A Case Study on Applying Machine Learning on Blockchain (MLOB) for Modular Integrated Construction Inspections

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Abstract

Modular Integrated Construction (MiC) is an innovative off-site building method that improves productivity, safety, and sustainability by manufacturing standardized modules in factories for on-site assembly. MiC inspections demand high levels of accuracy, efficiency, and security due to the low fault tolerance in factory environments. However, existing approaches fail to comprehensively address these combined requirements. This research explores the application of the Machine Learning on Blockchain (MLOB) framework to real-world MiC inspection tasks, assessing its feasibility and effectiveness. Additionally, a scientific evaluation is conducted to quantitatively measure the performance of MLOB-based MiC inspections. The results demonstrate that MLOB significantly enhances inspection performance by improving decision-making, streamlining processes, and ensuring the integrity of both inspection logic and data. To the best of the authors' knowledge, this is the first study to integrate MLOB into MiC inspections to consider the requirement on both accuracy, efficiency and security, providing a scalable and innovative solution for quality assurance in the construction industry.

Keywords

Machine Learning; Blockchain; Modular Integrated Construction; Inspection

1 Introduction

Modular Integrated Construction (MiC) is an innovative building method that transitions most construction activities from traditional on-site settings to controlled, off-site factories [28]. This method involves the production of standardized, 3D volumetric modules, which are manufactured and preassembled in factories before being transported for on-site assembly [8]. MiC offers numerous advantages, including improved productivity, enhanced safety, reduced waste, and lower carbon emissions. It follows a manufacturing plan that prioritizes precision and standardization, with minimal tolerance for errors in the factory environment [11]. However, any defects or inaccuracies during production can lead to severe complications during on-site assembly, resulting in costly rework and project delays [26]. Consequently, stringent quality control measures are essential to ensure the success of MiC projects.

Recent research underscores the potential of advanced technologies such as machine learning (ML) and blockchain to enhance inspection processes in MiC [22,23]. ML significantly improves inspection accuracy by analyzing large datasets to precisely detect defects, deviations, or anomalies, thereby minimizing errors associated with human oversight. Additionally, ML enhances efficiency by automating repetitive tasks, streamlining the inspection process, and enabling real-time decision-making without continuous human involvement [2]. Meanwhile, blockchain technology bolsters inspection processes by ensuring data integrity, transparency, and security [12]. By creating an immutable record of inspection data, blockchain enhances accountability and fosters trust among stakeholders.

While ML and blockchain independently enhance inspection processes, relying on these technologies in isolation reveals notable limitations. ML lacks robust security and transparency mechanisms, leaving it vulnerable to data tampering and manipulation [16]. Conversely, blockchain ensures data integrity and accountability but does not inherently offer intelligent data analysis or adaptive decision-making capabilities [4]. As a result, current approaches fail to comprehensively address the combined requirements of accuracy, efficiency, and security in MiC inspections.

Machine Learning on Blockchain (MLOB), as a novel computation paradigm, integrates machine learning (ML) with blockchain technology to ensure data and computational security [4]. Unlike conventional ML and blockchain isolated solutions [15,21,29,31], MLOB embeds ML logic directly on-chain, executing computations as smart contracts while preserving execution records on a distributed ledger. This framework offers distinct advantages to the Architecture, Engineering, and Construction industry. From a technical perspective, it mitigates risks associated with external interference, unauthorized alterations, and adversarial manipulations, ensuring the reliability of critical computations such as project progress monitoring, quality assurance, and risk assessment. Practically, its robust security mechanisms foster greater confidence in adopting advanced ML tools, leading to more precise, efficient, and secure project management.

This research adopts the MLOB paradigm for MiC inspection tasks. The primary objective is to leverage MLOB to significantly enhance the efficiency, accuracy, and security of MiC inspection workflows while assessing the feasibility of its application in real-world construction scenarios. To the best of the authors' knowledge, this study is the first to integrate the MLOB paradigm into MiC inspection tasks.

The structure of the paper is organized as follows: Section 1 introduces the research background and objectives. Section 2 provides a literature review, discussing current research on ML for MiC inspection, blockchain technology for MiC inspection, and the development of the MLOB framework. Section 3 defines the case, offering background and essential details of the MiC project. Section 4 describes the prototype implementation, outlining the four key steps of the MLOB process: ML acquisition, ML conversion, ML safe loading, and consensus-based computing. Section 5 presents the experimental results, while Section 6 discusses the contributions, limitations, and directions for future research. Finally, Section 7 concludes the study.

2 Literature review

2.1 Machine learning for MiC inspection

Liu, et al. [9] evaluates ML object detection algorithms for modular construction, demonstrating faster RCNN's superior accuracy and offering insights into ML's applicability and workflow for improving construction quality and safety. Tusnin, et al. [23] proposes adjustable ML models to efficiently analyze and design modular steel building blocks, achieving accurate stress–strain state predictions with a determination coefficient of 0.88–0.92, overcoming limitations of traditional numerical and engineering methods. Tan, et al. [22] proposes an automated BIM and LiDAR-based inspection method for modular box outer walls and rebars, achieving high accuracy with errors of 2.6 mm for flatness and 2.8 mm for protruding length measurements. Baek, et al. [2] presents an automated framework for monitoring on-site MiC module installation, combining object detection, activity classification, and productivity analysis, achieving 89% accuracy and enabling productivity measurement and improvement across diverse construction sites. Pan, et al. [14] explores future directions for applying artificial intelligence and robotics (AIR) in prefabricated and modular construction through a systematic literature review, proposing five key advancements to enhance interdisciplinary, integrated, and intelligent construction practices. Harichandran, et al. [5] proposes a hierarchical ML framework to enhance activity recognition in Automated Construction Systems (ACS), demonstrating improved precision, robustness, and noise tolerance compared to conventional approaches for monitoring and ensuring safe construction operations.

Moreover, numerous studies have explored the application of ML in inspection-related tasks. [19] applies ML to risk-based inspection (RBI) screening, achieving 92.33% accuracy and 84.58% precision, reducing variability, and improving the reliability and integrity of conventional RBI screening assessments. Ravikumar, et al. [20] explores ML-based visual inspection for defect identification, comparing C4.5 and Naïve Bayes classifiers, with results showing C4.5 achieving superior classification accuracy for automated machine vision system design. Park, et al. [17] proposes a CNN-based method for automated visual inspection of surface defects, demonstrating superior accuracy, efficiency, and cost-effectiveness compared to manual inspection, with applicability to both textured and non-textured surfaces.

The literature demonstrates the versatility and effectiveness of ML in construction and inspection tasks, offering enhanced accuracy, efficiency, and applicability across diverse contexts, from modular construction quality assessments to automated defect detection. However, ML lacks robust security and transparency mechanisms, leaving it vulnerable to data tampering and manipulation.

2.2 Blockchain technology for MiC inspection

Li, et al. [8] proposes a blockchain-enabled IoT-BIM platform (BIBP) for modular construction, achieving decentralized, secure, and efficient supply chain management, validated through a case study demonstrating improved transparency, traceability, and performance in storage, throughput, and latency. Olawumi, et al. [13] critically reviews digital tools and technologies (DTT) in modular integrated construction (MiC), identifying gaps in prefab transportation, highlighting leading countries, and proposing future opportunities for blockchain and integrated DTT adoption in MiC projects. Wu, et al. [26] develops a blockchain-enabled IoT-BIM platform (BIBP) for modular construction, addressing IoT network failures and BIM provenance issues, demonstrating improved reliability, reduced storage costs, and advancing practical applications in off-site production management. Wu, et al. [27] explores blockchain technology to enhance information-sharing accuracy in onsite modular construction assembly, developing and validating a prototype system that improves information endorsement and synchronization through blockchain's decentralized consensus mechanism.

Likewise, blockchain technology is widely applied in other inspection tasks. Wu, et al. [25] proposes a blockchain-based framework for on-site construction quality inspection (OCQI), integrating IoT and ontology technologies to enhance accountability, automation, and data integrity, validated through a prototype system and analyzed using the TOE theory. Pincheira, et al. [18] presents an end-to-end system for mining asset inspections, integrating IoT devices with blockchain to enhance data integrity, trust, and transparency, validated through a real case study in a mining inspection scenario. Wu, et al. [24] develops a blockchain-enabled framework for tower crane safety inspections, integrating smart contracts and consensus algorithms to ensure automation, transparency, and traceability, validated through a prototype system using Hyperledger Fabric architecture. Ning, et al. [12] proposes a blockchain-enabled secure transmission system (BEST) and improved market matching (IMM) algorithm for remote grid fault inspections, enhancing network performance and ensuring secure, efficient signal transmission using advanced optimization and deep reinforcement learning techniques. Zhang, et al. [30] proposes a blockchain-based performance-security balanced safety inspection framework (PSB-SIF), integrating smart contracts and a novel SIBFT consensus algorithm, ensuring authenticity, security, and efficiency in safety inspections with improved performance over conventional consensus methods.

The literature highlights the significant role of blockchain in MiC and inspection tasks. Blockchain-enabled IoT-BIM platforms improve supply chain transparency, traceability, and reliability, while blockchain-based frameworks enhance accountability, automation, and security in diverse inspection scenarios. However, blockchain ensures data integrity and accountability but does not inherently offer intelligent data analysis or adaptive decision-making capabilities.

2.3 Machine learning on blockchain

There are some existing research has explored the integration of blockchain and ML. Liu, et al. [10] surveys the integration of blockchain and ML for communications and networking systems, highlighting benefits, applications, and challenges, while addressing issues like resource management, data processing, scalability, and security for decentralized and intelligent network operations. Chen, et al. [3] reviews the integration of ML and blockchain, highlighting their collaborative potential for secure and efficient data sharing and analysis, and identifies future directions for deeper integration of these transformative technologies. Kayikci and Khoshgoftaar [7] explores the integration of blockchain and ML, highlighting their transformative potential in finance, medicine, supply chain, and security while addressing challenges like scalability, security, and workflow optimization for broader adoption and impactful applications. Acheampong [1] explores the interplay of big data, ML, and blockchain technology, highlighting big data's impact on ML advancements while proposing blockchain integration to enhance data security, reduce centralization challenges, and encourage further research for improved ML models.

In the context of MiC inspection, ensuring robust data security is imperative because the process involves collecting sensitive sensor and imaging data from multiple sources. Equally, computation security is crucial since the analytical algorithms and ML used for processing this data are vulnerable to adversarial attacks that could distort outputs and lead to erroneous decision-making. Addressing both aspects concurrently ensures that not only is the authenticity of the raw inspection data maintained, but also that the computational processes interpreting this data remain reliable and resistant to cyber threats. This dual security requirement is well demonstrated in the MLOB framework proposed by Dong and Lu [4], which is designed to safeguard both data and computation, thereby providing a comprehensive solution to the unique challenges of MiC inspection.

3 Methodology

3.1 The MLOB framework

The MLOB is a novel computational paradigm that integrates ML with blockchain technology to secure engineering computing processes [4]. The primary aim of MLOB is to safeguard both data and computational security by embedding ML processes entirely within blockchain smart contracts. The workflow of MLOB is shown in Figure 1. Methodologically, the MLOB paradigm encompasses four sequential steps: ML Acquisition, ML Conversion, ML Safe Loading, and Consensus-Based Computing Execution. Each stage systematically migrates traditional ML workflows into a secure blockchain-enabled environment, ensuring that all processes remain tamper-proof, transparent, and accountable.

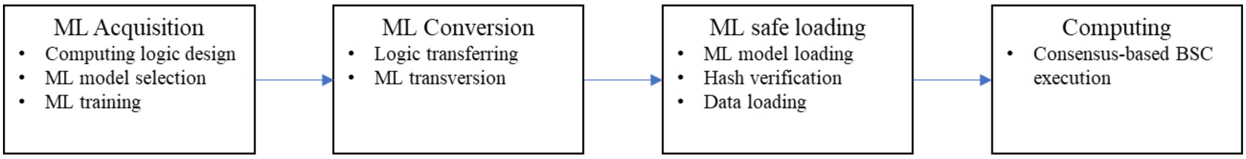

Figure 1. The MLOB framework.

The ML Acquisition phase initiates the methodology by defining and formulating engineering computing logic into ML-compatible tasks, followed by selecting appropriate ML models tailored to specific engineering scenarios and training them with relevant datasets. After acquisition, the trained ML models are converted into blockchain-compatible formats during the ML Conversion phase, ensuring compatibility with blockchain smart contract runtime environments. Subsequently, the ML Safe Loading step securely transfers both the computational models and the required input data onto the blockchain, employing cryptographic hashing to verify integrity and prevent unauthorized modifications during off-chain to on-chain transition.

In the final stage, Consensus-Based Computing Execution, ML computations are executed directly within blockchain smart contracts across multiple decentralized nodes. The transactions—including computational instructions, inputs, and outputs—are collectively validated by consensus algorithms across the blockchain network, significantly enhancing resilience against malicious manipulations. Any inconsistencies or tampering attempts are swiftly identified, preserving computational security. Through these methodological steps, the MLOB paradigm establishes a robust framework for secure ML deployment, effectively addressing both data and computational integrity in engineering applications.

3.2 Case description

The research is set in the empirical context of a MiC project in Hong Kong, specifically a student residential development. Selected as one of the Pilot MiC Projects by the Development Bureau of Hong Kong, the project comprises two 17-floor towers, providing 1,224 hostel places, with each room measuring approximately 6.5m². The project involves the assembly of 952 modules across six types. The podium transfer plate and core walls will be constructed using in-situ reinforced concrete, while MiC techniques will be employed for the floors above the transfer plate and the multi-unit bedrooms integrated with core walls. Each room will feature prefabricated polished flooring, anti-mould painted walls, and ceilings, all completed in the factory along with the installation of fixed furniture modules.

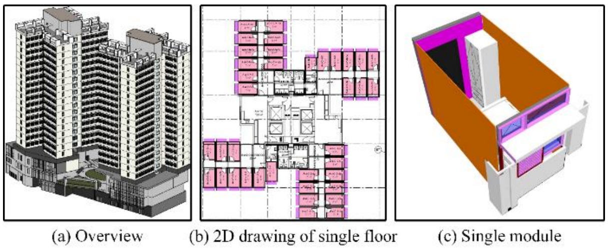

Figure 2. Background information of case study.

Figure 2 highlights the project's design details through both 3D models and 2D drawings. Specifically, Figure 2(a) provides an overview of the 3D model, while Figure 2(b) illustrates a 2D drawing of a single floor. In the 2D drawing, the pink segments indicate the key modules, which serve as focal points for inspection activities (Figure 2(c)).

Given the project's advanced and complex nature, it faces challenges such as cross-border transportation, multi-stakeholder collaboration, and stringent quality control. Consequently, the project imposes rigorous demands on inspection processes: accuracy ensures all measurements and installations align precisely with project standards; efficiency focuses on timely and streamlined inspections to prevent delays in prefabrication and on-site assembly; and security safeguards against data tampering and logic corruption. Therefore, adopting MLOB in this research case is essential to enhance the accuracy, efficiency, and security of inspection processes.

Building on insights from previous projects, this research aims to apply the advanced MLOB framework to enhance construction logistics and supply chain management [11]. A key component of the project management process involves image-based online inspections, which play a crucial role in ensuring quality and compliance. During these inspections, workers are required to upload images of installed structures or facilities, accompanied by a scale bar for dimensional reference. Inspectors then review the submitted images to verify adherence to inspection standards, with particular attention to the presence of the scale bar in the visual documentation to ensure accurate measurements and compliance.

3.3 Evaluation

Qualitative and quantitative methods are used for performance evaluation. The specific evaluation methods for accuracy, efficiency and safety will be introduced in detail below.

The accuracy performance is evaluated using the Accuracy metric. Accuracy is calculated as $Acc = (TP + TN)/(TP + TN + FP + FN)$, where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively, quantifying the proportion of correct predictions among all outcomes.

Efficiency is evaluated by measuring computing latency—that is, the total execution time required for processing engineering tasks. While the security is evaluated by qualitative discussion. Because this research aims to adopt MLOB into a real-world MiC inspection task rather than modify the MLOB architecture, the security performance remains unchanged and unaffected from the original. Therefore, our analysis primarily focuses on quantifying efficiency and accuracy performance, specifically, without altering the inherent security features, especially on safeguarding data and computational security.

4 Prototype implementation

Based on the MLOB framework, we reengineered the inspection workflow, which is shown in Figure 3. The first step (step 1) is to reengineer the current inspection process into the logic that can be loaded into MLOB framework. Then, the worker collects the image (step 2) and uploads it to the blockchain network (step 3) by a transaction. Then the smart contract is automatically invoked (step 4) to process the image data and call the ML model to output the inspection result (step 5). The inspection result is stored in the blockchain as an immutable record (step 6). After that, the blockchain network sends a response to the worker. The worker can check the inspection result (step 7). The worker also has the opportunity to appeal the result and applies for manual review (step 8). The inspector downloads the record from the blockchain and inspects it manually (step 9). If the result is different, the inspection record in the blockchain will be updated (step 10).

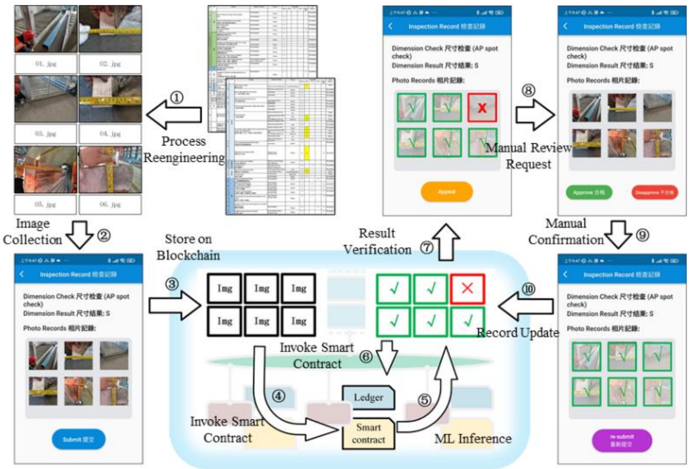

Figure 3. MLOB case study workflow.

4.1 Machine learning acquisition

MobileNet [6] was selected for this ML task, using 312 manually annotated images (qualified/unqualified) for training and 77 for evaluation. Training used sparse categorical cross-entropy loss, RMSprop optimizer, and 1000 epochs on TensorFlow 2.8 (Python 3.8), with accuracy as the metric. The trained model is saved in ".pth" format, storing weights and biases for inference or continued training in off-chain environments.

4.2 Machine learning conversion

The ML model with state dictionary format is used to run on local Python environment and cannot be used directly on blockchain smart contract. Therefore, it need a ML conversion process. As shown in Figure 4, such process needs two steps, firstly the state dictionary is converted to protocol buffer by a customized Python script, then the protocol buffer is converted to layers model by TensorFlow.js converter.

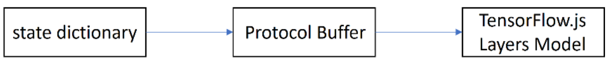

Figure 4. ML conversion workflow.

4.3 Machine learning safe loading

After conversion, an MD5 hash generates a unique value for the ML model. When uploaded to the blockchain smart contract, this hash is compared against the original to verify integrity. Upon verification, the smart contract loads the necessary vision data for ML-based inspection. This hash comparison effectively detects any tampering or unauthorized modifications, ensuring the model's reliability for inspection tasks.

4.4 Consensus-based computing

After preparation, the ML model executes when inspection images upload to blockchain (Figure 3, Step 4), automatically triggering the smart contract. Hyperledger Fabric manages this process, preventing tampering through its permissioned structure, cryptographic hashing, and consensus mechanisms. The immutable decentralized ledger makes unauthorized changes immediately detectable, maintaining the ML inspection's trustworthiness.

5 Results and evaluation

5.1 Results

We evaluated MobileNet variants' performance and inference times (Figure 5): V1 (blue), V2 (red), and V3 (green), using round markers for local inference and triangular markers for on-chain inference. Newer, larger models like MobileNet V3 (large) and V2 (alpha=1.0) achieved higher accuracy. Notably, models with fewer than 1 million parameters had faster on-chain inference than local inference, demonstrating our ML in BT framework's advantage for small models. This study confirms the framework's feasibility with satisfactory speed and accuracy.

5.2 Evaluation and comparison

Based on our results, we deployed MobileNet V3(large) in the MLOB framework, comparing it against a traditional ML-blockchain isolated solution (baseline 1) [31] and a pure blockchain solution (baseline 2) [11] as shown in Table 1.

Table 1. Comparison with baseline methods

	Accuracy	Efficiency	Data security	Computational security
MLOB	99.52%	106ms	√	√
Baseline1	99.52%	80ms	√	
Baseline2	99.8%	877.6ms		
Baseline2 (HI)	90.2%	1345.6ms	√	

MLOB and Baseline1 both achieve 99.52% accuracy with robust data security, but while Baseline1 is slightly faster (80ms vs 106ms), only MLOB provides computational security. Baseline2's manual inspection achieves 99.8% accuracy but runs slower (877.6ms) and degrades significantly under high interference to 90.2% accuracy and 1345.6ms processing time.

In summary, MLOB delivers the optimal balance of comprehensive security, high accuracy, and competitive efficiency across various operational conditions.

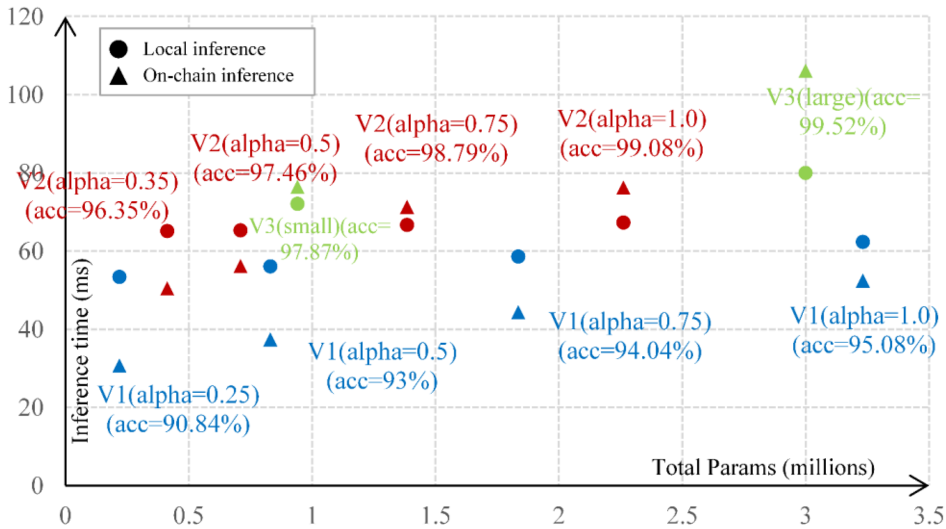

Figure 5. Comparison on different MobileNet variants.

6 Discussion

The contribution of this research lies both on theoretical and practical part. For the practical contribution, this study delivers a working prototype that applies the MLOB framework to reengineer the MiC inspection process. By integrating automated image-based inspections, secure model conversion, and consensus-driven decision-making via smart contracts on a blockchain network, the system achieves enhanced inference speed and robust accuracy while reducing delays and human errors. Its successful implementation in a Hong Kong MiC project demonstrates the approach's feasibility, scalability, and potential to establish new industry benchmarks for quality control and operational efficiency.

For the theorical part, the research offers a contribution by empirically mapping and optimizing the MiC inspection workflow. It identifies critical bottlenecks and validates that the integration of machine learning and blockchain can substantially improve inspection accuracy, efficiency, and security. This systematic re-engineering of traditional processes refines our understanding of how digital innovations can be seamlessly aligned with existing operational practices, setting a new standard for process optimization in construction.

The primary limitation of this research is its narrow focus on specific MiC inspection contexts, with limited real-world testing raising questions about broader applicability. Future research should address this by expanding the MLOB framework to more diverse scenarios and testing it on complex, large-scale projects with varied data characteristics to enhance generalizability. Additionally, collaboration with industry practitioners to integrate MLOB into practical workflows will provide valuable insights, promote real-world adoption, and help address potential implementation feasibility concerns across various construction environments. insights and promote adoption in real-world settings.

7 Conclusion

The MLOB framework integrates ML with blockchain to address accuracy, efficiency, and security challenges in MiC inspections. This approach ensures data integrity while enabling intelligent decision-making. Experimental results demonstrate significant performance improvements, showing potential to transform MiC processes. While proven effective in one real-world scenario, future research should test the framework across diverse construction contexts and optimize its computational resources.

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