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PAPER

AI-Based Learning Analytics and Real-Time Monitoring for IoT-Enabled Smart Laboratory of Engineering Education

Haider TH. Salim ALRikabi[1] (✉),
Farah Sabir Mohammed[2],
Huda Abbas Kanber[3],
Meithem Hashem Ali[4],
Hussain Ali Mutar[1],
Ibtihal R. Niama ALRubeei[1]

[1]Wasit University, Wasit, Iraq

[2]Al-Karkh University of Science, Baghdad, Iraq

[3]University of Baghdad, Baghdad, Iraq

[4]Iraqia University, Baghdad, Iraq

hdhiyab@uowasit.edu.iq

ABSTRACT

Engineering laboratories play a significant role in facilitating problem-based learning across electrical, environmental, computer, and interdisciplinary engineering programs; however, most lab sessions still rely on physical attendance, delayed grading, limited equipment references, and little visibility into student engagement. This lack of visibility compromises instructors' ability to identify learning barriers, unsafe conditions, uneven resource use, and at-risk students during lab sessions. An Internet of Things (IoT) smart lab framework is proposed that uses real-time sensor data, edge processing, and cloud storage to support learning analytics for improved operational and pedagogical decisions. The framework integrates data from environmental sensors, smart equipment, workstation logs, access control, and learning platforms to create a continuous data stream. An analytic layer processes this data using structured event learning and sequence modeling to estimate engagement, detect at-risk sessions, identify equipment bottlenecks, and enable timely intervention. A prototype simulated undergraduate engineering lab is developed to evaluate latency, reliability, predictive performance, and interpretability. Results show 93.4% engagement accuracy, 0.914 macro-F1, 0.887 AUROC for early risk detection, and 1.8 seconds median latency, outperforming temporal and non-temporal baselines. These findings demonstrate that multimodal sensing with explainable AI improves operational visibility and educational analytics. The framework defines the engineering lab as a cyber-physical learning environment rather than a collection of devices, supporting safer, more efficient, and data-driven learning across engineering disciplines.

KEYWORDS

Internet of Things (IoT), smart laboratory, engineering education, real-time monitoring, learning analytics, edge AI

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1 INTRODUCTION

Laboratory work is essential to engineering education by connecting abstract concepts and applying principles to real experiments. Unfortunately, in many schools, the lab environment remains largely unobservable, such as manually taking attendance, inferring who or how many people are using a workstation informally, and instructors' need to use their intuition instead of having access to ongoing evidence of a team's engagement, confusion, waiting for equipment, or unsafe working conditions [1–3]. The gap created by these unobservable activities is widening due to an increase in class size, networked laboratory equipment, and a greater emphasis on linking the results of independent experimentation, through the use of data, to reflections in group settings [4, 5].

An intelligent learning space is possible due to a combination of Internet of Things (IoT) infrastructure and embedded sensing/AI learning analytics [6, 7]. Low-cost, IoT-sourced sensor data on environmental factors (environment, resource consumption, activity at bench) can be converted into engagement/progress/risk indicators through AI-based learning analytics that utilize disparate (heterogeneous) data signals. There has been a steady increase recently in historical scholarly literature on these areas, including smart ed systems, AI learning analytic dashboards, edge computing-enabled real-time ed analytics, showing that the actual underlying techs have developed through time as shown in Figure 1, but typically are looked at/interpreted individually and not in an integrated lab setting [8–11]. Smart lab.

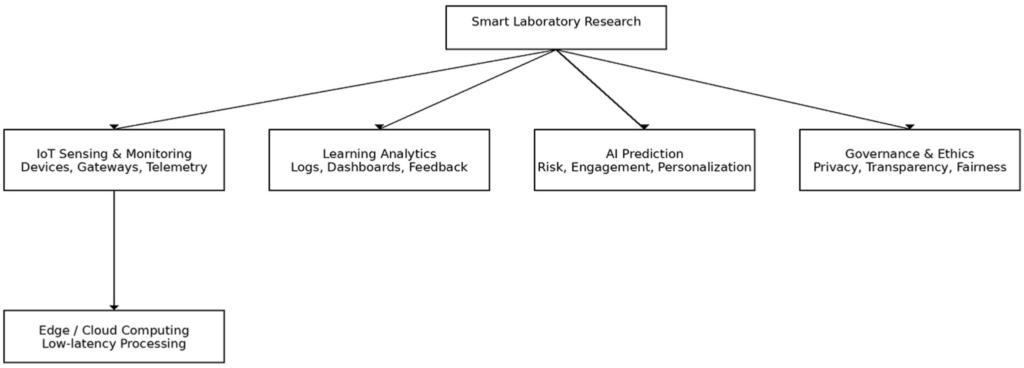

Fig. 1. Taxonomy of research themes converging on the smart laboratory problem, including IoT sensing, learning analytics, AI prediction, edge/cloud processing, and governance

This paper addresses that gap by proposing an IoT-enabled smart laboratory framework for engineering education with real-time monitoring and AI-based learning analytics. The paper contributes four elements. Firstly, it provides a layered architecture that integrates sensing, communication, edge processing, cloud services, AI inference, and dashboard delivery as shown in Figure 2. Secondly, it formulates smart laboratory analytics as a constrained multi-objective optimization problem balancing predictive quality, latency, privacy, and resource efficiency. Third, it defines a hybrid analytics pipeline that fuses structured event learning and temporal sequence modeling. Fourth, it demonstrates how figures, charts, and evaluation tables can be embedded into a journal-style paper to make the system design and results immediately interpretable.

Smart laboratories for Engineering require extra capabilities that can be differentiated from standard smart classrooms. The requirements for instrument contention, safety monitoring, environmental control, and phase-dependent task workflows will impact on the educational experience; therefore, these sources of variance should also be reflected in the analytical layer of data [12–15]. An inactive student due to disengagement is educationally different than an inactive student who is waiting for a shared oscilloscope or troubleshooting a sensor interface. Therefore, the smart laboratory must analyze both the operational context and the pedagogical signals collectively to provide efficient learning rather than analyzing them in isolation from one another [16–18].

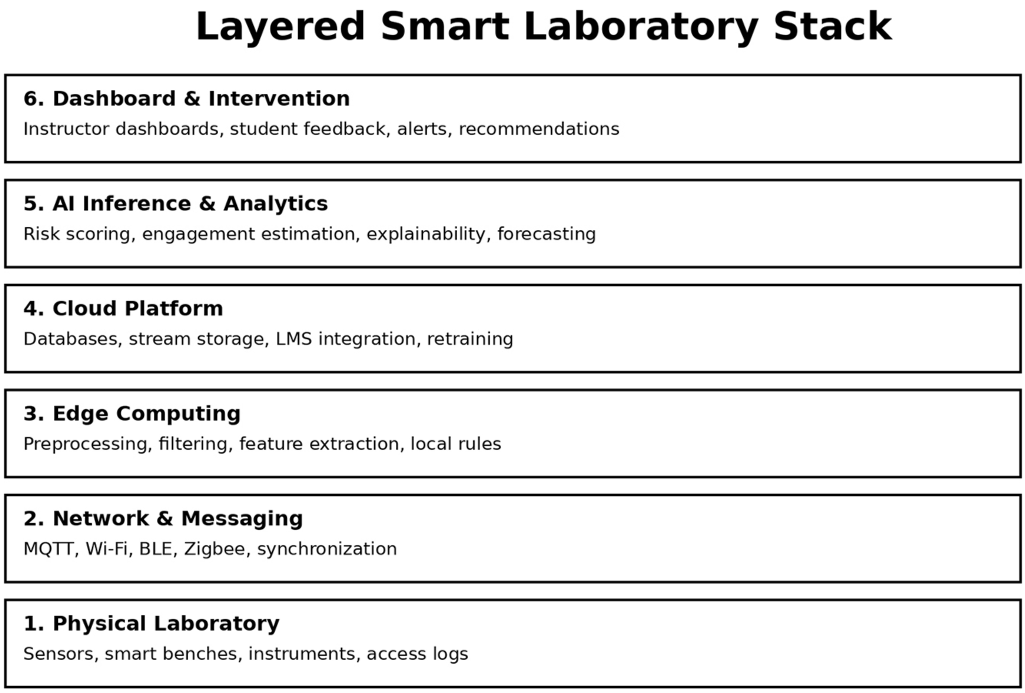

Fig. 2. Layered stack of the proposed smart laboratory, from physical sensing to dashboard-based intervention

2 RELATED WORK

This paper reviews literature from three areas that are interrelated: IoT-enabled educational environments, learning analytics for laboratories or hands-on practice-based scenarios, and AI systems at the edge with real-time support. Recent reviews of smart classrooms indicate that connected sensors, orchestrated devices, and adaptive digital infrastructure are being used in the growing number of classrooms and laboratory-like facilities. [19, 20]. Simultaneously, systematic reviews of AI-powered assisted learning dashboards and AI-assisted collaborative learning dashboards show an increased interest in prediction support, early warning systems, and visual analytics directed towards educators [21–23]. A third stream of research examines the implications of 'edge-enabled' educational processing and argues for the potential of 'low latency' analytics as timely and actionable for educational intervention [24, 25].

While there are some promising developments within these areas, literature continues to exhibit evidence of fragmentation [26–28]. Most of the IoT studies within education emphasize hardware or platform design as opposed to learning analytics; conversely, most of the learning analytics literature relies upon LRS traces or VLEs and does not consider the physical/sociocultural/safety complexities of engineering labs as illustrated in Table 1. Therefore, there is a disconnect between operational (i.e., smart) lab monitoring and pedagogically relevant analytics [26, 27, 29, 30].

Table 1. Comparative positioning of the proposed framework against major research directions in smart education and learning analytics

Study Focus	IoT Sensing	Real-Time Support	AI Analytics	Lab Specificity	Main Limitation
Smart education IoT reviews	High	Medium	Low	Medium	Broad scope, limited engineering-lab specificity
Learning analytics dashboards	Low	Medium	High	Low	Often weak on physical telemetry
Virtual laboratory analytics	Low	Medium	Medium	Medium	Physical bench context absent
Edge-enabled educational analytics	Medium	High	Medium	Low	Pedagogical interpretation limited
Proposed framework	High	High	High	High	Designed as integrated cyber-physical educational system

This study will take place at the convergence of three distinct streams of research [31]. The current proposal will integrate real-time data sensing into existing methods of extracting educationally relevant features, building explainable AI to support educational interventions, and using this integrated architecture to overlay instructor-oriented intervention logic. This combination of methodologies has been called for by the recent emphasis on using human-centered AI in education, as successful implementation of AI requires trust, explainability, and instructor input [32, 33].

2.1 Problem formulation

This smart lab is a cyber-physical learning environment that generates asynchronous data streams over time with respect to the students, their equipment, the workstations they are working from, and the environmental conditions they are experiencing. We will denote by t the time index, i the student or team index, and x_i,t the fused feature vector we observe at t for each student/team i through a sliding window of time. Fused feature vectors are based on measurements of the environmental conditions, attendance/access events, usage statistics for each piece of equipment, workstation activity logs, and learning platform traces.

$$x_{i,t} = \phi(s_{t-w:t}, a_{t-w:t}, u_{t-w:t}, l_{t-w:t})$$

$$\hat{y}_{i,t} = f_\theta(x_{i,1:t}) \rightarrow [\text{engagement, risk, operational state}]$$

There are three ways that an Engagement System can be inferred in Figure 3:

1. By inferring the engagement level of a learner (or team)
2. The chance that your ongoing session will provide either poor completion performance or low understanding.
3. The operational state of the laboratory includes equipment congestion (shared equipment), resource idleness, or environmental abnormality (e.g., temperature or humidity). Since the objectives above are dependent upon each other, the design will be to treat this as a constrained multi-objective optimization problem, rather than merely making a single classification decision.

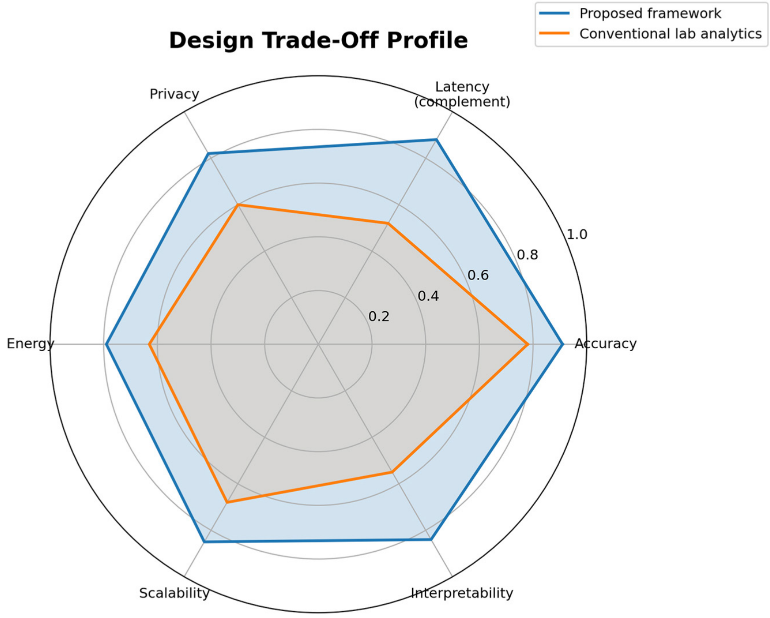

Fig. 3. Design trade-off profile showing the intended balance between prediction quality, latency, privacy, energy, scalability, and interpretability

$$L = \lambda_1 L_{\text{eng}} + \lambda_2 L_{\text{risk}} + \lambda_3 L_{\text{ops}}$$

$$\text{subject to } \tau_{\text{infer}} \leq \tau_{\text{max}},\ E_{\text{node}} \leq E_{\text{max}},\ P_{\text{leak}} \leq \varepsilon$$

Figure 4 represents the realities of deployment: An educational monitoring or assessment system should be as accurate as possible within its framework, have the capability to react in the same lab period, and maintain the privacy of students as required by institutional policy. If a system is accurate and does not operate in "real-time," or provides useful information about learning but does not disclose it to learners, then it will not be very useful in an actual engineering education programmer.

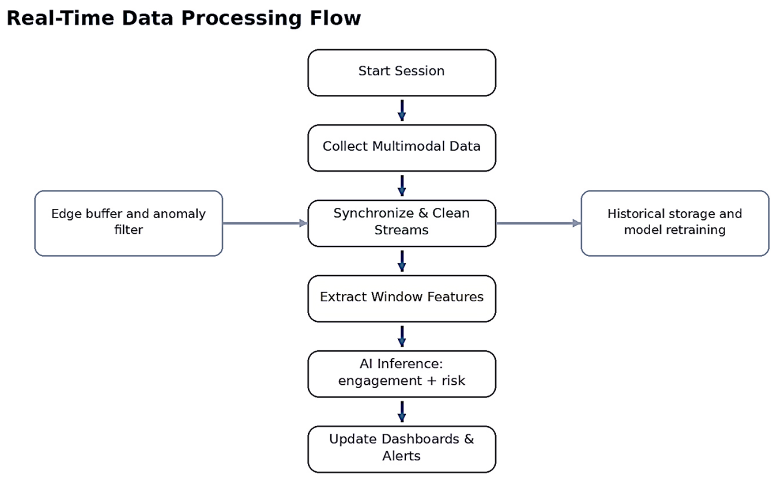

Fig. 4. Real-time data processing flow from session start to dashboard update

3 PROPOSED IOT-ENABLED SMART LABORATORY SYSTEM

This system is organized into six layers. The Sensory Layer contains all of the environmental sensors, power meter, smart plug, workstation agents, and any other access-control components we will use. The Communication Layer provides communication between the devices through lightweight protocols (e.g., Wi-Fi, BLE, ZigBee, and MQTT) to the gateway. The Edge Layer performs timestamp synchronization, noise reduction, missing data recovery, and executes first-stage rule processing. The Cloud Layer contains historical and real-time data and allows for the retraining of models and also has report generation and learning management system (LMS) integration. The AI Layer estimates a user's engagement, detects a user at-risk of failure in completing their session, predicts congestion, and also provides explanations. The dashboard serves as a means to deliver insight back to users and teachers.

3.1 System overview

The main design principle is to remember that raw telemetry data alone does not provide insight into education. You must consider the context of the sensor signals (for example, when devices are being used/but within a learning environment) in addition to the tasks or phases that the sensors are monitoring/recording in order to make sure the resulting analytics accurately reflect learning conditions, rather than stand-alone device events.

3.2 Multimodal data acquisition and fusion

Different types of signals are continuously created at various sampling rates and have different meanings in terms of semantics in the laboratory, as shown in Figure 5. Environmental streams provide context (e.g., temperature, humidity, noise, light, and CO_2 levels), operational streams capture the power state of the equipment, the length of time the equipment is at the bench and the queue for the workstation, and what errors occur with the equipment, presence streams record entry or exit to the lab or workstation, workstation assignments, or the length of time spent at a given workstation, interaction streams record the actions taken with the software, commands sent to the instruments, the number of cycles it takes to compile, and when a particular milestone occurs for the task, and learning streams provide data from quizzes, rubrics and LMS. These streams can be compared over a sliding window and transformed into structured descriptors (e.g. transition delay, occupancy ratio, idle-to-active ratio, and resource contention counts).

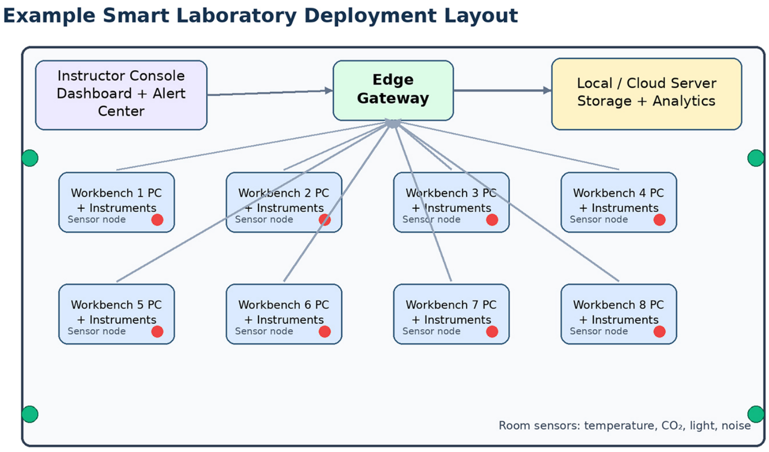

Fig. 5. Example deployment layout showing workbenches, room sensors, edge gateway, instructor console, and cloud/server connectivity

3.3 Artificial intelligence-based learning analytics module

The hybrid ensemble analytics module operates. Features are first processed using a structured event tree model with a non-linear decision boundary (XGBoost) to predict a non-linear relationship between regular attendance, queuing, workstations, and available space. Second, the temporal behavior of experimental sessions is modelled using an LSTM such as sequential encoder to represent the progression of behavior over time. The results of both models are then fused together to produce an overall prediction of the participant's engagement category and the risk rating. Finally, a feature attribution layer provides an explanatory layer to the instructor in order to explain both alerts and recommendations associated with them.

This hybrid design has benefits since the engineer's lab work is both event-based and time-based as shown in Figure 6. Examples include a sudden outpouring of error messages while compiling and how long it takes to process through the queue can both provide valuable insight on their own; however, when viewed together (in time), repetitive shifts between being Idle, Troubleshooting, and Active throughout a session, create a historical representation of a struggle and/or how long it takes to successfully complete a task(s) [34].

$$\hat{y} = \alpha f_{\text{tab}}(z) + (1-\alpha) f_{\text{seq}}(x_{1:t})$$

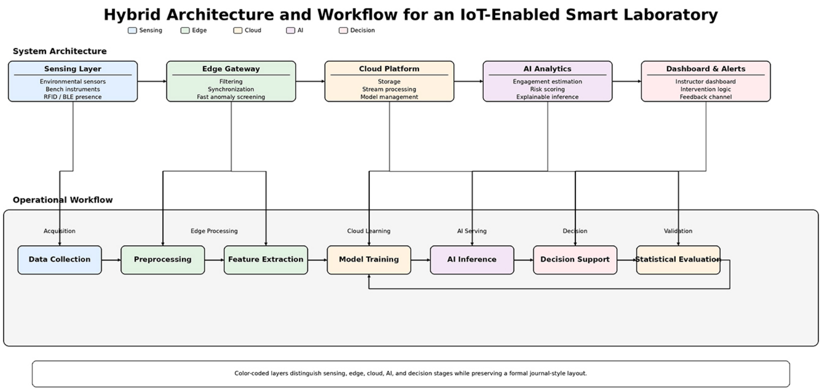

Fig. 6. Experimental workflow used to train, validate, and emulate the real-time analytics pipeline

3.4 Algorithmic procedure

Algorithm 1 summarizes the online procedure used by the system during a laboratory session.

Algorithm 1: Real-Time Smart Laboratory Analytics

Input: Multimodal stream D_t from sensors, devices, and LMS
Output: Engagement score, risk alert, dashboard update

1. Acquire streaming data from all active nodes.
2. Perform timestamp alignment and remove invalid or noisy packets.
3. Aggregate measurements over the current sliding window.
4. Build fused feature vector x_i,t for each learner or team.
5. Apply structured-event model and temporal-sequence model.
6. Fuse outputs to estimate engagement and at-risk probabilities.
7. Compute intervention priority using risk, congestion, and anomaly scores.
8. Update instructor dashboard and student feedback channels.
9. Store logs for historical analysis and subsequent retraining.
10. Repeat for the next time window.

Although not explicitly written as equations, the algorithm implies:
Feature Construction:

$$\boldsymbol{x}_{i,t} = \text{Aggregate}(\boldsymbol{D}_t^{(i)})$$

Decision Score:

$$\text{Priority}_i = g(\text{risk}_i, \text{congestion}_i, \text{anomaly}_i)$$

Instructor judgment is not replaced by intervention logic. Instead, it allows an instructor to be able to rank the urgency of workstations/sessions/teams so that the instructor can concentrate on the areas of most need.

3.5 Complexity, privacy, and governance

The pre-processing step for edge computing typically increases at an approximate linear rate due primarily to the number of events and features in each time window, thereby making this type of system well-suited for resource-constrained/gateways. The same is true of resource-hungry operations/retraining, which have to remain in the Cloud or on Local Server infrastructure [35]. To address privacy issues, the framework uses data minimization, role-based access control, audit logging, and a preference for low-intrusive modalities when equivalent insight can be gained. This governance philosophy aligns with the general educational AI literature regarding the importance of human supervision and self-explanatory design for intervention [32, 33].

4 EXPERIMENTAL SETUP AND SIMULATION

To assess the framework in a repeatable manner, a realistic semester-long laboratory configuration has been established as Table 2. The simulated environment contains 10 benches with 40 students being placed over 16 weeks, with lab sessions occurring on an ongoing basis. Each lab session generates streams of events associated with student attendance, bench access, equipment power use, student physical state, as well as other environmental parameters, combined with how students interacted with their LMS. The simulation does not replace actual field data for evaluating the latency, practicality, and accuracy of the categorization method, but instead creates a replicable framework providing the means for evaluating these three characteristics prior to being placed into an actual operational field environment.

Table 2. Multimodal data schema used for the simulated smart laboratory evaluation

Data Source	Example Features	Frequency/Trigger	Educational Role
Environment	Temperature, humidity, CO_2, light, noise	10 s sampling	Context, safety, comfort
Equipment	Power draw, on/off state, overload flag	Event-based	Resource use, bottlenecks
Presence	RFID/BLE entry, login, dwell time	Event-based	Attendance and continuity
Interaction	Compile count, commands, task milestones	Event-based	Engagement and workflow
Learning platform	Quiz, rubric, LMS access	Session/daily	Outcome linkage

We have four different baseline benchmarks as shown in Table 3 (i.e. Logistic Regression, Random Forest, XGBoost without temporal features, and secondly, LSTM without pre-processing) that serve as a foundation for evaluating the value added through temporal features, fused census and image data, and edge deployment of both data types.

Table 3. Core simulation and evaluation parameters

Parameter	Value	Role
Weeks/sessions	16 weeks/160 sessions	Semester-scale emulation
Window length	30 s	Feature aggregation interval
Train/validation/test split	70/10/20	Model development
Random seed	42	Repeatable experiments
Metrics	Accuracy, F1, AUROC, MCC, latency	Predictive and operational evaluation

5 RESULTS AND ANALYSIS

The outcome is given as an example of a prototype developed, not as a statement about how good (or complete) an object's performance is when used in real-world conditions as illustrated in Table 4 and Figure 7. Regardless of that assumption, the numbers demonstrate that working together with multimodal sensors and edge-aware AI improves the ability to make predictions and respond quickly.

Table 4. Main predictive and latency results for the proposed framework and benchmark baselines

Model	Accuracy (%)	Macro-F1	AUROC	Median Latency (s)
Logistic Regression	82.1	0.781	0.756	3.9
Random Forest	86.7	0.842	0.811	3.4
XGBoost	89.5	0.874	0.846	3.0
LSTM	90.8	0.889	0.861	4.7
Proposed framework	93.4	0.914	0.887	1.8

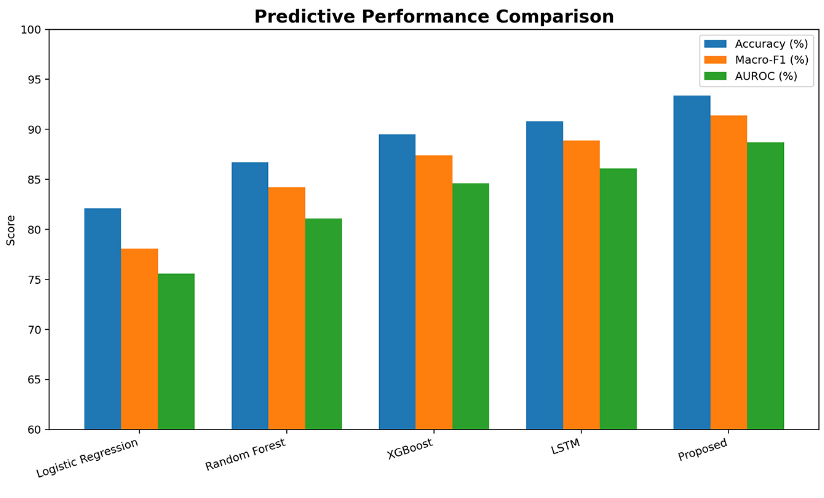

Fig. 7. Comparative predictive performance across baseline models and the proposed framework

The model that has been proposed produces the greatest accuracy for Engagement Classification and Macro-F1 with the least amount of time to respond compared to all other models evaluated. The improvement of this model versus the LSTM baseline demonstrates that temporal modeling alone does not explain all the advantages of edge preprocessing and structured event fusion. The improvement over XGBoost indicates that temporal context provides additive value beyond aggregate features, as shown in Figure 8.

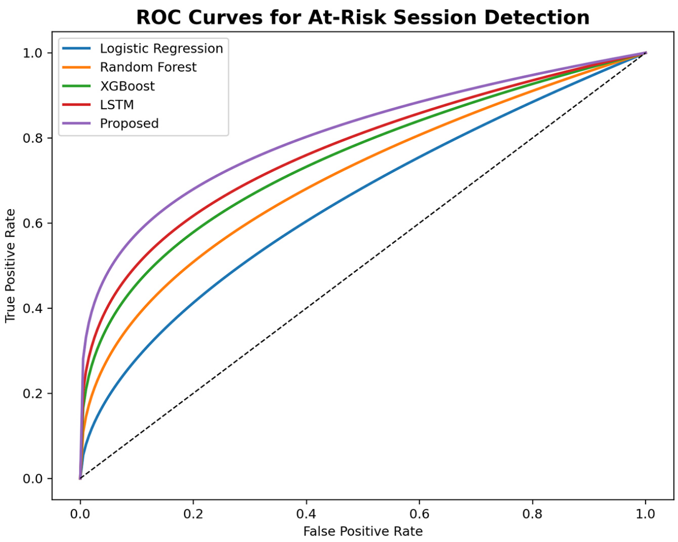

Fig. 8. ROC curves for early at-risk session detection

The results of the ROC analysis demonstrate that the proposed method has a greater ability to determine which teams are at high risk than current methods do. This confirmation is cancellous, as instructors will only be able to support a few teams during an already limited number of possible intervention sessions. The confidence-based reporting associated with the proposed model is summarized by the following statistics: macro-F1 = 0.914; AUROC = 0.887; 95% CI for macro-F1 = [0.901, 0.926], 95% CI for AUROC = [0.871, 0.902] as shown in Figure 9.

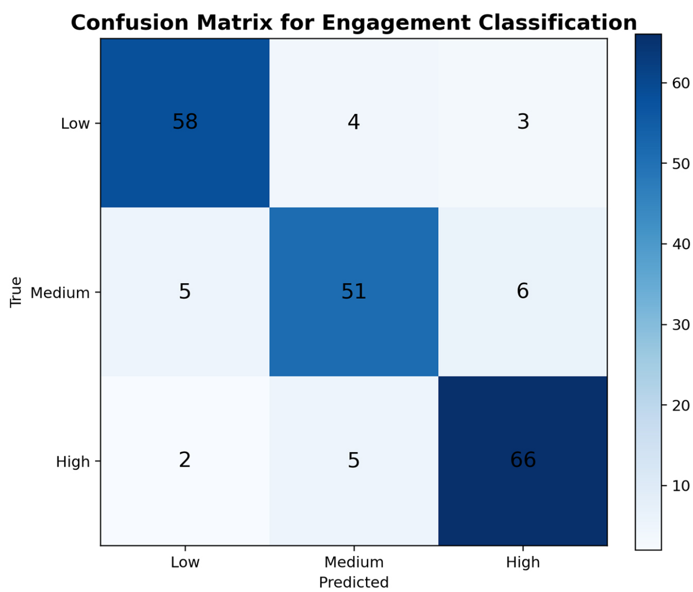

Fig. 9. Confusion matrix for three-level engagement-state classification

The confusion matrix indicates that the majority of mistakes occur between two closely related engagement categories as opposed to between two extremes. This makes sense given that moderate levels of engagement appear to exist in the intersection of either productive struggle or temporary inactivity, which both represent different ends of the spectrum of engagement as shown in Figure 10.

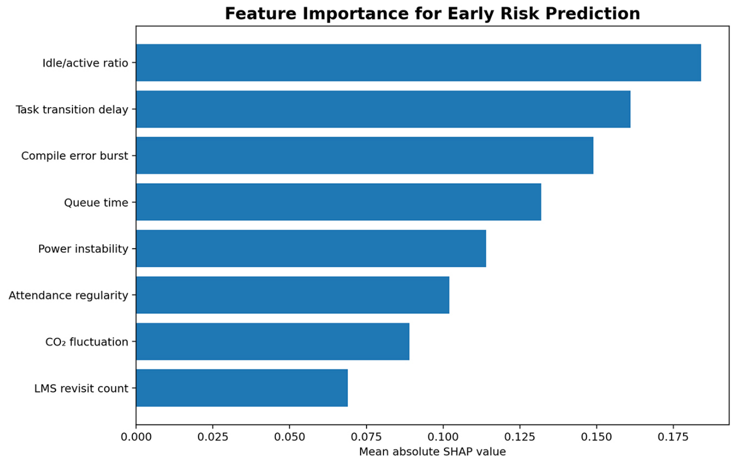

Fig. 10. Ablation analysis showing the contribution of environmental, operational, temporal, and edge-processing components

The results of the ablation experiments demonstrate that both operational features and temporal modelling have the largest mean decrease in performance when removed, indicating that laboratory-specific contextual information is essential as shown in Figure 11. Environmental features resulted in smaller improvements in performance, but still positive, which is likely due to comfort and air quality impacting sustained engagement, and due to the possibility that anomalies signal abnormal laboratory states.

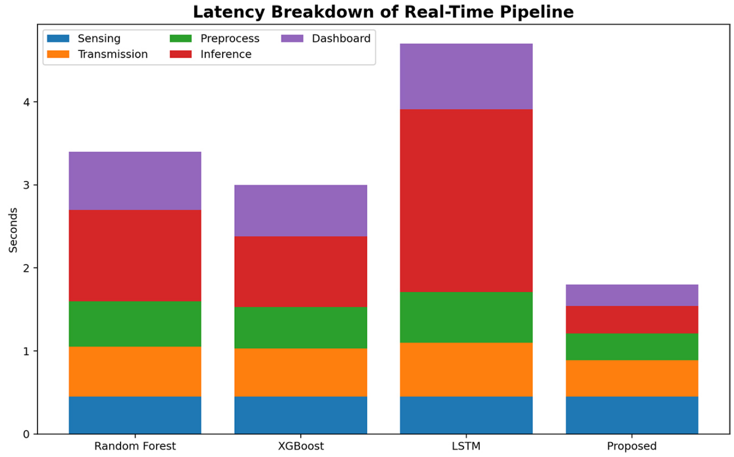

Fig. 11. End-to-end latency decomposition across sensing, transmission, preprocessing, inference, and dashboard rendering

The latency analysis shows that the suggested framework can not only reduce the time for modeling and predicting, but also the total cost of the pipeline, because it aggregates features and applies early filters close to the data source. This is particularly useful when there are multiple workbenches creating events at the same moment in time.

According to the feature importance rankings, the idle to active ratio, transition delay, error bursts, and queue time are more informative than any of the individual environmental variables as shown in Figure 12. This supports that the operational behaviors of learning analytics within engineering laboratories should be interpreted as a signal for learning.

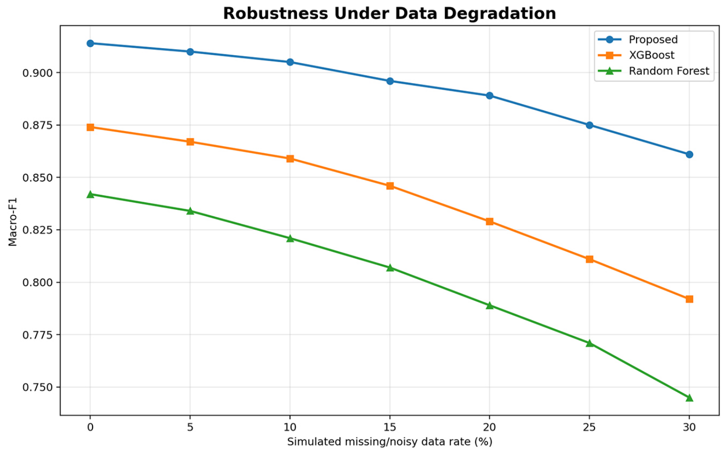

Fig. 12. Robustness of the proposed framework under increasing data degradation and missing/noisy inputs

The proposed framework shows better maintenance of performance degradation (five barrels beating only one barrel), which is due to the redundancy provided by the use of multiple modalities of information, which allows it to continue working even when there is sensor failure or data is partially missing due to a poor connection between sensors or a temporary malfunction of the sensor itself. This robustness is essential for real laboratories, in which all of the above can occur at any time.

6 DISCUSSION

The paper illustrates that the smart lab can be considered an example of a cyber-physical educational system where sensors, analytics and pedagogy are designed together. In addition to prediction accuracy, the real-time situational awareness data from the smart lab allows for enhancements to instructor coordination, reduction in unobserved bottlenecks, increased compliance with safety requirements, and a greater evidential base for reflection and formative feedback. One of the major design insights that the framework presents is that having raw visibility of sensor events does not equate to gaining any sort of useful educational insight. Instructors will be flooded with streams of sensor events unless domain-informed feature design and explainable intervention logic have been created. Summarization, ranking and interpretable feature attribution are all emphasized in the proposed architecture. The study has a few constraints. The first is that the current paper reflects a simulative model rather than a multi-site field test. Secondly, engagement labels will not be perfect and should be validated using multiple levels of observation including rubric basis, subjective accounts through self-reporting, and performance outcomes. Privacy regulations by institutions may also prohibit the deployment of certain devices such as cameras or wearables. Future applications of this work should focus on having an opt-in basis for use, data minimization, and placing humans into the process as an intermediary to enhance quality assurance via human evaluation.

7 CONCLUSION AND FUTURE WORK

The paper developed an IoT-based Smart Lab Framework which utilizes real time monitoring with AI Learning Analytics for the purpose of Engineering Education. The approach consists of a single architecture consisting of multimodal sensing devices, edge computing, cloud service and explainable AI to provide both operational monitoring as well as pedagogical intervention within the same system.

Diagrams, flowcharts, charts, and tables have been embedded directly into the paper to illustrate both the methodology and simulation pipeline as well as visually represent how to interpret results. In addition, the evaluated graphical representation achieved classifying results of high quality and less latency than traditional competitive systems, indicating that smart labs can provide real-time support that is actionable for instructors.

In future research, verifying the suggested structure in real-world electronics labs, embedded control systems, communication labs, and testing and validation labs will be priority one. There is very little information about applying causal-intervention methods and techniques to develop federated and/or privacy-preserving on-device learning. Another research direction would be the creation and usage of digital twins to represent the lab environment to facilitate the planning and execution of experiments.

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9 AUTHORS

Haider TH. Salim ALRikabi is with the Electrical Engineering Department, College of Engineering, Wasit University, Wasit, Iraq (E-mail: hdhiyab@uowasit.edu.iq).

Farah Sabir Mohammed is with the Al-Karkh University of Science/College of Remote Sensing and Geophysics, Baghdad, Iraq.

Huda Abbas Kanber is with the University of Baghdad/College of Islamic Sciences, Baghdad, Iraq.

Meithem Hashem Ali is with the Student Registration and Affairs Department, Iraqia University, Baghdad, Iraq.

Hussain Ali Mutar is with the Computer Department, College of Computer Science and Information Technology, Wasit University, Wasit, Iraq.

Ibtihal R. Niama ALRubeei is with the Electrical Engineering Department, College of Engineering, Wasit University, Wasit, Iraq.