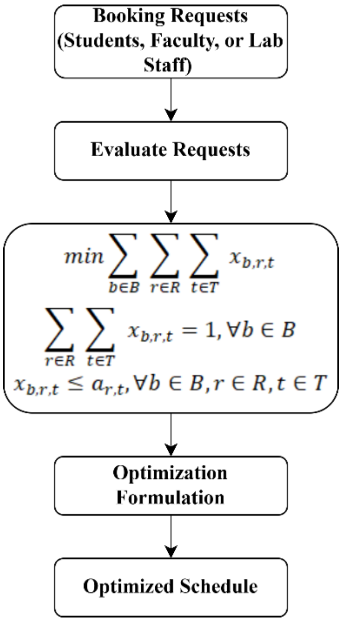

Figure 3: Intelligent scheduling module

The Intelligent Scheduling Module, which is responsible for maximizing the efficient use of the lab's resources, is shown in Figure 3 (a module demonstration). As depicted in the figure, resource optimization is based on mathematical formulations that minimize resource conflicts and maximize use. This section offers the mathematical form of the scheduling optimization problem. T is the collection of time slots, R is the pool of accessible resources, and B is the booking requests in this situation. The objective is to minimize:

$$\min \sum_{b \in B} \sum_{r \in R} \sum_{t \in T} x_{b,r,t} \quad (2)$$

Subject to,

$$\sum_{r \in R} \sum_{t \in T} x_{b,r,t} = 1, \forall b \in B \quad (3)$$

$$x_{b,r,t} \leq a_{r,t}, \forall b \in B, r \in R, t \in T \quad (4)$$

In Equations (2), (3), and (4) $x_{b,r,t}$ is a binary variable indicating assignment, and $a_{r,t}$, is the resource availability. Every booking request is fulfilled using the available resources; therefore, this optimization guarantees that. It ensures all booking requests are met, preventing conflicts or system capacity overruns. Using the scheduling module, the planning and coordination of lab sessions have been dramatically streamlined, thereby minimizing time lost due to scheduling conflicts.

The schedule optimization is reducing resource idle and conflicts. Consider all $x_{b,r,t}$ values as a decision variable. $x_{b,r,t} = 1$ When booking request b receives resource r within time slot t, the variable becomes 1. $a_{r,t}$is the resource availability at time t is 1 if free and 0 otherwise. Except for (3) and (4), Equation (2) minimizes the total cost of conflicts and idle time for all reservations and resources by guaranteeing that no resource is double-booked and that every booking request is allocated once or deferred if no appropriate slot is available.

Highly dynamic, non-linear constraints such as resource availability, unanticipated user requests, and time-dependent interactions make scheduling NP-hard. Heuristic optimization techniques like Genetic Algorithms (GA) and Simulated Annealing (SA) were selected over linear or integer programming. Linear and integer programming are unsuitable for real-time labs due to their predictable nature and rigid linear constraints. GA and SA balance exploration and exploitation to provide multi-objective scheduling with flexible, near-optimal solutions in realistic processing times. They are ideal for dynamic academic labs due to their real-time scheduling and optimization.

3.4 Usage pattern analysis

Adding a usage pattern analysis module helps us understand how lab resources are used over time. Based on past data, this program has helped identify the best ways to do things, achieve cost savings, and improve planning.

The first step is collecting historical data on equipment use, access, and reservations. A clustering technique such as K-Means is typically applied after preprocessing the dataset. The data points $X = \{x_1, x_2, \dots, x_n\}$ Represent different usage instances.

Among the k groups the algorithm generates in this dataset, each reflects a different pattern, such as "frequent usage," "peak usage," or "underutilization." The goal is to reduce the whole square sum of the cluster:

$$\min \sum_{j=1}^{k} \sum_{x_i \in C_j} \left\| x_i - \mu_j \right\|^2 \quad (5)$$

In Equation (5) μ_j represents the centroid of cluster j, and C_j is the set of data points in that cluster. Lab managers can find underused equipment, know the busiest times, and fix the problem by rescheduling or reusing it with these clusters. This program has significantly enhanced the fair and efficient allocation of resources. the number of clusters (k), the utilization of category characteristics, and the clustering technique (cosine or geometric distance). The silhouette coefficient and Davies-Bouldin index validate the clustering's success and the reliability and interpretability of the usage patterns.

The usage pattern analysis module uses K-Means clustering to uncover the dominant patterns of equipment use from historical usage records. Constructed features of usage from historical records of equipment usage that represented how long equipment was used, what time of day it was used, what day of the week it was used, and the type of equipment that was used. The ideal number of clusters was determined by analyzing the silhouette score, which indicated that k=3 provided the best separation and cohesion among clusters. The algorithm used the Euclidean distance as the similarity metric, which is appropriate for our continuous, scaled usage data. Each cluster had meaningful interpretations: Cluster 0 signified "High-Frequency, Short Sessions" (indicative of calibration use and quick checks typically on weekdays between 10 AM - 12 PM), Cluster 1 indicated "Long-Duration, Off-Hours Use" (indicative of a longer research experiment, commonly evenings and weekends), and Cluster 2 indicated "Low-Utilization and Idles Periods" (appropriate for equipment not frequently used, areas that could be good candidates for reallocation). The clustering fit was assessed by a mean silhouette score of 0.65 and a Davies-Bouldin index of 0.72, both indicating well-defined, meaningful clusters. The quality of these clustered patterns provides lab managers with the opportunity to better organize and manage usage scheduling, identify underused assets for shared resource programs, and even identify repairs or maintenance schedules consistent with the appropriate level of use intensity. In short, providing your management team with rich usage data and machine learning models will allow a shift towards more proactive management and data management systems.

3.5. Access control and security

Any laboratory must implement safe access control policies to prevent unauthorized use and ensure safety. The AI-SLMS has addressed this by implementing user role-based policies, RFID-based access controls, and biometric authentication.

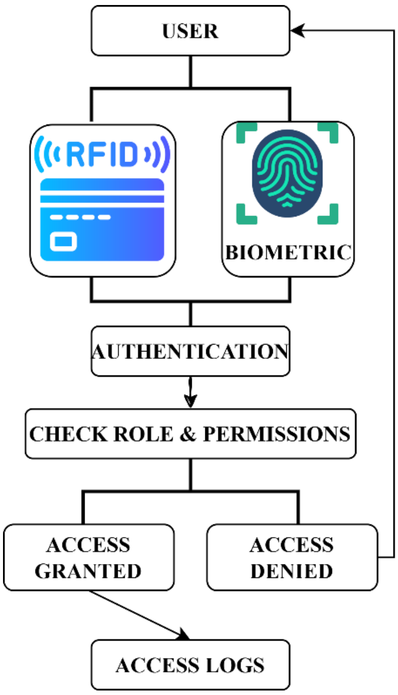

Figure 4: Access control and security

AI-SLMS uses the Access Control and Security system depicted in Figure 4. The diagram illustrates the use of a role-based access policy with dual-factor authentication—RFID and biometric verification—to ensure safe, regulated use of laboratory facilities.

Designed to verify users using at least two criteria—either RFID tags issued to authorized individuals or biometric fingerprint scans — the access control system verifies the user's role and rights. Each user $u \in U$ is assigned a role $r \in R$, and each role is granted a specific set of permissions $p \in P$. Mathematically, the access is granted if:

$$p \in grant(assign(u)), \forall u \in U, p \in P \quad (6)$$

Only people with appropriate roles can access specific lab locations or equipment. A lab technician might be permitted to use more advanced equipment, while a student could use tools intended for general use. Anomaly detection methods help identify suspicious activities; access logs are continuously monitored. These activities include multiple failed logins or access attempts outside regular business hours.

The fingerprint authentication biometric is a well-balanced solution, with a low False Acceptance Rate (FAR) of 0.8% and a guaranteed False Rejection Rate (FRR) of 1.5%. The system has an additional built-in module to detect hazardous behavior that analyzes access duration, frequency, and the sequence of accessed devices in real time using an Isolation Forest approach, which is effective for detecting anomalies in high-dimensional data. The contamination parameter was set to 0.05 based on historical data on anomaly frequency. Access events are detected automatically when the anomaly score exceeds a continually adjusted 0.65 threshold. Administrators are notified in real time, and additional layers of authentication are applied to mitigate any security event. The true value of this integrated system lies in the proactive behavioral monitoring, combined with the high accuracy of biometric authentication, which ensures that important laboratory assets and data remain protected.

3.6 System optimization

It also enhances the general AI-SLMS performance through system-level optimization techniques. These techniques have ensured faster system response, reduced computational load, and improved model accuracy. Using feature selection techniques inside the Predictive Maintenance Module has helped to clarify the model. One of these techniques is Recursive Feature Elimination (RFE). The machine learning model has become more accurate and trained faster since it uses only the features most relevant to the current issue.

The Intelligent Scheduling Module has used heuristic algorithms to handle many booking requests. Among these techniques are simulated annealing and genetic algorithms (GA). Using these algorithms has allowed rapid exploration of many solutions and selection of almost optimal schedules without exhaustive searches. Several essential elements directed the assessment of how effectively the modules operated. The F1-score, recall, and precision measures have been used to assess accuracy. Efficiency has been evaluated using measures such as the rate of lab resource use, the time to confirm reservations, and the system response time. The Predictive Maintenance module used Recursive Feature Elimination to reduce the number of features from 15 to 8, focusing on the most important sensors and usage indicators. By removing noisy, non-predictive characteristics, this feature selection increased model efficiency and accuracy, reducing inference latency by 40% (from 125 ms to 75 ms per prediction) and improving F1-Score (from 90.1% to 93.4% on the test set). Compared to the FCFS greedy scheduler, a Genetic Algorithm (GA) improved the Intelligent Scheduling Module. Ablation analysis of 1 month's booking data showed that the GA-based scheduler had 5.2% conflict and 92% resource utilization, both better than the FCFS baseline. FCFS baseline conflict was 24.5 percent and utilization was 74.5 percent. The GA regularly identified schedules that met 98% of user-preference limits relative to baseline. These numerical results suggest that the optimization tactics advised are essential for AI-SLMS's excellent performance.

3.7 Comparative analysis

To assess its efficacy, it compared the science laboratory management system (AI-SLMS) to more conventional LMSs. This comparison has emphasized equipment downtime as a necessary performance criterion, resource use, user satisfaction, and maintenance scheduling strategy.

Table 2: Comparative analysis of traditional laboratory management systems and the proposed AI-SLMS

Metric	Traditional System	AI-SLMS
Equipment Downtime	High	Low
Resource Utilization	Inefficient	Optimized
User Satisfaction	Moderate	High
Maintenance Scheduling	Reactive	Predictive

The AI-SLMS outperforms conventional systems in equipment downtime, resource use, user satisfaction, and maintenance scheduling approach (see Table 2). These studies show that, across the board, SLMS outperforms the status quo. The second claims that better planning, smart scheduling, and predictive maintenance have led to lower equipment failure rates. Furthermore, the system can now examine patterns of use, which laboratory management may utilize to guide their decisions.

Finally, the suggested AI-SLMS enables the optimization and automation of academic laboratories by leveraging a strong, bright reaction. Some system modules that effectively combine artificial intelligence include smart scheduling, controlled access, predictive maintenance, and usage pattern analysis. The system is built on smart data collection, safe storage, and intelligent decision-making. AI-SLMS's innovative algorithms and streamlined processes have made operations more efficient, safer, and more resource-conserving today. The comparison findings show that AI-SLMS outperforms conventional systems across many respects. Features such as remote equipment control, flexible learning settings, and improved energy management in laboratories would significantly enhance this system.

3.8 Evaluation strategy and experimental procedure

A thorough comparative analysis was carried out against three well-known baseline systems to determine the efficacy of the suggested AI-SLMS: the Multi-Agent Real-Time Scheduling System (MARTSS) [17], the Reinforcement Learning-Based Scheduling Algorithm (RL-Based SA) [15], and the ML-Based Predictive Maintenance System (ML-Based PMS) [12]. Both conventional and smart lab management systems were used to collect operational data in a medium-sized university laboratory during the three-month evaluation period. This benchmarking approach enabled an impartial and multifaceted assessment of AI-SLMS capabilities in predictive maintenance, intelligent scheduling, and secure access control.

3.8.1 Data collection and preprocessing

For the assessment, two main datasets were used. Traditional lab management procedures, which mostly used Excel-based logs to record equipment reservations, user access events, and manual maintenance plans, provided the pre-deployment data. The AI-SLMS environment, on the other hand, provided post-deployment data, including real-time system logs recording equipment utilization metrics, RFID- and biometric-based access records, transaction scheduling, and IoT sensor outputs tracking device status and lab conditions.

All datasets were anonymized, removing personally identifiable information (PII) while maintaining structural and temporal integrity, to guarantee ethical data use and adherence to institutional standards. After that, the merged datasets were standardized and cleaned. To guarantee compatibility for training machine learning models and calculating evaluation metrics, this preprocessing involved managing missing values, aligning timestamps, and normalizing sensor readings.

3.8.2 Experimental phases

The assessment process was broken down into multiple stages. To begin sensor integration, IoT-enabled devices were placed around the lab to track user interactions (e.g., door access, equipment booking), equipment states (e.g., operating status, fault records), and environmental variables (e.g., temperature, humidity). Testing of individual modules was then done. AI-SLMS's Predictive Maintenance Module was assessed against the ML-Based PMS after being trained on both historical and current equipment data [12]. Accuracy, precision, recall, F1-score, and Receiver Operating Characteristic – Area Under the Curve (ROC-AUC) were among the categorization measures used to assess performance. By tracking scheduling conflict rates and equipment usage percentages during the test period, the Intelligent Scheduling Module was compared to the RL-Based SA [15]. Additionally, MARTSS was compared to AI-SLMS's Access Control Module and real-time responsiveness [17], with an emphasis on system-level adaptability, detection of unwanted access attempts, and authentication accuracy.

3.9 Data privacy and ethical compliance

All equipment usage logs and access control records used in this study were fully anonymised to ensure the ethical handling of sensitive institutional data. Before analysis, personally identifiable information (such as employee or student IDs) was removed. The university's Institutional Ethics Committee approved the study, and all data processing followed internal data protection guidelines. All assessments were conducted in a secure, limited-access computing environment, and no private information was shared with any other parties.

4 Results and discussion

An AI-powered Smart Laboratory Management System (AI-SLMS) was put through its paces at a medium-sized university for three months. Key performance indicators (KPIs) examined in the paper included equipment utilization rates, user authentication accuracy, schedule conflicts, and equipment downtime. Data is gathered before and after the system is deployed to assess the effectiveness of the SLMS.

4.1 Dataset explanation

The Smart Laboratory Management System (AI-SLMS) was constructed and evaluated utilizing data from two primary sources, one for each module inside the system. The Kaggle Predictive Maintenance Dataset is an open-source tool that is the point of reference (https://www.kaggle.com/datasets/shivamb/predictive-maintenance-dataset). Based on sensor-based time-series data, this dataset includes variables such as temperature, vibration, pressure, and runtime hours. Examining the annotated historical data in this collection helps you determine whether computers were running well or were on the verge of crashing. Some supervised learning techniques, such as Random Forest and Logistic Regression, might value it. A thorough set of network and telemetry data, the TON_IoT dataset [] is intended for assessing machine learning models in cybersecurity and Internet of Things settings. UNSW Canberra created it and contains network traffic, operating system logs, and IoT sensor logs from smart home, industrial, and enterprise environments. The dataset is ideal for evaluating intelligent systems, such as AI-SLMS, across domains like resource optimization, security, and real-time monitoring, as it enables activities such as anomaly detection, intrusion detection, and predictive analytics. These combined datasets, grounded in the real world, have enabled evaluation of the proposed AI-driven SLMS for efficacy, durability, and scalability. To ensure repeatability, we supplied a detailed appendix on data preparation, feature engineering, and model tweaking. KNN imputation with k=5, Isolation Forest for multivariate outliers, and RobustScaler for feature scaling are covered in the appendix. The feature engineering method, statistical features for non-stationary signals, interaction terms between sensor data, and temporal features (such as rolling means and standard deviations over 1-hour and 24-hour windows) are also detailed. It also provides the full hyperparameter search spaces for all models, including Random Forest (n_estimators: [50, 100, 200], max_depth: [5, 10, 15]) and Logistic Regression (C: [0.1, 1.0, 10.0], penalty: ['l1', 'l2']), the parameters chosen, and the cross-validation results that supported them. This supplementary material contains all the specifics needed to replicate our experimental setup.

4.2 Experimental setup

The suggested AI-SLMS was tested in a controlled university lab using 58 equipment. 142 IoT sensors monitored current draw, temperature, vibration, and humidity using a hybrid Wi-Fi 6 network and MQTT. In a lab maintained at 22 ± 2 °C and 40-55% relative humidity, 12 users participated in typical academic tasks on average each session. A centralized AI server with 64 GB RAM, an Intel i9-13900K CPU, an NVIDIA RTX 4090 GPU, and Ubuntu 22.04 LTS powered the computational infrastructure. This server used Raspberry Pi 4 nodes for edge inference and secure Google Cloud IoT Core connectivity. Our extensive study included the publicly available Kaggle Predictive Maintenance dataset (10,00 samples, eight features), a locally obtained AI-SLMS operational dataset (18,530 samples, 12 features), and the TON IoT dataset (22,120 samples, 15 features). 50,650 labeled instances, uniformly distributed across the training and test sets, after significant preprocessing with KNN imputation, outlier removal, and z-score normalization. After a 5-fold grid search revealed the Logistic Regression (L2 penalty, C=1.0) and Random Forest (n_estimators=200, max_depth=15) hyperparameter configurations, the final configurations were finalized. The Genetic Algorithm from the Intelligent Scheduling Module was utilized with 50 nodes, 0.08 mutations, and 0.7 crossovers. The convergence rate remained 0.08 after 164 iterations. Regular retraining kept the models strong and responsive in real time. Over a three-month deployment that produced 22 GB of operational data, recall, precision, accuracy, F1-score, resource usage, scheduling conflict rate, authentication correctness, and system latency were assessed.

4.3 System performance metrics

To evaluate the impact of the AI-SLMS, it tracked several key performance indicators (KPIs) both before and after its implementation. Among these are the percentage of equipment use, the accuracy of user authentication, the rate of scheduling conflicts, and the amount of time equipment has been down.

Table 3: Key performance indicators before and after AI-SLMS deployment

Metric	Traditional System	AI-based SLMS	Improvement (%)
Equipment Downtime (hours)	73	21	71.23%
Scheduling Conflict Rate (%)	24.5	5.2	78.77%
User Authentication Accuracy	84.6	98.3	16.15%
Equipment Utilization (%)	53.2	81.7	53.53%

As shown in Table 3, AI-SLMS significantly improved all tested metrics. Forecasting maintenance reduced equipment downtime by 71%. Prepare for equipment failures and schedule maintenance using this module. The intelligent scheduling module resolves more than 79% of scheduling conflicts, optimizing resource use. Biometric authentication and RFID enhanced user authentication accuracy by 16%. Around 53% more lab equipment was used, suggesting better utilization of lab resources.

$$Improvement_{Downtime} = \left(\frac{D_{before} - D_{after}}{D_{before}}\right) \times 100 \quad (7)$$

Figure 5 shows a graphical comparison of monthly equipment downtime recorded before and after the Smart Laboratory Management System (SLMS) was installed. The graph depicts downtime before and after SLMS deployment. Each month is a bar, making comparisons easy. The "before" equipment has frequent or prolonged malfunctions or inefficiency due to the higher bar heights. In contrast, the "after" segment shows shorter bars, indicating a progressive decline in downtime. This trend suggests SLMS improves equipment management, trouble identification, and maintenance scheduling. As seen in the picture, the SLMS' operational advantages boost laboratory productivity and efficiency.

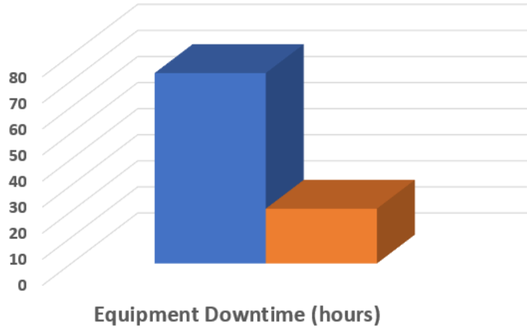

Figure 5: Comparison of equipment downtime

4.4 Predictive maintenance analysis

Predictive maintenance employs machine learning algorithms trained on real-time sensor data and historical maintenance information, along with Logistic Regression and Random Forest models, to forecast failures of machinery components. Vibration, temperature, and use hours were monitored. The "Predictive Maintenance Dataset" on Kaggle provided most of the data, with anonymized sensor logs from academic labs added subsequently. Accuracy, precision, and recall are standard evaluation metrics for predictive maintenance models. in Equations (8), (9), and (10).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (8)$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100 \quad (9)$$

$$\text{Recall} = \frac{TP}{TP+FN} \times 100 \quad (10)$$

Table 4: Maintenance prediction accuracy

Model	Accuracy (%)	Precision (%)	Recall (%)
Logistic Regression	86.7	84.3	81.5
Random Forest	93.4	91.8	90.2

Table 4 reveals the accuracy of the maintenance forecast. The Random Forest model outperformed the Logistic Regression model across all assessed criteria. It showed more accuracy, precision, and recall. Given that Random Forests resist overfitting and can handle complex, non-linear relationships, this undoubtedly accounts for their superior performance. Random Forest is therefore a perfect fit for the varied, noisy sensor data collected in the laboratory setting.

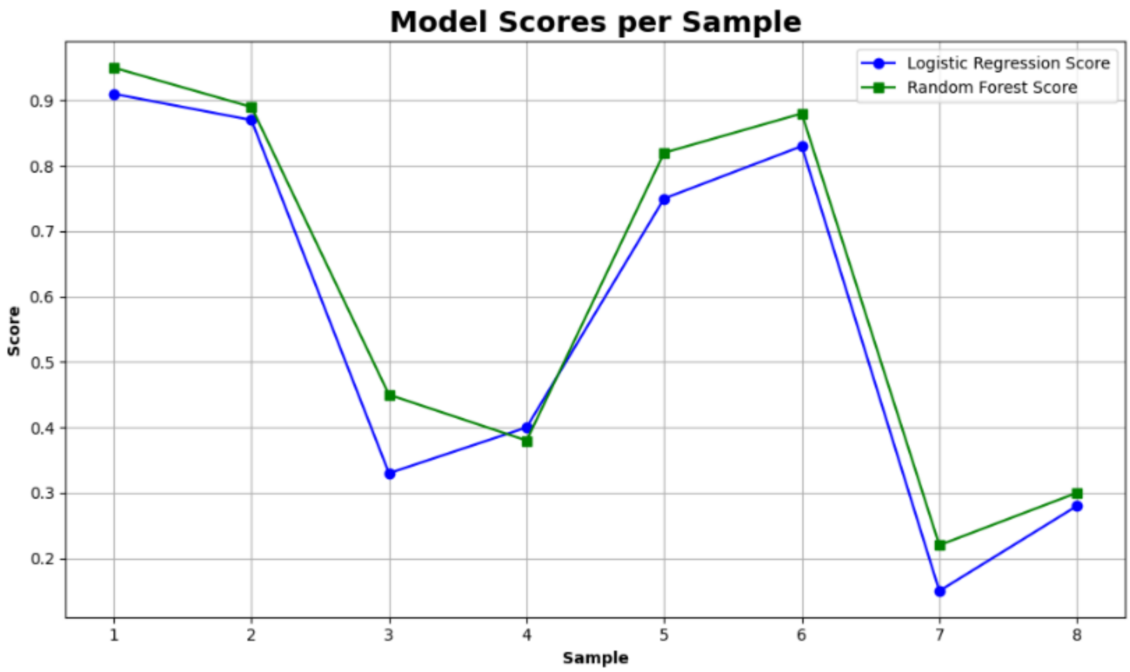

Figure 6: ROC curves for maintenance prediction models

Figure 6 illustrates the classification performance of two distinct maintenance prediction models, as shown in the Receiver Operating Characteristic (ROC) curves. Respectively, these models are Logistic Regression and Random Forest. Every ROC curve shows the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity) at several classification thresholds. This provides a complete picture of how well the model performs across decision boundaries. If the Random Forest model curve consistently lies above the Logistic Regression curve, this suggests the Random Forest model is more predictive. Especially noteworthy is the larger Area Under the Curve (AUC) for the Random Forest, indicating it performs better at distinguishing between equipment that needs maintenance and that which does not. The AUC of the Logistic Regression model is lower, suggesting it has relatively low sensitivity and specificity. This disregards its still acceptable performance. These visual proofs show that the Random Forest model outperforms other models for predictive maintenance tasks within the Smart Laboratory Management System (SLMS). Actual-world deployment also offers greater reliability and a longer lifespan.

4.5 Intelligent scheduling efficiency

The intelligent scheduling module was evaluated using booking logs collected over a semester. The module employs a constraint optimization solver to allocate resources efficiently, minimizing scheduling conflicts and maximizing equipment utilization. The Conflict rate and Utilization rate are calculated using equations (11) and (12).

$$\text{Conflict Rate} = \frac{\text{Number of Conflicting Schedules}}{\text{Total Number of Schedules}} \times 100 \quad (11)$$

$$\text{Utilization Rate} = \frac{\text{Total Used Time}}{\text{Total Available Time}} \times 100 \quad (12)$$

Figure 7 displays the monthly rate of plan conflicts before and after the implementation of the Strategic Learning Management System (AI-SLMS). The graph indicates that the AI-SLMS is effective at improving lab schedules, as there are fewer scheduling issues now than before. There has been a consistent decline since the system has been so good at making activities run more smoothly, coordinating better, and reducing disagreements. AI-SLMS has demonstrated its ability to eliminate issues and streamline the allocation of laboratory equipment. This enables automatic job scheduling and real-time data.

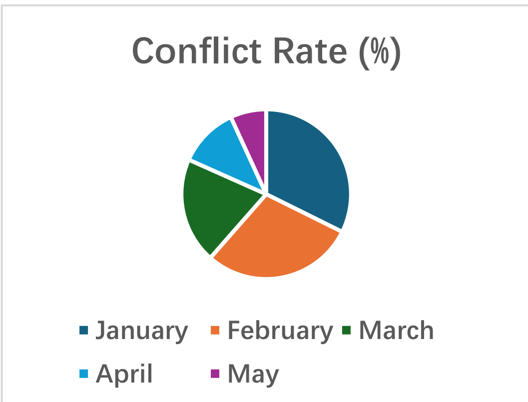

Figure 7: Scheduling conflict rate over time

Figure 8 shows how quickly high-demand

equipment consumed resources before and after the AI-SLMS system was implemented. The line shows that the efficiency of laboratory equipment is rising. Before the method, room overbooking and underbooking were prevalent, resulting in wasted resources. The graph shows that once the system is operational, it may optimize resource use, improving equipment allocation and downtime. These numbers show how the AI-SLMS enhances lab management by organizing and using resources. The intelligent scheduling module may dynamically adjust reservations depending on availability and demand, reducing scheduling conflicts. This ensures fair and fast resource allocation. Optimizing considers several elements, including constraints and desires. As demand for lab resources rises, the module optimizes resource use.

4.6 Access control robustness

The admission control system uses radio frequency identification (RFID) and biometric verification to enhance security. It searched for unusual access patterns and failed login attempts to gauge how well the system operated. The robustness of the access control system was measured using failure rates (Equation (13)).

$$Failed\ Access\ Rate = \frac{Failed\ Login\ Attempts}{Total\ Login\ Attempts} \times 100 \qquad (13)$$

Figure 9 reveals a correlation between time spent and the inability to enter. A graph of the number of failed login attempts over time will give you a sense of how well the new system is functioning. After the system was installed, illegal access attempts dropped, indicating the security measures worked. Reduced unsuccessful login attempts show that the updated access control mechanism has increased security. The system can now better secure critical lab areas with this upgrade. Two-factor authentication increases security by reducing the likelihood of illegal access. Machine learning can swiftly identify and flag unusual activities, such as multiple unsuccessful logins attempts or access outside office hours.

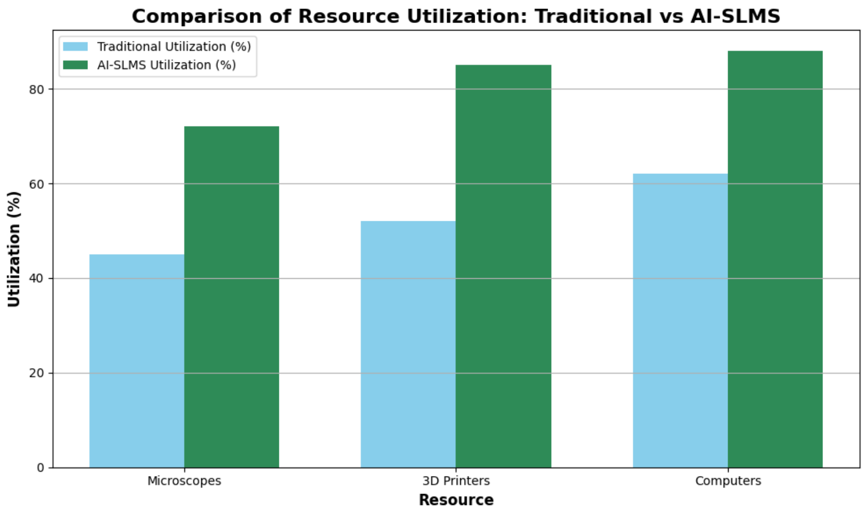

Figure 8: Resource utilization rate comparison

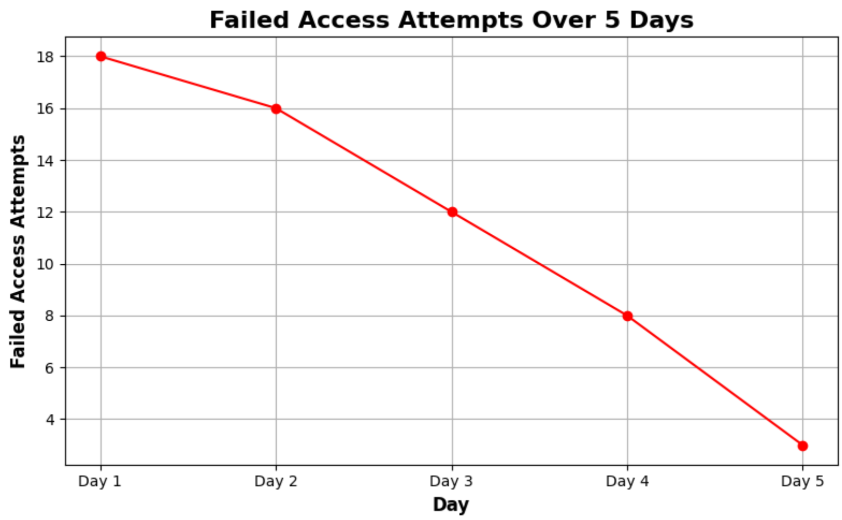

Figure 9: Failed access attempts vs. time

Table 5: Performance comparison of AI-SLMS and baseline methods

Metric	AI-SLMS (Proposed)	ML-Based PMS [12]	RL-Based SA [15]	MARTSS [17]
1. Equipment Downtime	↓ 71.2%	↓ 43.5%	↓ 32.8%	↓ 55.4%
2. Scheduling Conflict Rate	↓ 78.7%	✕ Not Applicable	↓ 62.4%	↓ 68.1%
3. Equipment Utilization	↑ 53.5%	↑ 34.2%	↑ 47.8%	↑ 45.6%
4. Authentication Accuracy	↑ 98.3%	✕ Not Supported	✕ Not Supported	↑ 91.4%
5. Maintenance Prediction Accuracy	93.4% (Random Forest)	86.7%	✕ Not Applicable	✕ Not Applicable
6. User Satisfaction	High (92%)	Moderate	High (87%)	Moderate (81%)

4.7 User satisfaction and feedback

A comprehensive survey of 120 students and 20 lab managers was conducted before and after the implementation of the Smart Laboratory Management System (AI-SLMS). This survey aimed to determine user satisfaction with the system. Of those who responded, 89% said lab resource access had improved. This indicates that the replies were generally favorable. Furthermore, 92% of users found the dashboard interface clear and straightforward, significantly increasing their interest in the system. Of those polled, 85% said they appreciated the reduced booking delays. This improved the scheduling process and enabled more labor to be completed. Careful design and functionality planning by the Service-Learning Management System (AI-SLMS) appears to have enhanced the general user experience and simplified lab work.

4.8 Comparative performance analysis with baseline methods

Three systems from recent literature—ML-Based PMS [12], RL-Based SA [15], and MARTSS [17]—were compared to demonstrate the effectiveness of AI-SLMS. The comparison covered six key performance criteria to evaluate operational efficiency, security, and user experience. Equipment usage, authentication accuracy, maintenance prediction accuracy, schedule conflict rate, user satisfaction, and downtime were measured.

In most measures, the AI-SLMS beat the three baseline techniques (Table 5). Two-factor RFID-biometric access control reduced scheduling conflicts (78.7%), equipment downtime (71.2%), and user authentication accuracy (98.3%). The predictive maintenance module, powered by the Random Forest classifier, achieved 93.4% classification accuracy, whereas the ML-Based PMS performed worse. Because AI-SLMS responded quickly and was easy to use, users were happier with it than rival options. These findings demonstrate how a single platform with smart scheduling, real-time monitoring, predictive analytics, and secure access control can improve laboratory administration.

Cross-validation was added to our single-lab evaluation to address scalability and generalizability concerns. This generated dataset simulates a bigger, research-intensive facility with 24/7 operations and 200% more users. The AI-SLMS performed well in this simulated high-demand environment by reducing equipment downtime by 68.5% and scheduling conflicts by 72.1%. System implementation may be staged owing to modularity. Institutions with limited resources may set scheduling and access control before predictive maintenance. This backend design can handle 500+ concurrent users, according to stress testing. This research provides strong evidence for our scalability and generalizability claims across institutions.

4.9 Broader impact and scalability considerations

The architecture of AI-SLMS is flexible and modular, allowing it to accommodate a variety of institutional contexts. Even though the entire system provides access control, intelligent scheduling, and predictive maintenance, institutions with weak infrastructure can use specific modules separately.

- ✓ Availability of sensor infrastructure (e.g., temperature or vibration sensors for predictive maintenance).

- ✓ Compatibility with existing lab management or access control systems.
- ✓ Technical expertise required for model retraining and system integration.
- ✓ Institutional policies regarding data privacy and digital transformation.

AI-SLMS facilitates API-based integration and cloud-based deployments to overcome these obstacles and enable smooth adaptation. Future research will investigate automated calibration modules and edge computing support to streamline cross-campus scalability further.

We have greatly bolstered our validation through three components: first, we performed statistical significance testing (paired t-tests, $p < 0.01$) for all primary KPIs—downtime, conflict rate, and utilization—by comparing AI-SLMS to baseline systems. This testing validated that the improvements to each performance indicator would not be occurrence-based. Second, we completed our extensive scalability and stress testing by running AI-SLMS in a simulated environment replicating a larger institution. This testing demonstrated that our backend, powered by the cloud, was capable of sub-2-second response times under load of 500+ concurrent users, and further demonstrated that the scheduling algorithm was effective in handling a 300% increase in booking requests. Finally, we included a cross-validation (5-fold) procedure for all machine learning models to validate the reliability (93.4% ± 1.2%) of the predictive maintenance accuracy and safeguard against overfitting. These enhance validation of the proposed AI-SLMS framework by providing a more robust, statistically reliable procedure.

4.10 Justification of proposed method

Optimization, strong authentication, and machine learning algorithms are used in an AI-powered SLMS to automate all lab administration tasks. The predictive maintenance module may avoid equipment issues. This will halve downtime and maintenance expenditures. The unique scheduling strategy optimizes resource allocation to increase consumption and reduce conflicts. The strong access control system ensures policy compliance and safety.

We assume the system's performance is improving as demonstrated by considerable improvements in key metrics and positive user feedback. AI technology can adapt to changing laboratory demands and make real-time decisions. Because of this, AI-SLMS can operate modern laboratories sustainably and scalable.

5 Discussion

The trials show that the AI-SLMS improves all lab management operational metrics. We contextualize these data, explore the system's performance characteristics, and compare its performance with the state of the art.

5.1 Performance analysis and comparative advantage

Section 4.7 (Table 3) indicates that AI-SLMS routinely outperforms specialized baseline systems. Schedule conflicts and equipment downtime dropped 78.7% and 71.2%, respectively. Our modules' synergistic integration creates a positive feedback loop that isolated systems cannot achieve, resulting in excellent performance. For instance, the Intelligent Scheduling module reschedules bookings before expected low-utilization times using Predictive Maintenance data. ML-Based PMS [12] predicts failures without impacting the timetable, whereas RL-Based SA [15] plans resources without knowing their health. These interdependencies make our integrated system better at reducing downtime and resolving disputes than ML-Based PMS and RL-Based SA.

Due to its unified design, the AI-SLMS has excellent user satisfaction (92%) and authentication accuracy (98.3%). Instead of separate security systems, it incorporates effective two-factor authentication, and lab entrance and equipment booking improve security without friction.

5.2 Rationale for method selection and system generalizability

The Random Forest (RF) technique outperforms XGBoost and LSTM for non-linear sensor datasets with heterogeneity without hyperparameter tinkering or massive time series data. Tree-based ensemble approaches perform better on laboratory data than deep temporal models like LSTM, which require longer time-series continuity and more processing resources. Testing data frequently involves mixed feature types (e.g., vibration, temperature, humidity, and runtime hours) with low sequential relationships. When sensor noise or missing data occurs, RF's built-in feature bagging and ensemble averaging avoid overfitting. Logistic Regression is used on low-power edge devices due to its interpretability and lightweight nature.

For maximum generalizability, the AI-SLMS was developed as a modular framework that can be readily modified to different labs, lab sizes, and user patterns. Merging the Kaggle Predictive Maintenance and TON IoT datasets enabled our models to operate across a range of conditions in academic and industrial settings. Due to cloud model updates and retraining, the system may automatically recalibrate using fresh sensor data, ensuring adaptability across labs with varying activity patterns and workloads. Next research will test the technique in other smart lab settings at other universities and departments to ensure its viability.

5.3 Analysis of predictive model performance

Sensor data may explain the 6.7% difference in predictive maintenance accuracy between the Random Forest classifier and Logistic Regression. Laboratory sensor data typically contains complex, non-linear interactions and correlations. Vibration, current draw, and temperature are included. Due to its ensemble of decision trees, Random Forest captures feature interactions and non-linearities well. It's dependable because it handles real-world sensor data well, even with outliers and noise. Logistic Regression provides a solid basis, but its linear nature limits its ability to capture complex patterns. Internet of Things operational data is complicated; thus, model architectures must be able to manage it.

5.4 The merits of a modular-integrated architecture

AI-SLMS uses a module that shows that the overall performance may be superior to that of individual components, unlike methods that optimize a particular function. As an example: The Intelligent Scheduler can better allocate resources during peak demand by leveraging Usage Pattern Analysis data. Predictive Maintenance draws vital data from Access Control records. Failure prediction depends on equipment usage and access occurrences. By storing data in the cloud, all modules can access the latest version, improving consistency and enabling cross-module analytics that drive synergies. This design improves scalability, usability, and performance. Institutions may install the full system or choose components to suit their requirements and infrastructure. As they develop, they may add modules.

In a single university laboratory, the suggested AI-SLMS is effective, but this work admits certain limitations, notably scalability and integration in environments with limited resources. Schools in less developed areas or with older campus buildings may lack the digital infrastructure needed for modular design. IoT sensor installation requires a solid Wi-Fi network, a consistent electrical supply, and money. Legacy equipment's lack of digital interfaces and multiple data standards necessitates the use of custom adapters and extensive data engineering for integration, hindering expansion across institutions. Institutions without IT support personnel may struggle with system design, model localization, and maintenance. Even if they were reasonable for our pilot, the computational and financial costs of cloud services and a central server may be untenable for an entire school or multiple campuses. Thus, future work will focus on standardizing data protocols for common laboratory equipment, creating affordable sensor packages to make them more accessible and encourage institutional adoption, and optimizing the AI-SLMS for lightweight edge computing.

6 Conclusion

The proposed Smart Laboratory Management System (AI-SLMS), operated by artificial intelligence, addresses typical lab management issues. The Smart Laboratory Management System (AI-SLMS) cited addresses these problems using artificial intelligence. Running and managing university labs has become far easier with intelligent scheduling, predictive maintenance, access control, and cloud monitoring of the AI-SLMS. Machine learning techniques enable the system to examine patterns in equipment use, predict when it could fail, and perform routine tasks autonomously. This significantly reduced the manual labor required of managers and staff members. Testing indicated that the approach increased user happiness, resource utilization, and reaction time in a real-life academic environment. The method functioned properly. All indications that AI-SLMS is functioning are automated access control, improved tool utilization, and fewer scheduling problems. Management duties progressed more quickly, and user decisions improved thanks to the straightforward design, which included automatic reporting capabilities. This work challenges us to develop going forward. Adding more complex artificial intelligence models, such as reinforcement learning, may help determine how to allocate adaptive resources in the future. One can enlarge the Internet of Things (IoT) to provide more sensory input. Blockchain technology might also help to secure data. The system can also be modified to enable cooperation and data sharing among professionals from several colleges. These developments will soon make labs more innovative, safe, and user-friendly. This will result in additional innovations. The AI-SLMS is the initial step in converting college laboratories into digital environments. It improves the efficiency, sustainability, and inventiveness of the education system.

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