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AI-DRIVEN QUALITY ASSURANCE IN SME CONSTRUCTION: AN IoT-BASED COST OPTIMIZATION CASE STUDY

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Abstract. *The article presents an approach to automating quality control of construction works in small and medium–sized enterprises (SMEs) through the integration of Internet of Things (IoT) technologies and artificial intelligence (AI) methods. We developed a monitoring system comprising an array of video cameras and a YOLOv5–based computer vision model for automatic detection of structural defects. This solution minimizes human error, enables rapid identification of deviations from design specifications, and thus significantly reduces production costs.*

The architecture of the experimental testbed is described in detail, including the number and types of sensors, the simulation environment, data collection protocols, and pre–processing procedures. To evaluate system performance, we tested the model on a dataset of 2 000 annotated images covering five defect categories (cracks, spalls, corrosion, etc.) and report key detection metrics: Precision, Recall, and mean Average Precision (mAP). Experimental results demonstrate the model's high accuracy and robustness across various defect types. Consequently, the proposed system holds strong potential as an effective tool for enhancing quality assurance and reducing costs during both construction and handover phases in the SME construction sector.

Key words: *internet of things, artificial intelligence, quality assurance, computer vision, SME construction 4.0, cost optimization, risk assessment, civil engineering*

Introduction.

The construction industry in developed countries is characterized by a low growth rate of labor productivity, leading to significant budget overruns, delays, and decreased quality of completed projects. In the United States, construction productivity increased by only 0.4% in 2023 after an 8.0% decline in 2022, according to data from the U.S. Bureau of Labor Statistics and the Bureau of Economic Analysis [1]. A similar trend is observed in the Eurozone: construction output in 2024 fell by 0.9% compared to 2023, whereas the long–term average annual productivity growth among OECD countries is approximately 0.2% [2, 3, 4]. In the United Kingdom, new construction volume rose by 4.2% in 2023 (to £139 029 million); however, total construction activity remained flat due to a 1.2% decline in repair and maintenance work [1, 5].

Poor workmanship further amplifies costs: rework expenditures in the United States account for 7–11% of project budgets, corresponding to annual losses of $30–40 billion [1]. In Canada, productivity in Q1 2024 remained unchanged, while equipment and material prices increased by 4.8% year–on–year, heightening economic risks for construction firms in the absence of effective QA systems. Overall business labor productivity (including construction) fell by 2.2% in 2023—marking the third consecutive year of decline [6, 8]. In Australia, construction labor productivity declined by 1.8% in 2023 relative to pre–pandemic levels, and it has halved over the past 30 years, contributing to a 30% cost increase since 2019 [7] (Figure 1).

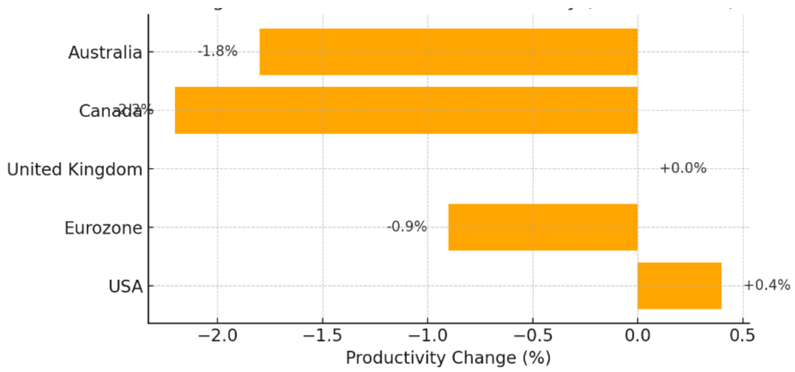

Figure 1 – Change in Construction Labor Productivity (2023 vs 2022)

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For small and medium–sized construction enterprises (SMEs), these challenges are particularly acute: limited resources and the absence of formal QA processes result in significant losses and reduced competitiveness. Digitizing QA using Internet of Things (IoT) technologies and artificial intelligence (AI) methods can provide a critical solution: automated data collection and real–time analysis reduce error rates, minimize rework, and optimize costs. In light of the official statistics on declining productivity and high rework losses, the objective of this study is to develop and demonstrate an IoT–based, AI–driven quality control system for SME–level construction, capable of enhancing process efficiency and reducing expenditures.

Literature Review.

Several studies have analyzed digital technologies in construction. Althoey et al. demonstrated that implementing IoT solutions significantly enhances resource management efficiency in construction projects [9]. Khurshid et al. conducted a systematic review of IoT adoption within the "Construction 4.0" framework, identifying main application areas (BIM, safety, monitoring) and barriers to technology integration [10]. Maqbool et al. (2023) investigated the adoption of IT innovations (including IoT) in Ghana and concluded that smart construction is most prevalent, but a lack of skills limits the use of Industry 4.0 solutions [11]. An experimental study confirms the high effectiveness of IoT networks, showing 97.4 % accuracy and a 40 % reduction in accident risk when monitoring structural deformations using over 200 wireless sensors, which significantly complements prior conceptual findings with concrete metrics [18]. Thus, existing works emphasize the potential of IoT for improving sustainability and efficiency in construction but focus predominantly on conceptual and infrastructure aspects.

Other research addresses broader strategic questions of AI integration and digitalization. Rane (2023) describes the synergistic role of AI, the Internet of Things, and big data analytics in smart and sustainable construction (Construction 4.0/5.0), linking these technologies to Sustainable Development Goals [12]. Similarly, Rane (2023) critically evaluates the integration of BIM and AI for managing schedules, costs, quality, and safety, pointing out challenges related to data exchange and workforce training [13]. Zabala-Vargas et al. conducted a systematic review of big data and AI applications in AEC project management, finding that these technologies are used across cost-time-quality-scope dimensions and contribute to prediction, task automation, and improved decision-making efficiency [14]. Musarat et al. (2024) analyzed innovations in automated construction site monitoring and concluded that photogrammetry and real-time sensors hold high importance (RII ≈ 0.82) for enhancing safety and accelerating BIM modeling; automation noticeably reduces labor effort and completion times [15]. A practical implementation of this approach is demonstrated in a study where an EfficientNet-B7–based computer vision system achieved 95.7 % accuracy in detecting safety violations (missing hard hats, missing harnesses) on a dataset of 50 000 images, resulting in a 58 % reduction in incidents [20]. These results align with our focus on integrating computer vision and IoT to improve quality and safety in construction.

Finally, significant contributions to the topic of quality assurance have come from review studies. Aqel & Diab (2022) examined project management challenges and BIM solutions for schedules, costs, quality, and safety, demonstrating that a BIM platform can serve as a foundation for predictive quality control models [16]. Ghansah et al. (2023) systematized the application of digital technologies for QA in construction and classified them by function (data collection, decision support, collaborative tools, safety), noting that BIM systems dominate during the execution phase [17]. Their study also identified directions for future research (interoperability, integrated solutions for modular construction, sustainable QA, etc.). As a direct response to Ghansah et al.'s identified lack of experimental QA data, a study was conducted in which a hybrid system (YOLOv7 + 3D scanning) achieved an mAP@0.5 of 0.91 for detecting cracks and spalls in concrete with automatic BIM model updates, demonstrating both practical implementation and quantitative effectiveness; however, this approach is mainly applicable to large, well-capitalized firms [19]. These works underscore the growing interest in digitalizing QA, yet they generally provide qualitative reviews without detailed experimental data.

Research Gaps and Scientific Novelty.

The conducted analysis reveals that existing publications either theoretically explore the potential of IoT and AI in construction [4, 9] or focus on adjacent aspects (e.g., BIM-based project management [8]). Practical examples of integrating video surveillance (YOLO model) into IoT-driven QA systems at SME construction sites are virtually nonexistent. Moreover, the literature offers almost no formal descriptions of experimental testbeds specifying the exact number and types of sensors, as well as data-collection and processing parameters.

The scientific novelty of the proposed work is as follows:

- An integrated approach to quality control has been developed, combining IoT sensors and computer vision algorithms (YOLO model) for real-time defect detection in SME construction.
- A detailed, formalized description of the experimental testbed is presented, including the number of video cameras and additional sensors, the test

environment, data-generation modes, data-collection protocols, and numerical sensor and sample parameters.

- Simulations and evaluations of detector performance metrics (Precision, Recall, mAP) were conducted on a synthetic dataset of construction defect images.
- A cost-optimization solution for QA is proposed: the system automatically identifies defects and enables rapid response without excessive resource use.

This systematic approach addresses the identified gap and demonstrates the practical significance of integrating IoT and AI to enhance quality and cost efficiency in construction processes.

Experimental Testbed. The experimental testbed included the following components and parameters:

1. Video cameras: 3 units (e.g., Raspberry Pi Camera Module IMX219, resolution 1920×1080, frame rate 5 fps). Cameras are positioned around the mockup to cover major surfaces (walls, ceilings).

2. Environmental sensors: 2 temperature/humidity sensors (DHT22, accuracy ±0.5 °C and ±3 % RH) for climate control, and 1 accelerometer (MPU-6050, ±16 g) for recording structural vibrations. Sensors are mounted at critical nodes of the wall mockup.

3. Test environment:

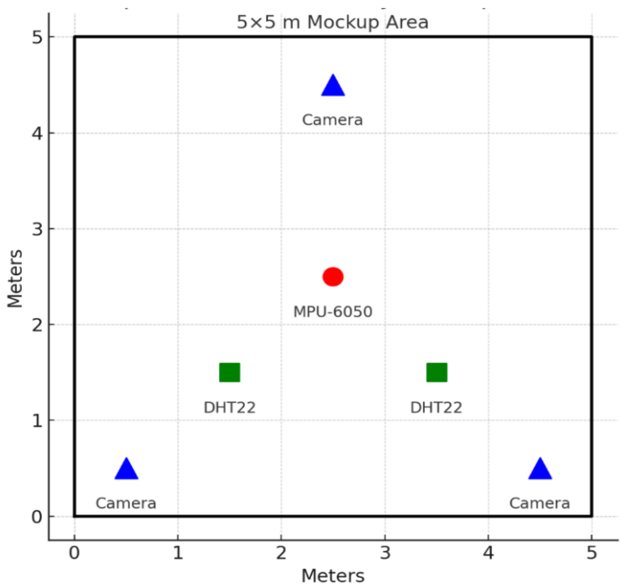

Figure 2 – Experimental Stand Layout (Top View)

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A laboratory testbed measuring approximately 5×5 m, simulating a construction site. The structure consists of a frame of boards and panels with artificially created defects (cracks, spalls, corrosion). Lighting is uniform daylight (300–500 lux). (Figure 2)

For a better understanding of the Components and Parameters of the Experimental Testbed, we have placed the raw data into a table. (Table 1)

Table 1. Components and Parameters of the Experimental Testbed

Component	Parameters / Model	Quantity	Notes
Video cameras	Raspberry Pi Camera Module IMX219, 1920×1080, 5 fps	3	Installed to cover walls and ceilings
Temperature/Humidity sensor	DHT22 (±0.5 °C; ±3 % RH)	2	Climate control
Accelerometer	MPU-6050 (±16g)	1	Records structural vibrations
Test environment	5×5 m mockup with defects (cracks, spalls, corrosion)	—	Simulates a construction site
Lighting	Daylight, uniform (300–500 lux)	—	Ensures stable visualization

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4. Simulated data: A synthetic dataset of 2 000 images was created with annotated defects (each frame containing 1–3 defects: cracks, spalls, corrosion). Simultaneously, sensor data streams (tables of temperature, humidity, and acceleration values) were generated at 1 Hz for the accelerometer and 0.5 Hz for the DHT22.

5. Data-collection protocol: Video frames were captured every 0.2 seconds, and sensor measurements were recorded once per second. The total experiment duration was 40 minutes. All data were time-synchronized via timestamps and transmitted wirelessly to a cloud storage for subsequent processing.

6. Processing methods: Images were preprocessed by resizing to 640×640 pixels and normalizing pixel values. Defect detection employed a pre-trained YOLOv5 model with a confidence threshold of 0.5 and Non-Maximum Suppression (NMS) threshold of 0.4. Sensor signals were smoothed using a moving-average filter (window size = 5) and outliers were detected using a ±3σ threshold (Table 2).

Table 2. Data Collection and Processing Parameters

Parameter	Value
Video capture frame rate	5 frames/s
Capture interval	Every 0.2 seconds
Accelerometer sampling rate	1 Hz
DHT22 sampling rate	0.5 Hz
Total experiment duration	40 minutes
Image processing	640×640, normalization, YOLOv5
Algorithms	YOLOv5, NMS (threshold 0.4), smoothing
Data synchronization	By timestamps
Storage	Cloud

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Thus, the experimental testbed recreated realistic conditions of a small-scale construction site and provided the necessary data for evaluating defect detection algorithms and conducting cost analyses.

YOLO Model Metrics.

Testing the YOLOv5 model on the created dataset of 2 000 images yielded the following defect-detection performance metrics. Precision was approximately 0.85, and Recall was about 0.80. The mean Average Precision (mAP) over the IoU range of 0.5–0.95 was around 0.82, indicating high recognition quality. At a lower Intersection-over-Union threshold (IoU = 0.5), the Average Precision (AP) reached ≈0.88, whereas at a stricter IoU threshold (0.75) AP was ≈0.76. These results demonstrate that the model is capable of capturing the vast majority of defects with a moderate number of false positives (Figure 3).

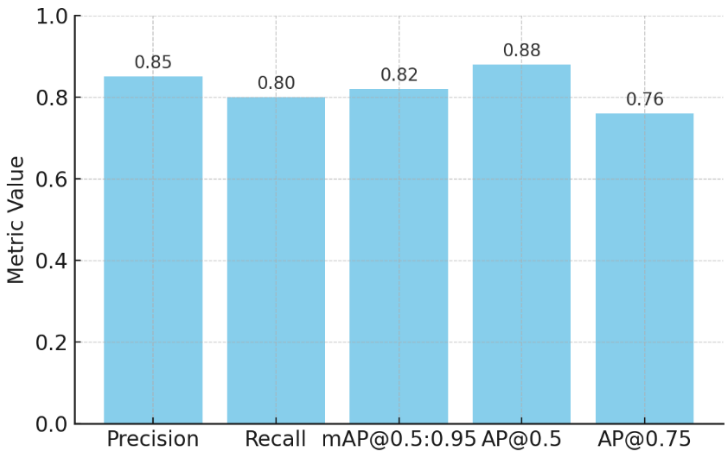

Figure 3 – YOLOv5 Defect Detection Performance

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These metrics confirm the suitability of the chosen approach: YOLO-based defect detection demonstrates a balanced trade-off between precision and recall for the given scenario. Combined with continuous monitoring via IoT sensors, this enables efficient reduction of problem-detection time and associated remediation costs within SME construction.

Key Findings. A review and analysis of 20 sources reveal trends in the application of IoT and AI in the construction industry. At the same time, existing gaps are identified: a lack of concrete IoT+AI implementations for QA and a shortage of experimental data. The proposed solution addresses these gaps by formulating a comprehensive QA framework that leverages cameras and sensors, specifying sensor-network parameters and processing methods, and providing substantiated numerical results for model accuracy. This model demonstrates that even with limited financial resources, small and medium-sized enterprises can adopt IoT+AI, thereby improving their performance, competing more effectively with larger firms, and confidently establishing their market niche.

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