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AN INTEGRATED SENSOR DATA AND MACHINE LEARNING SYSTEM FOR WORK PROGRESS MONITORING IN INDUSTRIALIZED CONSTRUCTION

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Abstract

Industrialized Construction (IC) is an approach to address ongoing challenges in the construction industry. Barriers affecting IC adoption include manufacturing inefficiencies caused by inaccurate production monitoring on shop floors. This paper presents the integrated use of machine learning and sensor data collected from IMUs and load cells installed on manufacturing platforms to monitor work progress. The research method includes the development of data collection, processing, and data analysis methods in a controlled laboratory, followed by validation on a real-world shop floor. Results present an accurate model robust against stochastic noise, achieving 77% F1-score monitoring through temporal windows and weighted deltas.

Introduction

The construction industry faces several challenges related to low productivity on-site (Kauppinen et al., 2024). The traditional approaches to monitoring production in on-site construction rely on error-prone and time-consuming manual operations, which lead to ineffective resource allocation, quality failures, high volumes of waste, rework, delays, and budget overruns (Hasan and Sacks, 2023).

Considering this context, Industrialized Construction (IC) has been pointed out as a viable alternative to address these gaps, adapting traditional construction methods through the integration of manufacturing-oriented design and optimization tools (Qi et al., 2021). IC involves performing activities and producing construction components in a controlled shop floor environment before assembling on-site (Melgar et al., 2025).

Despite its potential, current obstacles affecting IC performance include the difficulty in monitoring the production and identifying bottlenecks on the shop floor in a timely manner, thus requiring a change from manual methods (e.g., stopwatches, visual observation, or analysis of pre-recorded video footage) to automated methods (Rashid and Louis, 2020). Indeed, manual methods lack accuracy in representing actual working conditions (Chen et al., 2024). Besides, Barkokebas et al. (2023) argue that current strategies and decision-making processes in IC shop floors are largely based on workers' personal experience rather than on empirical and real-time data, which hinders process improvement. Moreover, Qi et al. (2021) argue that the adoption of emerging digital technologies can address current obstacles and thereby unlock the full potential of IC.

A step toward increasing productivity in IC is the implementation of automated work monitoring and tracking techniques, enabling managers to determine what and when work is being performed on the shop floor. Despite recent advances, existing techniques exhibit significant room for improvement. Authors such as Panahi et al. (2022), Chen et al. (2024), and Martinez et al. (2021) have applied computer vision (CV) in IC for progress monitoring and productivity measurement. However, this technique presents limitations due to general occlusions, illumination issues, and limited field of view (Alsakka et al., 2023). Although static cameras can provide an adequate viewing angle during the fabrication of linear or 2D components (i.e., wall and floor panels), it is challenging to follow the manufacturing of volumetric modules, considering that the components closer to the camera can occlude those positioned behind them (Rashid and Louis, 2020; Alsakka et al., 2023), resulting in a "black box" effect.

Other authors, such as Demiralp et al. (2012), Altaf et al. (2018), and Li et al. (2017), have proposed the use of tracking solutions based on radio frequency identification (RFID) and real-time location systems (RTLS). However, despite the capability of tracking the location of different elements, these techniques have limitations in interpreting the context and identifying the activities performed. In light of this, Rashid and Louis (2020) proposed a method based on machine learning (ML) that analyzes the sound of the shop floor environment to automatically identify activities, such as hammering and nailing. The main limitation is the difficulty in isolating and classifying only the sounds of interest in real-world conditions. Rashid and Louis (2020) also highlighted the advantages of inertial measurement unit (IMU) techniques, which can identify activities through parameters, such as motion and vibration. However, they argue that in previous applications, each sensor is attached individually to each element of interest, causing practical difficulties due to the multiple components and elevated costs.

Rashid and Louis (2021) proposed a framework for modular construction to automatically measure active and idle times at workstations using IMU vibration data and a deep learning network. However, the framework limitations include issues related to data resolution, sampling frequencies, ground-truth labeling, and the lack of clearly defined methodological steps.

Considering the gaps and limitations highlighted in the literature, this paper proposes a novel system combining ML models with data acquired from sensors to monitor manufacturing activities of volumetric modules on IC shop floors. Real time data is collected from IMUs and load cells installed beneath the monitored IC workstations to identify whether work is being actively performed at workstations and therefore determine work progress. This paper's contribution is bi-fold: (1) it proposes ML-based methods to monitor manufacturing IC activities in real-time, and (2) it demonstrates their application.

Research methods

This paper presents the development of a system in a laboratory setting, followed by its final testing and validation on a shop floor in a bathroom pod in the Los Lagos Region, Chile. By applying both experiments, this research aims to validate the following hypothesis: "*The integrated use of sensors, such as IMUs and load cells, coupled with ML models, enables activity classification and work progress monitoring for manufacturing operations of volumetric modules on IC shop floors*." Additionally, this research aims for the proposed system to achieve a technology readiness level (TRL) 5, in which the system is validated in a relevant environment (Kimmel et al., 2020).

As illustrated in Figure 1, the research steps and its workflow are divided into Laboratory and Shop Floor phases. Following its initial development in the Laboratory, the proposed method is then adapted and validated on the Shop Floor. The Laboratory phase follows a controlled experiment design as per the steps below:

- **Data acquisition:** Design of the experimental setup and data acquisition.
- **Data processing and algorithm development:** Conducting an exploratory data analysis (EDA) for ML model development and refinement.
- **Internal validation:** Checkpoint to assess performance within Laboratory experiments.

If the internal validation criteria are not met, the workflow loops back to the algorithm development stage for further refinement. Conversely, successful validation allows for further development of the proposed system. Following a quasi-experiment research design, the Shop Floor phase consists of the following stages:

- **System's adaptation:** Adapting the proposed system to shop floor conditions, including data acquisition procedures and the ML model.
- **External Validation:** Assessment of the proposed system in real-world operating conditions.

To verify the presented hypothesis, the proposed system relies on the monitored workstation being transformed into an instrumented platform (i.e., physical platform with sensors placed under it) so the manufacturing operations can be monitored as per Figure 2.

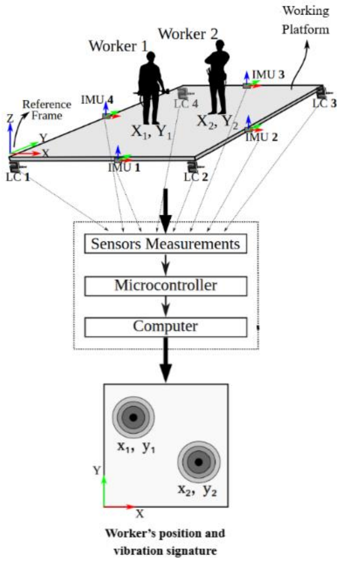

Figure 2: Graphical representation of the experimental setup.

The specific technical details of each environment are elaborated upon in the following subsections.

Laboratory experiment

A timber frame platform was built in the laboratory to replicate conditions in the shop floor and install sensors underneath it. The platform built measured $2{,}40 \times 2{,}40\ m$ and was designed to maintain structural stability during experiments.

The primary objective of this phase was to generate a high-fidelity dataset that captures the distinct kinematic and weight patterns of typical production activities as demonstrated in Figure 3a. This controlled environment allowed for the development and refinement of the machine learning pipeline, which was executed using the RapidMiner platform to evaluate model performance before industrial deployment.

Data acquisition

The data acquisition (DAQ) network comprised the following components:

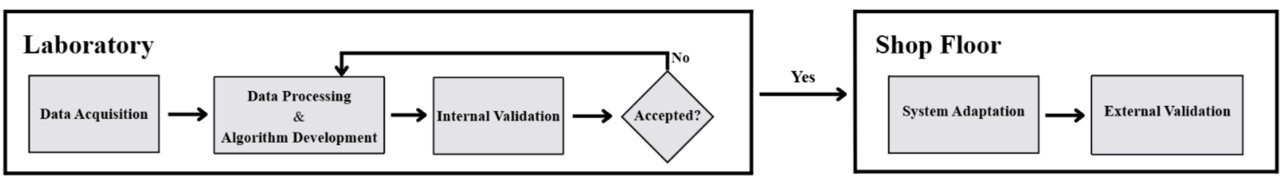

Figure 1: Research Methodology for the 2-Phase System Development and Testing.

- **Load cells:** Four industrial TRB load cells (15-ton capacity, 2.85 mV/V rated output) were installed under the platform at each corner. The weight signal (in kg) was acquired using HX711 ADC modules.
- **IMUs:** Four MPU-6050 3-axis IMUs were equidistantly mounted at the center of each lateral side of the base. The data was recorded in m/s^2.
- **Data management:** The hardware architecture was governed by an ESP32 microcontroller for each load cell and IMU pair, which facilitated data sampling at a constant Hz. Raw data transmission was executed via MQTT protocol and consolidated into temporal blocks for subsequent analysis, with each block being transmitted every second.

To replicate conditions typical of IC shop floors, several activities, such as "None", "Walking", "Hammering", and "Drilling" were executed in the laboratory. These were all recorded by the proposed system and video cameras. Furthermore, composite activities (i.e., two activities performed at the same time) were also performed and recorded. Recording manufacturing operations from both the proposed system and video cameras allows researchers to train and validate ML models to classify whether work is being performed or not under the platform, as demonstrated in Figure 3b.

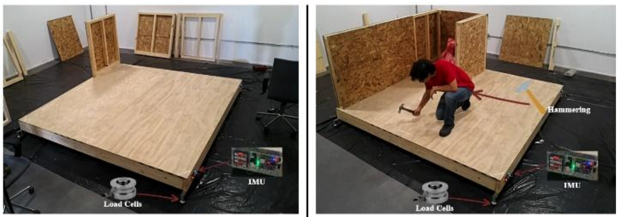

Figure 3A Figure 3B

Figure 3: Images of the laboratory's experimental setup.

Data from the proposed system was acquired via the load cells and IMUs, transmitted by the ESP32 controllers and subsequently concatenated using Python scripts. The final data structure was exported as a comma-separated values (CSV) file containing nine primary features: a timestamp, four independent weight readings (w_1, w_2, w_3, w_4), and four IMU sensor streams (s_1, s_2, s_3, s_4). Tri-axial IMU measurements within each stream were combined using a semicolon (;) as the delimiter. Recordings from the video cameras were also stored locally and later processed to train the ML classification models.

Data processing and Algorithm Development

The raw CSV dataset was processed through a Python pipeline to enhance feature compatibility for the ML model. In that spirit, each rotational velocity column was decomposed into its tri-axial components (*x, y, z*), generating a total of 12 inertial features. This decomposition provides a higher dimensional representation of the kinematic signatures inherent to each activity.

To handle temporal resolution, a temporal alignment procedure was implemented. Given the 10 Hz sampling rate, 10 discrete rows were generated for every second of data, ensuring each IMU measurement was mapped to its specific time slot.

Final synchronization of the temporally aligned data relied on a multi-modal verification process. The documented activities timestamps were validated against the video recordings to guarantee ground-truth accuracy. This processed dataset was then organized into a matrix comprising seventeen variables, including: four weight readings, twelve inertial axes, and the target label, as detailed in Table 1.

Table 1: Initial Dataset: first three observations

Obs.	**Weights** (kg)	**Acc.** (m/s^2)	**Target Variable**
1	$w_{1,(1:4)}$	$a_{1,(1:4)}$	1_{st} value
2	$w_{2,(1:4)}$	$a_{2,(1:4)}$	2_{nd} value
3	$w_{3,(1:4)}$	$a_{3,(1:4)}$	3_{rd} value

An exploratory data analysis was then conducted on it to evaluate data quality and distribution before modelling. The primary objectives of this phase included:

- Analyzing the class distribution and balance across the dataset.
- Implementation of noise reduction and data cleansing protocols.

Internal Validation

The target variable was defined as a multiclass Activity feature. In instances of concurrent activities, a hierarchical labeling priority was implemented ("Walking" > "Hammering" > "Drilling") to maintain a mutually exclusive, single-label-per-timestamp structure.

To evaluate the contribution of each sensor modality, the models were subjected to an ablation study involving three distinct configurations: (1) load cells and IMU data, (2) load cells data exclusively, and (3) IMU data exclusively. The macro-averaged F1-score performance metric for each configuration was recorded and compared to assess the relative predictive power of each sensor type.

This metric was selected to mitigate the risk of an "Accuracy Paradox", "Walking" and "None" activities were more present in the dataset than others. This allowed that the high frequency of "None" and "Walking" couldn't mask poor model performance on shorter, more high-intensity tasks like "Hammering" or "Drilling".

The development of this phase successfully places the system in a TRL 4. By validating the technical integration of the hardware components and the initial classification models, this phase demonstrates that the basic technological elements can function together as a cohesive system in a laboratory environment, establishing a solid proof-of-concept before subjecting the system to the complexities of a real-world IC shop floor environment.

Shop floor experiment

System's adaptation

The experiment was conducted at an active bathroom module production facility using a $2{,}40 \times 1{,}80\ m$ mobile industrial platform. The platform featured a wooden deck integrated into a steel frame and, while equipped with casters for transit between production stages, it was secured in a stationary position for the duration of all data acquisition sessions, which were also recorded for ground-truth synchronization.

The experimental protocol mirrored the laboratory phase, with the only difference being that the sampling frequency was increased from 10 Hz to 90 Hz.

However, the dataset itself was processed through three extra stages to transition from the raw data-driven approach used in the Internal Validation to a robust supervised learning architecture. This progression was designed to better interpret the more complex physical signatures within the high-noise environment of industrial production facilities.

External validation

To isolate the sensing system from environmental noise, the platform was elevated by the load cells themselves, effectively bypassing the casters. This "floating", configuration visible in Figure 4**,** ensured that all vertical loads and mechanical vibrations were transmitted exclusively through the load cells and the DAQ system, replicating the controlled environment of the IMA laboratory.

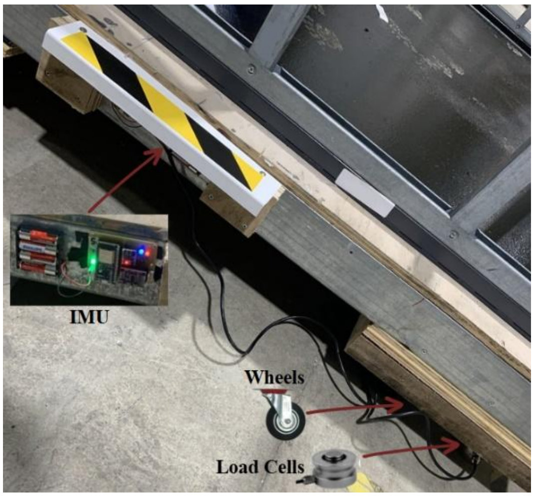

Figure 4: Shop Floor's experimental setup.

Operational activities (categorized as Working) were defined based on the assembly protocols established in the manufacturer's technical manuals, which were comprised of sub-activities like the "Walking", "Hammering", and "Drilling" activities tested in the laboratory. This label was assigned to any Value-Added (VA) construction task performed on the module structure, regardless of whether the operator was positioned on the platform or the factory floor.

Conversely, non-contributing activities were classified as Not Working. This category encompasses Non-Value-Added (NVA) tasks such as platform cleaning, the handling of secondary materials (e.g., relocating toolboxes), or worker random movement across the platform.

The development of this phase represents an advancement beyond laboratory experiments by exposing the system to the operational constraints inherent to an active IC shop floor. It marks the beginning of the transition towards TRL 5, allowing for verification of whether the ML model architecture and the system in general maintain their predictive capacity and robustness in a relevant environment.

Results and discussion

The performance of the proposed classification architecture was evaluated through a two-stage validation process. First, the laboratory dataset was used to develop and benchmark the algorithm performance and select a lead architecture. Second, the model was subjected to an external validation phase using the 90 Hz industrial shop floor dataset, where the impact of feature engineering and temporal windows was analyzed. This dual approach ensures that the final model is not only statistically accurate but also robust against stochastic noise, inherent to IC environments.

Laboratory experiment results

The Temporal Alignment procedure for the IMA dataset resulted in 28,120 observations, representing approximately 52 minutes of operational data. The class distribution was intentionally balanced across seven recorded activities to ensure the model could distinguish between similar kinematic signatures.

Five machine learning algorithms were implemented in RapidMiner to establish a performance baseline. As demonstrated in Table 3, the Random Forest (RF) ensemble emerged as the superior model with 86.77% accuracy. This performance is attributed to the RF's inherent bagging approach, which offered significant robustness against the inherent sensor noise and local outliers' data. Finally, the RF's built-in feature importance provided a layer of interpretability, allowing for an internal validation of which specific inertial signals were most indicative of the activities monitored.

Table 3: RapidMiner ML models average accuracy of the ablation study.

Model	Parameters	Accuracy
Random Forest	100 trees, max depth 15	86,77%
Gradient Boosted Tree	50 trees, max depth 7	83,81%
k-NN	k = 5	78,92%
SVM	RBF kernel	75,61%
Naive Bayes	10 Kernels	73,3%

Table 2: Random Forest's ablation study results

Activity	IMU and Load Cells		Load Cells Only		IMUs Only	
	Precision	Recall	Precision	Recall	Precision	Recall
Walking	89.56%	96.47%	97.95%	96.29%	71.34%	94.01%
Hammering	94.53%	72.49%	78.03%	98.24%	97.31%	50.70%
Drilling	91.06%	87.45%	91.38%	98.54%	91.32%	61.77%
None	91.89%	91.07%	97.23%	93.03%	86.47%	79.87%
F1-Score	88.91%		93.50%		76.13%	

Ablation Study

To further understand the contribution of each data source (IMU and load cells), an ablation study was conducted using the RF algorithm. The results, visible in Table 2, reveal a significant disparity between sensor modalities.

The Load Cells Only configuration achieved the highest overall performance with an F1-score of 93.50%. Specifically, the Recall for "Hammering" (98.24%) and "Drilling" (98.54%) indicate that the kinetic energy and vibration patterns transferred to the platform are highly distinct. This suggests that force-based sensing captures the "mechanical signature" of industrial tasks more reliably than human kinematics.

Conversely, the IMUs Only model yielded the lowest F1-score (76.13%), struggling particularly with "Hammering" (Recall 50.70%). This suggests that while inertial sensors capture the worker's gross motor movements, the high-frequency vibrations of manual tools are likely aliased or obscured at lower sampling rates. This implies that capturing such work signatures via kinematics would require a higher sampling frequency (Hz) to move beyond the noise floor.

Shop Floor Experiment Results

To capture higher-frequency mechanical transients, the sampling frequency in this experiment increased from 10 Hz to 90 Hz. Thus, the temporal alignment process done on the Shop Floor dataset yielded an initial 491,760 observations (61 minutes) with 58.6% of it labeled as Working and 42.4% as Not Working.

Model adaptation and Feature Engineering

Stage I (Baseline Configuration and Bias Identification): An initial Random Forest model was established using a standard 80/20 random split and optimized via *RandomizedSearchCV*. While this model achieved an F1-score of 0.97, a subsequent feature importance analysis revealed a structural flaw: static weight features accounted for 86% of the decision-making weight. This indicated that the model was functioning as a "digital scale" (identifying that a worker or object was on the platform), rather than recognizing the assembly processes.

Stage II (Feature Sensitivity, Class Balancing, and Temporal Integrity): To transition from presence detection to activity recognition, the raw weight columns were temporarily excluded. The goal was to evaluate the predictive power of the IMU data independently. This analysis yielded two critical architectural adjustments:

- A Signal Magnitude Vector (SMV) was calculated to ensure the model's robustness against sensor mounting variations. By transforming tri-axial data into a rotation-invariant magnitude, the model is prevented from overfitting to specific hardware orientations, mitigating the risk of memorizing axial-specific patterns.
- The standard random split was found to induce data leakage. The high-frequency (90 Hz) sampling rate caused adjacent samples to be highly similar, meaning that random shuffling placed temporally correlated fragments into both training and testing sets, resulting in inflated performance metrics. To rectify this, the protocol transitioned to a 73/27 Chronological Split (*TimeSeriesSplit*).

The 73/27 split was used to maintain a consistent class distribution across the Training and Test subsets, since the Working state was mostly concentrated in the initial portion of the dataset, while Non-working intervals were more prevalent in the latter half. This partitioning strategy ensured a more balanced representation in both the training and validation sets.

Stage III (Feature Aggregation and Temporal Context): Rolling Windows (RW) of one and three seconds were implemented, providing the model with a "short-term memory". This allowed the algorithm to filter transient noise and prioritize the sustained vibration signatures from Working activities. Finally, the raw weight data was replaced with a single 3-second Weight Delta (ΔW) feature. By calculating the change in weight across the platform, this feature emphasizes loading transitions and dynamic events, rather than static mass. The final dataset variables are summarized in Table 4.

Table 4: Final dataset: First three observations

Obs.	1s RW	3s RW	ΔWeight	Target
1	$w_{1,(1:4)}$	$a_{1,(1:4)}$	Δw_1	1_{st} value
2	$w_{2,(1:4)}$	$a_{2,(1:4)}$	Δw_2	2_{nd} value
3	$w_{3,(1:4)}$	$a_{3,(1:4)}$	Δw_3	3_{rd} value

This final model's *RandomizedSearchCV* reached an optimized configuration of 100 estimators, a maximum depth of 8, and a minimum sample split of 5.

Table 5: Final model Classification Report

	Precision	Recall	F1-Score
Not Working	0.71	0.73	0.72
Working	0.81	0.79	0.80
Weighted Average	0.77	0.77	**0.77**

As detailed in Table 5, this configuration achieved a Weighted F1-score of 0.77. Notably, the model demonstrates a sensitivity (Recall) of 0.79 for the Working class. Given the stochastic nature of the shop floor, this result suggests that the feature engineering process successfully filtered out ambient mechanical noise, typical of industrial settings.

Analyzing feature importance analysis, illustrated in Figure 5 identifies the 3-second vibration windows as the primary predictor for the final classifier. This confirms that temporal signal stability offers superior predictive power compared to instantaneous, high-frequency movement. Notably, weight variables were successfully attenuated to secondary support features. This shift transitioned the system from a presence detector to an activity monitor, capable of identifying true production cycles.

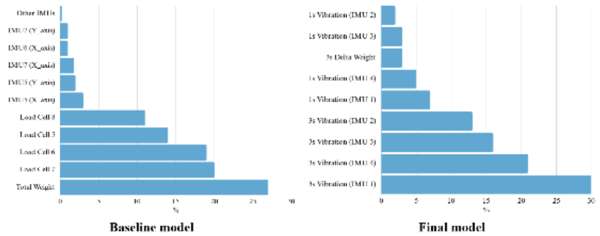

Figure 5: Baseline and Final models' most important features

The final normalized confusion matrix (Figure 6) identifies two primary error types: 12.37% (11,039) false negatives, where active work was classified as Not Working, and 11.15% (9,650) false positives, where NVA tasks (mostly walking on the platform) were misidentified as Working.

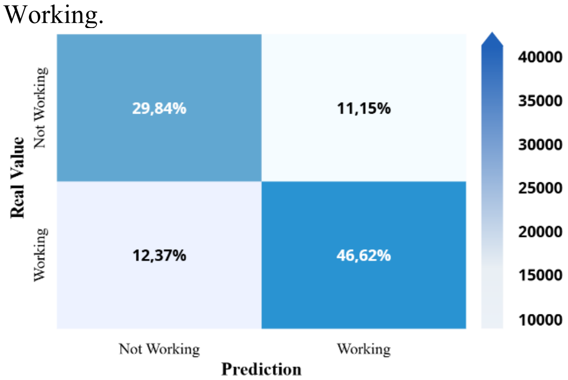

Figure 6: Final model's normalized confusion matrix

Key Differences Between Laboratory and Shop Floor Results

This section discusses the key differences between the laboratory and shop floor experiments, including variations in environmental conditions, data acquisition, and operational constraints that influenced the model performance.

In the laboratory, the Load Cells Only configuration achieved the superior F1-score, by capturing the isolated mechanical signatures of "Hammering" and "Drilling". However, it was later revealed that the model had become a "digital scale", meaning that, while load cells are excellent at detecting high-energy impulses in controlled settings, they can overshadow kinematic data in complex environments if not properly regulated. By replacing raw weight with the ΔW, the bias was mitigated, effectively forcing the model to prioritize dynamic events over static mass.

Another notable difference was observed in the classification of "Walking". In the laboratory, "Walking" was identified with high precision (only 3,05% false positives), but in the shop floor model there were 11,15% False Positives. This error is attributed to the environmental constraints of the active production site, since, unlike the spacious and relatively unobstructed laboratory platform, the shop floor required workers to perform short, irregular steps and weight shifts while reaching for tools or standing still during inspections.

On the other hand, the implementation of 1-second and 3-second temporal windows (Stage III) represented a shift towards a more human-centric monitoring logic. Just as a supervisor does not judge productivity based on a single millisecond of movement, the rolling windows allowed the model to account for "micro-rests" (i.e., the brief pauses when a worker catches their breath or adjusts a tool), which the Laboratory model could not do with its millisecond-scaled observations.

Ultimately, the integrated use of SMV and ΔW successfully enabled activity classification validating the hypothesis. However, the integration revealed a "weighted partnership" where the ΔW contributed only 3% to the model's predictive power. While this confirms the system is a functional activity monitor, it suggests that the weight sensors' primary value may lie in secondary applications.

Conclusions

The proposed approach integrated weight sensor data with IMU data, introduced a Random Forest model, and detailed the complete data flow and feature engineering process from raw data to the final model. By capturing weight shifts and mechanical vibrations, the system can infer internal activities, identifying internal assembly tasks without the need for line-of-sight or invasive wearable sensors on the workers. Since the system captures data directly through the volumetric module platform, it is not affected by the 'black-box' effect caused by occlusions, which commonly occurs in camera-based data capture. In addition, general technical advances include a more accurate distinction between working and idle states, higher data resolution, and customized ground-truth labeling based on exact activity execution times rather than fixed windows.

Building on these technical foundations, this research validates the system's effectiveness within the specific context of volumetric module production (IC) shop floors. During experimental testing in a bathroom pod facility, the methodology achieved a 77% Weighted F1-score, effectively elevating the technology to TRL 5. This successful deployment under real-world operating conditions confirms the system's feasibility as a monitoring solution for relevant complex industrial environments.

While initial laboratory results suggested that load cells alone could achieve a 93.50% F1-score, the shop floor validation revealed that such models are prone to structural bias toward simple presence detection. The implementation of feature engineering, specifically the use of Temporal Rolling Windows, allowed transitioning from a "digital scale" to a true activity recognition system.

Nevertheless, this paper also identifies different limitations such as the need for experiments to make ML models more robust, improvements in hardware to guarantee the integrity of sensors in the instrumented platform, and the difficulty in distinguishing between the high-frequency mechanical transients of manual tools and the erratic movements or weight shifts of workers in confined spaces. Furthermore, the current reliance on fixed platform locations suggests that future iterations should explore configurations that adapt to more complex, mobile, or dynamic shop floor layouts.

Several avenues for future research also arise from the experimental findings. First, the impact of extending the temporal windows to better capture the context needed to distinguish between active work and brief pauses should be studied. In addition to that, the ΔW feature's low contribution to the classification model suggests its utility may lie elsewhere. In that sense, future studies could leverage weight sensor data to detect the placement of heavy components on the platforms, providing a more robust mechanism for tracking production progress by creating an automated validation process of assembly sequences. In practice, a rule-based system could be developed to connect, in real time, the measured weight of heavy components to their corresponding positions on the platform according to the module plans. Thus, the final position of each component, as confirmed by sensor data, could indicate in real time the progress of module completion.

Finally, the study concludes that while human movement on confined IC platforms is inherently random and interwoven with production, it can be mathematically distinguished through the integrated use of IMUs and load cells, coupled with ML models. Ultimately, this system empowers IC managers with empirical data to identify bottlenecks and optimize shop floor workflows, unlocking the productivity potential inherent in industrialized methods.

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