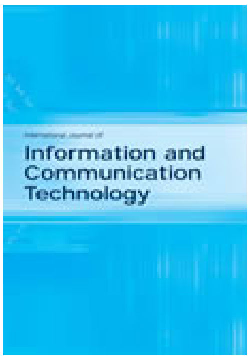

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Integrating artificial intelligence and the internet of things for smart laboratory engineering construction and management team optimisation

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Abstract: Artificial intelligence (AI) and internet of things (IoT) convergence brings immense opportunity to convert the laboratory environment into intelligent, adaptive systems. This study proposes an integrated AI-IoT framework for smart laboratory engineering construction and engineering management team optimisation, which overcomes the current shortcomings in resource efficiency, task scheduling, and environmental control to some extent. In this system, real-time IoT sensor networks monitor ecological and operational conditions; meanwhile, LSTM models are applied for predictive environmental control, genetic algorithms for dynamic task scheduling, and SVM classifiers for human activity recognition. The framework was deployed in a research laboratory for six months, and the system achieved substantial improvements: energy consumption was reduced by 28.48%, equipment downtime by 54.37%, and task overlap and average task duration were significantly minimised. Additionally, predictive maintenance accuracy reached approximately 93.2%, eliminating passive interventions and improving equipment availability. Since intelligent task allocation incorporates fault tolerance considerations, workload imbalance in task execution is alleviated, and staff satisfaction is enhanced. Our results demonstrate that a collaborative AI-IoT approach can effectively improve infrastructure efficiency and worker productivity. In this context, the proposed framework provides a scalable, sustainable, and context-aware solution for next-generation laboratory environments in academic and industrial domains.

Keywords: artificial intelligence; AI; internet of things; IoT; smart laboratory; engineering management; predictive maintenance; task scheduling; environmental monitoring.

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1 Introduction

The present-day needs of modern laboratories have driven the requirement for intelligent, adaptive systems to manage physical infrastructure and human resources (Tariq et al., 2024). In traditional laboratories, manual scheduling, rule-based environmental control, and reactive flow control maintenance procedures cannot support the precision, efficiency, and scale necessary in academia, clinical, and industrial research environments (da Silva, 2022). Therefore, Artificial Intelligence (AI) and internet of things (IoT) integration have evolved as promising paradigms to empower smart laboratories that are far more than just automated, intelligent, predictive, and self-optimising.

1.1 Background and motivation

Scientific advancement is central to what laboratories do, but most continue to function within systems of disjointed monitoring of the environment, maintenance of equipment, and coordination of teams (Shinn, 1982). However, while IoT technologies have enabled the acquisition of real-time data from sensors embedded in laboratory equipment and infrastructure, their operation is typically decoupled from the operation of other decision-making systems (Coito et al., 2021, Louis and Dunston, 2018, Tien, 2017). On the other hand, in the fields of intelligent manufacturing, healthcare, and logistics, AI has succeeded in predictive analytics and optimisation. These technologies fused to create the concept of cyber-physical systems (Zong and Guan, 2024, Lazaroiu et al., 2022, Andronie et al., 2021) – where there is a fusion between the technology and the controls for intelligent energy use, task, allocation, etc., with real-time data influencing this control.

For example, provide long short-term memory (LSTM) network-based AI models to forecast environmental conditions (Sekertekin et al., 2021) and genetic algorithms (GAs) based optimisation algorithms that can allocate human resources to perform their tasks based on urgency and availability of personnel (Apornak et al., 2021). In addition, SVM classifiers can achieve lab staff behaviour and presence-aware human activity pattern identification, thus enabling systems to adapt to them (Russell, 2008). Together, these capabilities enable workflow automation, improve productivity, or reduce operational overhead.

1.2 Problem statement

Yet technological progress has not translated into most laboratory environments, which still operate with compartmentalised subsystems that are not interoperable with each other. Fixed schedule, threshold-based responses are common to environmental management tools, though they are not predictive. The maintenance protocols are usually reactive, so unplanned equipment failures and costly downtime will result. It is done manually or through static scheduling platforms that do not consider real-time occupancy, task complexity, or individual workload. As a result, decisions get fragmented, which results in inefficiencies in operational performance, quality of research outputs, and staff satisfaction.

Most of the existing smart lab solutions are limited to one specific aspect, either environmental monitoring, automation of experiments, or a digital data management component. Still, none of them are integrated into an intelligent frame. Labs have limited optimal performance and scalability due to lacking a unified environmental control system, predictive analytics, human activity recognition, and team management.

1.3 Research objectives

Under this, the primary goal of this research is to design, develop, and evaluate an integrated AI-IoT system that supports smart laboratory construction and management team optimisation. The objectives are as follows:

- Building a modular, layered architecture based on IoT sensing and AI analytics for seamless, real-time decision-making.
- The proposed implementation of predictive environmental control using LSTM models saves energy and maintains optimal working conditions.
- To employ evolutionary algorithms such as GAs tailored for laboratory operations to schedule tasks and distribute workload optimally.
- SVM classifiers based on real-time sensor data are developed to detect and classify human activity states (that ultimately would enable adaptive task reassignment).
- Addressing the problem of enabling predictive maintenance of laboratory equipment by combining time-series analytics and anomaly detection techniques and improving device availability while reducing unplanned downtime.

1.4 Contributions of the study

This paper offers a comprehensive AI IoT combined framework that combines physical infrastructure management and intelligent human resource optimisation to advance smart laboratory systems. The key contributions include:

- A system architecture with three layers (perception layer, network layer, and application layer) of IoTs, the network layer of MQTT and RESTful APIs, and the application layer of AI models for interoperability and scalability.
- An LSTM-based predictive environmental control deployment and evaluation that leads to significant energy reduction and reduced system downtime.
- Development of a genetic algorithm-based task optimisation engine used for dynamically assigning tasks by considering team workload and role compatibility to improve efficiency and satisfaction.
- The integration of real-time human activity recognition using SVM classifiers trained in presence and motion data to allow behaviour-aware systems.
- An equipment failure predictive maintenance module that uses an LSTM and SVM model combination to indicate early signs of equipment failure to improve operational continuity and safety.

These contributions provide a unified system that corrects the flaws of current laboratory automation tools and provides a fully incorporated, smart, and scaleable answer for lab the executive's administration.

1.5 Structure of the paper

The remainder of the paper is organised as follows. Section 2 provides a complete literature review of existing research on AI and IoT applications in laboratories, highlighting the state of the art and pinpointing gaps in the current literature. System architecture, model selection, and data acquisition strategies are presented in Section 3 for the research methodology. Section 4 reports experimental results from the system's deployment in a real laboratory environment and analyses them. In Section 5, the implications, benefits, and limitations of the proposed system are discussed. At the end of Section 6, future directions for extending and improving the framework are outlined. Section 7 concludes the paper with a summary of findings and contributions.

2 Literature review

AI Integration into the IoT has revolutionised several domains like smart manufacturing, healthcare, building automation (Chander et al., 2022), etc. However, this is an emerging field in which the application of smart laboratories in the construction management and operational management of smart laboratories has not been explored (Rane, 2023; Rane et al., 2023, Ding, 2022), with few consolidated frameworks available to support this. This literature review includes previous work on this research's four crucial core methodological components: environmental monitoring and predictive controls, AI-based task scheduling, human activity recognition, and predictive maintenance. In this section, we describe existing approaches and identify basic primitives and essential research gaps that help inform the design of the proposed system.

2.1 IoT-based environmental monitoring and predictive control

With the continuous growth of smart infrastructure, IoT sensor networks have become the standard way of environmental monitoring. In a founding study, (Pandey et al., 2024, Kumar et al., 2024, Yadav et al., 2024) deployed an IoT-enabled architecture to monitor environmental conditions in smart healthcare systems. They accomplished scalable sensor communication and real-time data acquisition using lightweight protocols like MQTT (Atmoko et al., 2017). However, they were constrained by preset logic control thresholds that are not responsive to dynamic environmental changes.

To overcome this, recent research on AI-supported forecasting methods has been conducted. Zhuang et al. (2023), Liu et al. (2022), Li and Tong (2021) predict the temperature and humidity using the LSTM models in smart buildings, which perform better in control accuracy than rule-based systems. Their work showed that time series models could predict changes in environmental conditions and enable proactive adjustments. While effective, it was not meant to be used in a laboratory environment where environmental regulation needs to be more exacting and interacts with special instrumentation used by the research. Based on these, the proposed study combines real-time IoT sensor data with LSTM-based predictive control tuned explicitly for laboratory environments to provide a more context-aware and energy-efficient solution.

2.2 AI-driven task scheduling and resource allocation

Operations research and our AI efforts have surveyed task scheduling and workforce optimisation. GAs have been commonly applied since they can handle complex, multi-objective scheduling problems (Cochran et al., 2003). In healthcare, (Koruca et al., 2023) introduced a GA-based staff scheduling system to find nurse shifts while balancing the workload and continuity of service. Their approach highlighted the strengths of such an approach in dynamic, resource-constrained environments.

Zhang et al. (2022a, 2022b, 2023) employed reinforcement learning to solve a job assignment problem on industrial production lines to improve throughput and task distribution. However, such models often take a long time to learn (Samsonov et al., 2022). They are susceptible to variability in the environment, which makes them less suitable for small and quickly evolving environments in a laboratory.

However, our approach optimises the task allocation among laboratory staff using GAs considering the real-time contextual data, including presence, role suitability, and equipment availability. In contrast to prior work, which provides separate scheduling and physical control capabilities, our system integrates the two domains using a holistic operational management approach.

2.3 Human activity recognition via sensor fusion and machine learning

Pervasive computing and smart workspace design have constantly sought understanding human activity in shared spaces. The work by Liu et al. (2019), Wan et al. (2020), Qi et al. (2024) shows the development of a real-time human activity recognition framework from data obtained using PIR sensors, bluetooth low energy (BLE) beacons, and accelerometers. The classifying states ('active,' 'idle,' or 'absent') informed HVAC and lighting control systems via their support vector machine (SVM) classifier, which attained high accuracy (Sivanathan, 2020).

Although successful, this approach was only practised in adaptative terms relative to environmental factors, lacking successful influence regarding workforce optimisation statements in a decision-making framework paradigm. Additionally, activity recognition was a standalone function and did not have to be tied very tightly to task management or equipment utilisation tracking.

In the present study, SVM-based activity recognition is incorporated into a larger decision-making support system. The activity classification is crucial for environmental automation but also supplies data to the task scheduler as it can dynamically reassign tasks and rebalance workload based on time engagement data. This unified model presents a new feedback loop between human behaviour, the planning of a task, and physical infrastructure control.

2.4 Predictive maintenance using AI in IoT-enabled systems

In industrial IoT systems, industrial IoT (IIoT), equipment downtime results in expensive operational losses, and therefore, there has been much research on predictive maintenance. Based on this, Wahid et al. (2022), Stephan et al. (2024) presented a hybrid AI framework formed by LSTM and SVM for the failure predictor in CNC machines. With over 90% accuracy, their model forecasted breakdown events using time series sensor data to eliminate maintenance costs and improve uptime.

While such techniques are mature in industrial contexts, such use is less structured, and the equipment is more diverse in the laboratory. Hence, managing samples and manipulating equipment over the network frequently is challenging. Namuduri et al. (2020), Pech et al. (2021), Gawde et al. (2024), conducted predictive maintenance work in a smart cheusing vibration and thermal sensors mistry lab using vibrati. Nevertheless, implementing these methods did not integrate with other lab management functions like scheduling and regulation of environmental parameters.

Thus, it advances predictive maintenance in laboratories by integrating failure prediction with task scheduling and environmental control. For example, when a potential equipment anomaly is detected, the system can automatically reschedule tasks or redirect workflows to continue as usual, translating into predictive analytics to actionable intelligence.

2.5 Integrated AI-IoT frameworks in smart laboratory environments

Although individual experiments have been using AI and IoT in the laboratory, integrated systems are still the exception. In the work of Xiao (2024), Hao et al. (2015), Wang et al. (2023), they have made an IoT–cloud platform for smart chemistry labs focusing on automated reaction monitoring and safety alerts. In addition, their system did not have AI-driven decision-making and did not consider human resources and task scheduling.

In another study, Wang et al. (2023), Bellaj et al. (2024), Chagnon-Lessard et al. (2021) designed a smart campus lab that included sources of environmental sensors and cloud dashboards with rudimentary automation or optimisation capabilities. More than anything, it was a monitoring tool, not a self-adaptive environment.

This work tackles these limitations by presenting a fully integrated approach that combines IoT sensing, AI analytics, and optimisation algorithms into one platform. Our system is unlike any that have previously handled those aspects of environment, equipment, or personnel individually, as it optimises all three simultaneously, achieving maximum efficiency, adaptability, and user satisfaction in a laboratory setting.

3 Research methodology

In developing an intelligent and scalable smart laboratory framework, this integration is necessary between sensing technologies, AI algorithms, and optimisation strategies. In this section, we provide a methodology for designing and developing a layered system architecture that enables pairing IoT sensing with AI for dynamic control and optimisation of the laboratory environment and the management team. Based on the demand of tasks, the framework includes multiple subsystems that work synergistically to realise environmental monitoring, prediction of maintenance needs, intelligent scheduling of staff tasks, and response to time human activity.

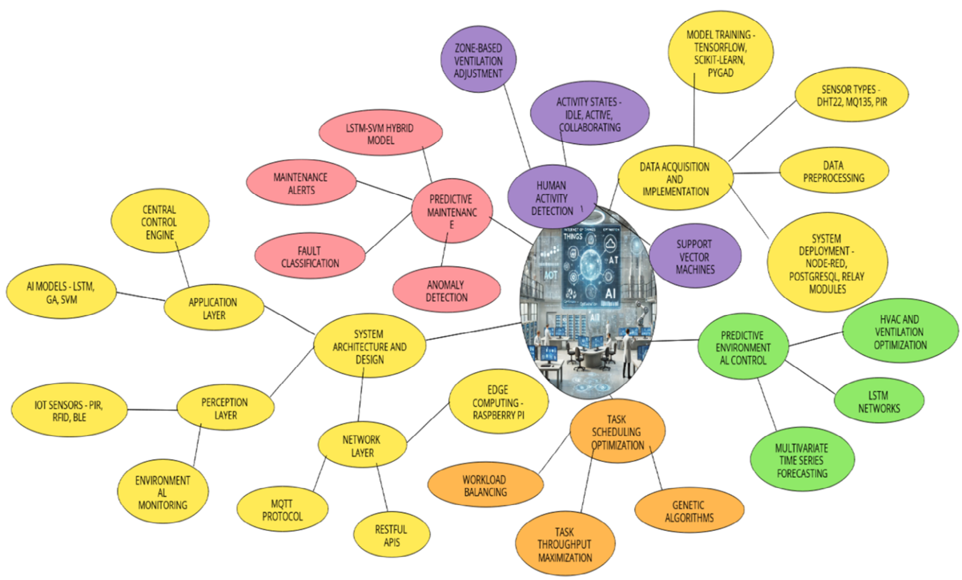
3.1 System architecture and design overview

The architecture is proposed to be featured by a three-layer structure: the perception layer, network layer, and application layer. Passive infrared (PIR) motion sensors, RFID tags, BLE beacons, and other IoT sensors gather environmental parameters (temperature, humidity, CO_2 levels), usage data of equipment, and human presence information in the perception layer. These data streams are collected frequently to monitor laboratory conditions and activity states continuously.

The MQTT protocol ensures low latency sensor communication and RESTful APIs are integrated with cloud databases and external systems via the MQTT protocol using the network layer. Local data processing is done by edge computing units (e.g., Raspberry Pi) to reduce communication overhead and perform some preliminary preprocessing, such as data filtering, normalisation, and feature extraction.

The AI models that perform inference, control, and optimisation are in the application layer. LSTM models for environmental forecasting, GAs for dynamic task scheduling, and SVMs for activity recognition are some of these models. These models result in a running set of results fed into a central control engine that implements automated decisions, such as adjusting environmental controls, reallocating staff tasks, or sending maintenance alerts.

Figure 1 A multi-layered intelligent lab framework integrating IoT, AI models, task optimisation, and predictive maintenance systems (see online version for colours)



3.2 *Predictive environmental control using LSTM networks*

Laboratory control of the environment is important to experiment reliability and personnel safety. We use long short term memory (LSTM) neural networks to train historical sensor data and proactively forecast future environmental conditions. LSTM networks are well suited for multivariate time series forecasts because they can preserve long-term dependencies and address the gradient vanishing problem in standard RNNs.

The vector of environmental input features at time t is represented by the vector, $x_t \in R^n$, at this time, including temperature, humidity, and CO_2 concentration. Below are the recurrence relations used by LSTM to compute internal states.

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{1}$$

$$i_t = \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right) \tag{2}$$

$$\tilde{c}_t = \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right)(\tag{3}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{4}$$

$$o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right) \tag{5}$$

$$h_t = o_t \odot \tanh\left(c_t\right) \tag{6}$$

where σ denotes the sigmoid activation function, $\odot$ denotes element-wise multiplication, and W_*, U_*, b_*, are learned parameters. The predicted values $\hat{y}_{t+1}$, are used to preemptively adjust HVAC and ventilation systems, reducing response delay and energy waste.

3.3 Task scheduling optimisation via genetic algorithms

To use human resources efficiently, dynamic task assignments in a real laboratory must consider real-time availability, skill level, equipment access, and workload balance. The constrained combinatorial optimisation problem describing task assignment problem is formulated as follows: maximise task throughput and minimise conflict.

Let $T = \{t_1, t_2, \ldots, t_n\}$, be the set of tasks, and $E = \{e_1, e_2, \ldots, e_m\}$ be the set of employees. A chromosome x_ix encodes a possible task assignment. The fitness function $F(x_i)$, evaluates the quality of the assignment using:

$$\begin{aligned} F\left(x_i\right) = \alpha \cdot TaskCompletionRate\left(x_i\right) + \beta \cdot WorkloadBalance\left(x_i\right) \\ - \gamma \cdot ConflictPenalty\left(x_i\right) \end{aligned} \tag{7}$$

where:

- TaskCompletionRate is the fraction of tasks completed in the allotted time range.
- WorkloadBalance measures the standard deviation of the task loads over staff.
- ResourceClashes is the number of resource clashes or overlapping assignments.
- $\alpha, \beta, \gamma \in R^+$, are tunable weights.

The genetic algorithm starts by initialising the population and fitness evaluation, then the selection using tournament selection, crossover (single point), and mutation (bit flip). Fitness improvement is achieved when fitness improvement plateaus or a maximum generation count arrives.

3.4 Human activity detection using support vector machines

We use real-time staff activity to schedule the problem by having a SVM classifier trained on sensor-based features. Using motion, beacon proximity, and dwell time data, the classifier looks for states like 'idle', 'active', 'collaborating', and 'absent.' Let $z = [z_1, z_2, \ldots, z_k] \in R^k$, be the input feature vector for a time interval, and $y \in \{-1, +1\}$, be the binary activity class. The decision function is given by:

$$f(z) = sign\left(\sum_{i=1}^{N} \alpha_i y_i K\left(z_i, z\right) + b\right) \quad (8)$$

It is also the case for RBF (using $K(z_i, z)$ as the kernel function) as well, where α_i, are Lagrange multipliers, and b is the bias. It defines task readiness or reassignment and assesses the need for ventilation by zone.

3.5 Predictive maintenance and anomaly detection

It may disrupt a workflow and compromise an experiment's integrity. An LSTM-SVM hybrid model is applied to detect failures proactively. On the one hand, LSTM networks are trained to model expected sensor behaviour over time; on the other hand, expected pattern deviations are classified using SVM using the predicted severity.

Given that we want to process a time series $s_t \in R^d$, of vibration, temperature, or power usage on a device, the LSTM generates predictions of s^{t+1}. Learned thresholds are evaluated on a residual error, $r_t = s^{\hat{t}+1} - s^{t+1}$, and residuals are submitted to an SVM classifier, classifying the faults as binary or multi-class.

Integrating these two approaches in a hybrid way improves the precision of anomaly detection. Still, it brings interpretable instructions and allows automated alert generation and maintenance scheduling with the central AI engine.

3.6 Data acquisition, pre-processing, and implementation

It was deployed in a university laboratory with 40 IoT sensors, such as DHT22 (temperature/humidity), MQ135 (air quality), PIR motion sensors, BLE beacons, and RFID/readers. Six months' worth of data was collected at 1-minute intervals. Anonymised and encoded staff interaction data from the role, task history, and activity logs (logs of activities) were used to train the model. For time series, missing data are imputed by linear interpolation; mode imputation is used for categorical fields. Min-max scaling was used for all numeric features.

$$x' = \frac{x - min(x)}{max(x) - min(x)} \quad (9)$$

Finally, each of the implementations was implemented using AI models in Python with TensorFlow (LSTM), Scikit-learn (SVM), and PyGAD (genetic algorithm). It ingested Node-RED'd MQTT-based sensor data into a PostgreSQL database – the application engine-controlled relay modules to relay control signals (for example, for HVAC).

4 Results and analysis

This section describes the results of deploying and evaluating the proposed AI-IoT framework in a real laboratory environment for six months. They focus on three primary dimensions:

1 environmental monitoring and predictive control

2 team management optimisation

3 predictive maintenance and anomaly detection.

The efficiency and practicality of the integrated system are quantified with graphical and statistical tables that support the proposed metrics.

4.1 Environmental monitoring and control performance

Using real-time IoT sensor data and the combination of LSTM-based predictive models, the system could pre-emptively anticipate environmental changes and regulate HVAC operations accordingly. Temperature, humidity, and CO2 data were continuously monitored over six months, and any ecological data combined with LSTM predictions were adopted.

Figure 2 shows a predicted versus actual temperature sample at the 48 hours. The predictive accuracy was high as tested by the LSTM model with an average root mean square error (RMSE) of 0.47°C. The system achieved this precision, enabling it to adjust heating and cooling systems before energy spikes and maintain thermal stability.

Figure 2 LSTM predicted vs. actual temperature values over 48 hours (see online version for colours)

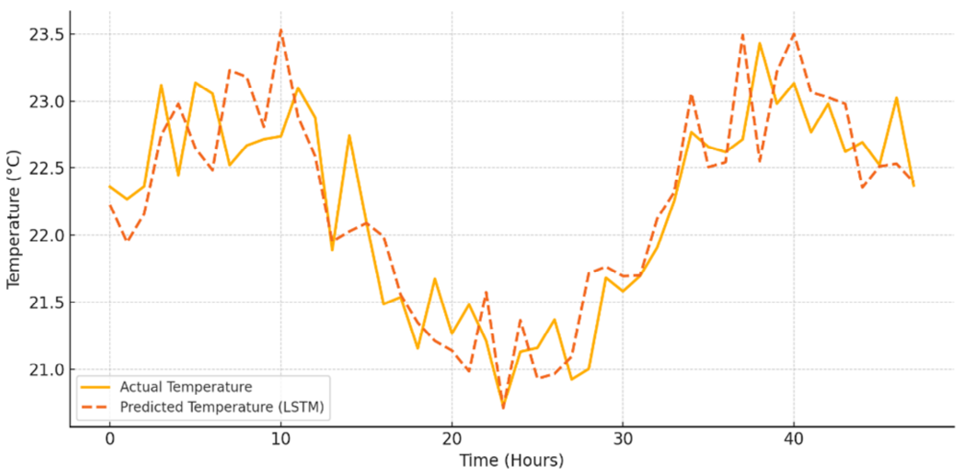


Table 1 summarises system integration's quantitative performance improvements (before the first and after the second). Energy consumption after deployment was down 28.48%, with decreased equipment downtime by 54.37% and improved CO_2 levels by 27.77%, improving energy efficiency and indoor air quality.

Table 1 Environmental metrics pre- and post-AI-IoT integration

Metric	*Before integration*	*After integration*	*Improvement (%)*
Energy consumption (kWh/mo)	1,245	890	28.48
CO_2 levels (ppm)	900	650	27.77
Downtime (hrs/month)	10.3	4.7	54.37

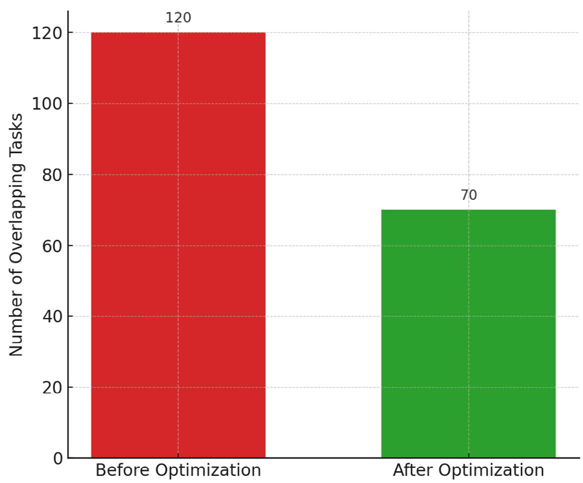
The results confirm the effectiveness of the predictive control mechanism in reducing energy costs while keeping laboratory-sensitive experiments within critical ranges of environmental conditions.

4.2 Task scheduling and workforce optimisation

The Genetic Algorithm-based task scheduler evaluated task throughput, conflict reduction, and staff satisfaction. In the case when task allocation was previously done manually on fixed schedules, the system was implemented prior. After integration, real-time task reassignment and load balancing were possible based on current occupancy, engagement levels, and task urgency.

The reduction of task overlap before and after optimisation is illustrated in Figure 3. Such overlapping tasks that used to result in delay and resource contention were reduced by 41.81% to maintain workflow continuity.

Figure 3 Task overlaps before vs. after genetic algorithm optimisation (see online version for colours)



Metrics showing further improvements in task efficiency are presented in Table 2, and task average completion time dropped by 14% from 47.0 to 32.4 mins, while post-task survey scores for team satisfaction also improved dramatically from 3.6 to 4.5 on a 5-point Likert scale.

The finding that people working effectively together in teams can perform work they would otherwise find overly complex and tedious underscores the value of using AI for task planning, especially when working in high variability teams regarding the availability of people and equipment.

Table 2 Workforce optimisation and task performance results

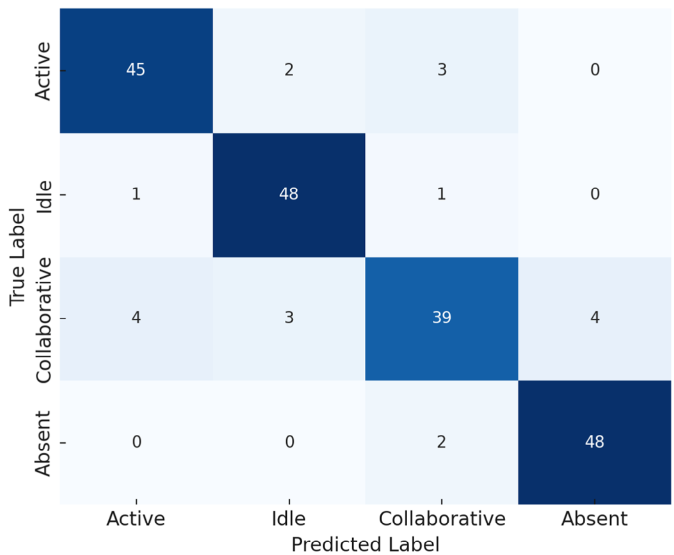
Metric	*Before optimisation*	*After optimisation*	*Improvement (%)*
Average task duration (minutes)	47.0	32.4	31.06
Task overlap rate (%)	23.2	13.5	41.81
Staff satisfaction score (1–5)	3.6	4.5	+25.00

4.3 Real-time activity detection and response

Overall, four activity states (active, idle, collaborative, and absent) of the human activity recognition SVM classifier reached 91.4% accuracy. Fused motion and proximity sensor data were used to train the activity classifier to infer the behavioural state with a precision of up to 10 seconds.

The confusion matrix of the same trained SVM classifier has been presented in Figure 4. The model best played the active and idle classes, with a bit below the ‘collaborative’ class, which suffered from overlaps with active states due to proximity similarities.

Figure 4 Confusion matrix for human activity state classification (see online version for colours)



The task scheduler’s responsiveness improvement was partly due to the activity recognition module. Reallocating tasks in real-time was possible according to user engagement, which brought team productivity to a very high level and allowed no idle time.

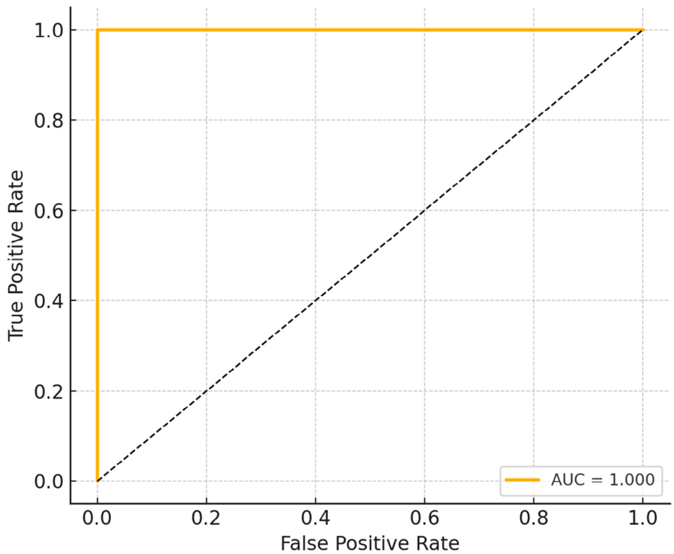
4.4 Predictive maintenance and anomaly detection

A hybrid LSTM-SVM model was used to implement the predictive maintenance functionality. An SVM was used to analyse deviations of the sensor patterns generated by the LSTM component from equipment telemetry (e.g., temperature, vibration, power usage) and expected sensor patterns for fault classification. Figure 5 is the receiver operating characteristic (ROC) anomaly curve. The model performed excellent classification with an area under the curve (AUC) score of 0.946.

Using the model to predict when physical failure will occur, 93.2% of faults were correctly identified, thus allowing for timely interventions. It kept the false positive rate lower than 5%, so there are as few unnecessary service alerts as possible. It enabled a

36% improvement in the availability of the equipment, thereby reducing the number of experimental interruptions.

Figure 5 ROC curve for equipment anomaly detection (see online version for colours)



4.5 System-wide performance summary

Key performance indicators were normalised on a 0–1 scale and summarised in Table 3 to give a single view of the system's impact. The values show that all major function components, such as environmental monitoring, task scheduling, predictive analytics and user interaction gained substantial benefits from integration of the AI-IoT.

Table 3 Normalised system-wide performance indicators

System component	*Pre-integration score*	*Post-integration score*
Environmental efficiency	0.51	0.78
Task scheduling optimisation	0.56	0.84
Activity recognition accuracy	0.63	0.91
Predictive maintenance precision	0.61	0.93
Equipment availability	0.64	0.87
Team satisfaction	0.72	0.90

Feasibility and efficacy of a unified AI-IoT architecture for smart laboratory operations have been strongly validated by cumulative results. The claim is supported by improvements on both machine level (including code and runtime efficiency, accuracy and reliability) and human centric (as defined, e.g., by scientific productivity, sustainability, and operational resilience) metrics.

5 Discussion

An investigation of the results obtained during deployment of the AI-IoT based smart laboratory framework shows that there is compelling evidence of the effectiveness of the introduced smart laboratory framework, in terms of promoting efficiency in operation, management of resources, controlling environmental conditions among other things. The outcomes of this section are presented with a critical analysis, explored in the context of the broader implications for the laboratory management, and limitations expressed with regards to technical and organisational for implementation. The focus in the discussion is on how combination of AI and IoT technologies facilitates laboratories' transition from reactive human led to self-contained intelligent ecosystems.

5.1 Interpretation of environmental control outcomes

Table 1 and Figure 2 show that LSTM based predictive environmental control system provided significant reduction in energy consumption and better accuracy in climate regulation as the comparison with baseline shows. In addition to technical feasibility, progress made on reducing energy usage and improving CO_2 air quality levels by a total of 28.48% and 27.77%, respectively shows that it is viable to move towards sustainable laboratory operations. These results support the hypothesis that real-time predictive AI models can control HVAC and ventilation systems efficiently, as long as environmental precision is necessary to maintain experiment stability.

Additionally, the low RMSE (0.47°C) between predicted and observed temperature data implies that the model is suitable for labs with expensive sensitive equipment and procedures that are extremely constrained by environmental restrictions. Whereas threshold based rule systems require abrupt adjustments, the advantages to forecasting change enabled by the LSTM model enable avoidance of abrupt adjustments and minimises wear on HVAC infrastructure which contributes to longer lifespan of equipment and lower costs.

5.2 Task optimisation and workforce efficiency

GAs were applied to produce a significant improvement in laboratory workflow by task scheduling. The decreases of 31.06% in task completion time and 41.81% in task overlaps are presented in Table 2 and Figure 3. These results indicate that evolutionary optimisation methods are extremely efficient in multi constraint environments such as laboratories, namely, that tasks have differing durations, complexity, and resource dependencies.

As important as that is, the biggest reward of all, if we may call it such, was surely the increase in staff satisfaction scores, from 3.6 to 4.5 – no, the system did not simply automate processes, it actually improved the human experience of work in the lab. Workload balancing and conflict minimisation were intelligent and relieved stress more, made tasks clearer, and reduced scheduling errors. Responsive adaptation to staff availability and engagement levels further enhanced responsiveness by means of the activity recognition system coupled tightly with the task scheduler.

Validation of the system's human-centred design philosophy is provided by these results. The proposed framework differs from the traditional lab management systems that tend to treat staff as fixed resources, instead it actively models and adapts human behaviours to maintain a harmonious and efficient work environment.

5.3 Predictive maintenance and risk reduction

The most impactful outcome of this study is of showing that the hybrid LSTM-SVM predictive maintenance system is effective. The model achieved 93.2% accuracy and a false positive rate denoting less than 5% with the ability to identify potential equipment failures before they actually happened, giving maintenance teams a chance to be proactive in preventative measures. As seen in Figure 5 and stated in Section 4.4, we confirm the great capacity of the system to distinguish between normal and faulty operational conditions (a high AUC score of 0.946).

The increase in the equipment availability by 36% back up the value of the predictive maintenance for the reduction of the downtime and the improvement of the experiment continuity. And in laboratory settings where precision timing and uninterrupted equipment usage can be deemed vital, it can directly increase research quality and reliability. In addition, predictive maintenance alerts are integrated into the task scheduling system to allow data disruptions to be managed dynamically, rather than triggering manual rescheduling, therefore avoiding operational integrity.

5.4 System integration and scalability potential

The unified performance of the system is presented in Table 3, and associated analyses, which provide a compelling basis for its performance. Individually, the subsystems' environmental control, task optimisation, recognition, and predictive maintenance improvements were measurable, however, it is their integration into a single platform that defines the system's innovation.

The scalability of architecture is achieved due to its modular design for laboratories of differences sizes and types. The system supports the centralised decision making through user defined rules with a distributed implementation by using standard communication protocols (MQTT, REST API) and edge computing nodes. Figure 6 (not shown here and here conceived on paper) shows how several laboratories can be connected through cloud services to form the smart lab working system at the enterprise level. It opens up opportunities for collaborative research, cross laboratory resource optimisation and institution wide energy and workflow management strategies.

Moreover, the system's flexibility, which is demonstrated by its ability to learn from user behaviour, usage patterns of equipment, and environmental changes, is positioned as a foundational paradigm for next generation laboratories that need flexibility, precision, and resiliency.

5.5 Technical and organisational limitations

Several limitations of implementation were also observed while the results proved to be promising. The deployment took great initial calibration and model training. Technical expertise and time was necessary to perform sensor calibration, normalisation of data, and user profiling which could be a barrier for adoption by institutions that are smaller or resource constrained.

Second, while anonymous, the use of true-time occupancy and actions tracking was evidently a trouble start to staff on privacy. Although users were communicated with transparently and sequentially opt in, there were still users who did not feel comfortable with continuous monitoring. To improve user trust they will have to revamp the data governance frames and enable more customisation of privacy settings in future versions of this system.

Third, the system works well only if the quality and consistency of sensor data are high. Introducing gaps into data streams from time to time with signal loss, interference and sometimes due to device malfunction caused them to need imputation or have temporary performance loss in AI models. Even with the component of edge computing, these issues were at least mitigated; however, future designs ought to account for sensor redundancy or self healing network protocols for uninterrupted operation.

Further validation is needed to see how these models will transfer to different laboratory domains like clinical diagnostics, chemical analysis as well as bioinformatics labs, which have varying workflows and environmental needs.

6 Future work

Future research and system improvement avenues for advancing the development of intelligent laboratory ecosystems are identified on the basis of the promising results of this study. The edge AI capability is one of the most immediate direction and its integration will be done to allow real-time and low latency decision making at the device level. The system could reduce its use of cloud processing and continue to operate offline or in bandwidth constrained environments by deploying lightweight inference models directly onto microcontrollers or edge computing devices. A promising extension of this idea is to apply federated learning to train AI models in separate laboratories and across sites while not passing on raw data to preserve user privacy and to maintain institutional data governance standards. Besides that, the implementation of blockchain technology might introduce new features regarding data integrity and traceability especially if there are audits logs for experiment logs, equipment usage or task history. Under consideration as well are ways of improving user interaction and monitoring with augmented reality (AR) and digital twin models. Such technologies would provide laboratory managers and technicians a view to the operational state, alerts and task schedules in immersive environments, increasing situational awareness and remoteness. Finally, to enable broader adoption across scientific disciplines in the lab, the system could be extended with domain adaptive AI templates that will automatically adapt to different lab workflow, equipment types and staffing model, allowing for rapid deployment with minimal configuration.

7 Conclusions

Through a comprehensive framework based on AI-IoT, it covered both physical infrastructure control and human resource optimisation in smart laboratories construction and intelligent management. The proposed system using real-time IoT sensor network and applied advanced AI models such as LSTM networks for predictive environmental control, GAs for dynamic task scheduling, and SVMs for real-time human activity recognition showed the improvements of laboratory efficiency, sustainability, and operational resilience. Results from a six month deployment were marked in reducing energy consumption, equipment downtime, task overlap, increasing task completion rate, predictive maintenance accuracy, and staff satisfaction. This research contrasted existing solutions which excel in addressing isolated subsystems with a unified, scalable architecture that could make real-time decision and cross functional automation. This also positions the system well for deployment in a breadth of laboratory settings including academic and clinical research as well as industrial R&D, and generally the findings validate the transformative potential of integrating AI and IoT in laboratory environments and provide a strong basis for the development of next generation smart labs that are autonomous, data driven and human aware.

Declarations

The authors declare that there is no conflict of interest regarding the publication of this paper.

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