CONSTRUCTION QUALITY IMPROVEMENT BY ADOPTING WORKER-ROBOT COLLABORATION TEAMS AND DECENTRALIZED BLOCKCHAINS

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PhD

The Hong Kong Polytechnic University

2023

The Hong Kong Polytechnic University

Department of Building and Real Estate

Construction Quality Improvement by Adopting Worker-Robot Collaboration Teams and Decentralized Blockchains

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A thesis submitted in partial fulfilment of the requirements

for the degree of Doctor of Philosophy

June 2023

CERTIFICATE OF ORIGINALITY

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Abstract

Quality is a critical metric for evaluating the value of a construction project since it directly impacts the building resilience against accidents (e.g., floods and earthquakes) and pertains to public property and lives. Unfortunately, quality failures seem to be an ever-present reality in the construction industry. Researchers have proposed various approaches for construction quality management, such as adopting quality management theories like total quality management and lean construction and implementing cutting-edge digital technologies, e.g., building information modelling, computer vision, and sensing techniques. However, the following three issues persistently impede quality performance improvement in construction practices: (1) labor-intensive construction conventions, which pose difficulties in quality control. Specifically, workers often experience fatigue due to physically demanding tasks and harsh working conditions. Fatigued workers are more prone to making mistakes, thereby degrading workmanship; (2) manual postconstruction quality inspection, which brings difficulties to effective quality control. Manual quality defect inspection (QDI) is time-consuming, subjective, and inefficient, thus reducing the reliability of quality inspection results; (3) easy-to-manipulate quality information records, which create obstacles in dispute resolution, accountability, and traceability. Quality is not determined by a single organization but by the joint work of several parties. Unfortunately, opportunistic behaviors, e.g., cutting corners and using inferior materials, are usually observed in construction collaborations, which will significantly degrade quality performance. An effective traceability system recording quality information records is required to mitigate opportunistic behaviors.

The rapid development of digital technologies, especially worker-robot collaboration

(WRC) and decentralized blockchains, provides creative solutions to tackle the above quality issues. WRC can integrate the robots' advantages in strength and accuracy with human ability in intuitive decision-making and adaptability, reducing workers' physical fatigue and minimizing quality errors. Similarly, a multi-robot system can be developed to ensure the reliability of quality inspections. Moreover, blockchain, a cryptography-based decentralized system, can meet the information management requirements for quality traceability. However, there are some gaps when utilizing these technologies. First, very few studies noticed the reliable interaction between workers and robots for safe WRC. Second, previous studies neglect the data availability and privacy in robot-based defect inspections. Third, limited attempts have been made to explore blockchain-based information management for construction process quality traceability. Finally, although blockchain seems to be a transformative tool for construction applications, we have seen very few implementations from the practices, and it is unclear related to its adoption barriers.

This research aims to introduce methods to tackle these gaps and then facilitate the implementation of WRC teams and blockchains in construction quality management. Notably, this is motivated by practical industry problems rather than mere interest in new technology. The specific objectives of this research are as follows: (1) To develop a user-friendly and reliable interaction method for facilitating the transition from human-based construction to WRC; (2) To develop a multi-robot-based framework for automatic QDI; (3) To develop a blockchain-based framework for process quality traceability and accountability; and (4) To investigate barriers hindering blockchain implementation in the construction industry and identify key ones.

This research first provided a comprehensive literature review on each research objective and highlighted gaps in the body knowledge. In light of these gaps, specific solutions were proposed. Specifically, this project proposed a safe and efficient method to support worker-robot interactions in WRC based on the thermal modality. An image dataset containing seven types of hand gestures was established using the thermal camera. A lightweight deep learning algorithm was developed to accurately (high accuracy) and efficiently (low latency) recognize hand gestures, even in resource-constrained mobile construction robots. Experimental results demonstrated the superiority of the proposed model compared to other lightweight algorithms and validated the feasibility of thermal image-based WRC. Subsequently, this dissertation proposed a hierarchical federated learning (FL) framework for multi-robot based QDI, allowing different construction robots to train the defect detection model collaboratively without sharing their local data. Crack detection was selected as a case study, and a lightweight segmentation algorithm was proposed to reduce communication costs. Experimental results indicated that the proposed FL method utilizes the potential of big data analysis while addressing data security and privacy concerns. After that, this thesis introduced a Hyperledger Fabric blockchain framework for extracting and recording construction process information. A consortium prototype was established using a general Blockchain as a Service (BaaS) platform. The performance was evaluated with throughput and latency metrics. Finally, this dissertation explored barriers to blockchain adoption in the construction industry, employing the technology-organization-environment (TOE) framework and identifying key obstacles through the fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. Twenty experts were invited to the survey process. Seven key barriers were identified, and corresponding policy suggestions were proposed at the government, industry, and organizational levels.

This research makes contributions to the knowledge by firstly introducing a thermal image-based interaction method for safe WRC applications, exploring the potential of FL in QDI tasks, developing a blockchain framework for construction process information management, and enhancing the understanding of barriers to blockchain adoption. Moreover, the practical implications of this research include the potential to enhance quality performance by transitioning from human-based construction to WRC teams, improving the reliability of inspection results through the implementation of a robot-based QDI system, and mitigating opportunistic behaviors through blockchain-based quality traceability.

Publications

*An asterisk * indicates corresponding author.*

Journal Papers (Published)

1. **Wu, H.**, Li, H., Luo, X., and Jiang, S. (2023). Blockchain-based On-site Activity Management for Smart Construction Process Quality Traceability. *IEEE Internet of Things*. https://doi.org/10.1109/JIOT.2023.3300076.
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Acknowledgements

During the past three years at the Hong Kong Polytechnic University (PolyU), I have gained a lot from my academic and life journey. I must show my sincere thanks to PolyU and all those who have helped me.

First and foremost, I will always be grateful to my chief supervisor, Prof. Heng Li. Prof. Li has taught me what good research is and how to be a good researcher. I will benefit from these experiences for the rest of my life. He has provided me with inspiring ideas, given me support, and motivated me to pursue cutting-edge research. I really appreciate all his support, time, and guidance in my studies. It is my luck to meet Prof. Li, and I will strive to become a researcher like him.

Then, I would like to sincerely thank my co-supervisor, Dr. Hung-Lin Chi, for his constructive suggestions on my research. His rigorous research attitude has encouraged me to do influential and meaningful research. Additionally, my gratitude goes to Prof. Botao Zhong, who has provided me with continual guidance and supports for my research.

Furthermore, many thanks go to my friends and colleagues in the Smart Construction Lab for your incredible help and support throughout my life at PolyU. Finally, I would like to express my deepest gratitude to my parents and my wife (Dongxu Liu), for their support and love. In the midst of the challenges posed by the pandemic, our love stood resilient, transcending the physical distances that separated us. Our love has not only

survived the challenges of these years but has flourished amidst them. In the tapestry of my doctoral journey, your presence is woven into every chapter. Thank you for being my source of love and strength. This achievement is as much yours as it is mine, and I am grateful to have you by my side as we embark on the next chapter of our lives and family together.

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Abbreviations

AI	Artificial Intelligence
AUC	Area Under Curve
BaaS	Blockchain as a Service
BIM	Building Information Modelling
BN	Batch Normalization
BiSeNetV2	Bilateral Segmentation Network
CNN	Convolutional Neural Network
CQM	Construction Quality Management
CV	Computer Vision
DAO	Decentralized Autonomous Organization
DEMATEL	Decision-Making Trial and Evaluation of Laboratory
DL	Deep Learning
DLT	Distributed Ledger Technology
DPoS	Delegated Proof of Stake
FedAvg	Federated Averaging
FL	Federated Learning
GAP	Global Average Pooling
HGR	Hand Gesture Recognition
HLF	Hyperledger Fabric
HOG	Histogram of Oriented Gradients
ICT	Information and Communication Technologies
IoU	Intersection over Union
IoT	Internet of Thing
KNN	K-Nearest Neighbors
LSTM	Long Short-Term Memory

PBFT	Practical Byzantine Fault Tolerance
PDCA	Plan-Do-Check-Action
PMIS	Project Management Information System
PoS	Proof of Stake
PoW	Proof of Work
P2P	Peer to Peer
P-R	Precision-Recall Curve
QDI	Quality Defect Inspection
ReLU	Rectified Linear Unit
SCO	Smart Construction Object
sEMG	Surface Electromyography
SHA	Secure Hash Algorithm
SVM	Support Vector Machine
TAM	Technology Acceptance Model
TL	Transfer Learning
TOE	Technology-Organization-Environment
TQM	Total quality management
UAV	Unmanned Aerial Vehicles
UGV	Unmanned Ground Vehicle
WRC	Worker Robot Collaboration
YOLO	You-Only-Look-Once

CHAPTER 1 Introduction

1.1 Introduction

This chapter briefly introduces the research background of the thesis, which discusses the main issues hindering the quality performance improvement of construction projects. Then, focusing on these issues, this study determines possible solutions, research gaps, and research objectives. Finally, the overall structure is illustrated.

1.2 Research Background

Construction quality is widely defined as adherence to contractual requirements, industry standards, and permissible specifications (Harris et al., 2021). It is a matter of concern for governments, stakeholders, and the public, as it directly impacts the delivery resilience against accidents such as fires, floods, and earthquakes, thus pertaining to public property and lives (He and Wu, 2016). Unfortunately, the construction industry has long been associated with poor-quality performance. Evidence of this can be found in alarming quality-related accidents worldwide. For instance, in 2022, a 39-story apartment building in Gwangju, South Korea, experienced a collapse during the construction process, resulting in the tragic death of six workers. In December 2018, cracks appeared in the structure of the “Opal Tower” in Sydney Olympic Park, Australia, forcing the evacuation of 3,000 residents. Similarly, in 2016, the early removal of formwork by a contractor led to the collapse of the Fengcheng power station in China, causing the loss of more than 74 lives. Another devastating incident occurred in 2016 when the Weiguan-Jinlong building in southwestern Taiwan collapsed rapidly during an earthquake, resulting in over 100 death. This serious accident can be attributed to poor quality stemming from contractors taking shortcuts during construction. Similar incidents include the Grenfell Tower fire in London, United Kingdom. These accidents indicate that quality failures seem to be an ever-present reality in the construction industry, which usually causes significant economic and societal repercussions.

Today, construction quality management is of particular importance under global competition. We acknowledge that construction quality is a complex system that requires the integration of various management theories, such as total quality management (TQM), lean construction, and plan-do-check-action (PDCA) control along with the utilization of diverse digital technologies. Recently, researchers have been actively exploring the utilization of various digital technologies to achieve quality goals (Luo et al., 2022), such as Building Information Modeling (BIM), Internet of Things (IoT), Computer Vision (CV), and others. These technologies provide great opportunities for quality management. BIM, for instance, addresses information asymmetries by facilitating exchanges across different stages and enabling the 3D simulation of construction plans (Chen and Luo, 2014; Lee et al., 2016; Ma et al., 2018a). CV can automatically detect quality defects or unsafe behaviors from visual inputs (Ai et al., 2023; Liu et al., 2020a; Wu et al., 2021a). The advancement of IoT sensors allows for the easy collection of diverse types of quality data from the physical world (Han et al., 2022). While these efforts greatly enhance quality performance, achieving excellence remains a challenge. Several factors restrict the improvement of construction quality performance throughout the entire lifecycle of construction processes.

Firstly, labor-intensive construction conventions result in uncertainties and difficulties in quality control. The automation levels of the construction industry are deficient. On-site construction jobs, e.g., bricklaying, painting, and concreting, are completed by human workers. However, high-physical demanding tasks make workers, particularly older workers, easily experience physical fatigue (Anwer et al., 2021). Note that the proportion of older workers in the construction industry is rising dramatically due to an aging population globally and the reluctance of younger people to join the construction workforce (Kim et al., 2020; Kamardeen and Hasan, 2022). For example, 37.7% of skilled and semi-skilled construction workers in Hong Kong were over 55 years old (CIC, 2019). Similarly, 80% of general contractors face challenges in hiring sufficient young craft workers (AGC, 2018). As workers age, they quickly enter fatigue conditions in physical activities. Fatigued workers may make mistakes and take unsafe behaviors, degrading craft and quality performance.

Secondly, post-construction quality inspection is conducted manually, suffering from low reliability. Manual inspections are subjective, inefficient, and unreliable since they depend on an individual's knowledge, experience, and responsibilities (Ai et al., 2023; Liu et al., 2019). Inherent human opportunism further diminishes the reliability of quality inspection results. Contractors and supervisors may collude to deceive the owner. The American Society of Civil Engineers reports approximately $340 billion in corruption costs annually in the global construction industry (Sohail and Cavill, 2008). Furthermore, manual inspections struggle with handling large amounts of data, leading to errors and time-consuming processes (Wu et al., 2021b). Kopsida et al. (2015) discovered a lack of consistency among inspection reports from different inspectors.

Manual quality inspections can also be tedious and pose safety hazards, such as when inspectors must work at heights during the surface defect inspection of bridge stay cables (Liu et al., 2019).

Thirdly, the poor reliability of quality information (e.g., construction process information and quality inspection results) hampers traceability. The quality of final construction products is not solely determined by a single organization but relies on the collaborative efforts of multiple firms, including owners, contractors, sub-contractors, and supervisors. However, inter-organizational collaboration in the construction industry is challenging and often fails. Construction projects are characterized by their enormous scale, extended timeframes, and non-repetitive nature, resulting in high levels of complexity and uncertainty (Galvin et al., 2021). According to Ho et al. (2015), higher complexity and/or uncertainty transactions are more susceptible to opportunism. Contractors may engage in opportunistic behaviors, such as cutting corners, using inferior materials, and hiring unqualified workers, to compensate for shortfalls in expected profits arising from fierce competitive bidding (Mohamed et al., 2011). An effective traceability system can mitigate opportunism by enabling construction stakeholders to demonstrate compliance with regulations and achieve accountability (Lee et al., 2021b). Successful practices in the manufacturing industry demonstrate the potential of traceability. For example, platforms like “Lazada,” “eBay,” and “Tmall Global” have already implemented blockchain technology for high-end products, such as diamond jewelry and luxury handbags, enabling customers to access product information instantly through their mobile phones. However, achieving traceability requires recording quality information in a secure, transparent, and reliable manner, which traditional information and communication technologies struggle to meet. In construction practices, quality managers usually tend to record quality information on paper (e.g., drawings and checklists) while walking around the construction site and then upload the information to a centralized information system like the PMIS (Project Management Information System) at the office (Ma et al., 2018a). However, recording quality information on paper documents or in a centralized server poses challenges regarding transparency, equivalence, fairness, and verifiability (Wu et al., 2021b). If data fraud or tampering occurs, the centralized system becomes untrustworthy (Wu et al., 2022c).

Addressing the issues above is crucial for enhancing the quality performance of construction deliverables. The rapid involvement of digital technology, especially robots and blockchains, offers solutions for the above quality issues. Firstly, robotics-driven automation can alleviate persistent construction issues, such as stagnant productivity, high accident rates, and young labor scarcity (Ma et al., 2022). Various single-task construction robots have been developed for specific industry tasks, including the Semi-Automated Mason (SAM) 100, Hadrian X, and rebar-tying (TyBot) robots. However, adopting robots is not straightforward. The adoption of construction robots remains limited on construction sites. Current robots are technically incapable of autonomously completing construction tasks in unstructured and dynamic working environments (Liang et al., 2021). Today's construction robots are designed as pre-programmed machines that perform simple and repetitive actions (Wu et al., 2022a). They cannot tackle new problems in a complex environment. The tacit and skilled knowledge possessed by human workers presents a challenge in measurement and programming. Complex construction tasks require human decision-making (Brosque et al., 2020). Moreover, pursuing full automation creates anxiety that it will replace a sizable portion of the workforce and may lead to unanticipated consequences on quality management (e.g., negative attitudes to work). Thus, workers continue to play a crucial role on-site, leveraging their talents, procedural knowledge, tactile sensibility, and ability to adapt to unforeseen challenges (Loveridge and Coray, 2017). In this context, worker-robot collaboration (WRC) teams will emerge as a critical component of future construction, allowing robots to perform tasks they excel at (e.g., lifting bricks or moving drywall sheets) while workers focus on their areas of expertise, e.g., task planning and monitoring (Wu et al., 2023a). Adopting WRC teams could reduce worker physical workloads and minimize errors during construction.

Secondly, the advancements in robots and deep learning (DL) algorithms have opened up possibilities for an autonomous quality inspection scheme. Various robots, such as unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs), can form a robotic system to collect quality defects based on different sensors. DL algorithms can automatically extract defects from the raw data, improving quality inspections' efficiency and reliability. Hence, multi-robot-based quality inspections could be implemented in future construction sites to avoid limitations in current manual quality inspections.

Thirdly, blockchains provide a creative solution for information management among various parties. Blockchain is a cryptography-based decentralized system characterized by information immutability (almost), transparency, and traceability (Wu et al., 2021b).

Compared with traditional information exchange methods, blockchain guarantees data transparency, shares data control rights, and significantly reduces data fraud risks (Wu et al., 2023b). Each party in the blockchain system has a unified view of the data, and such trustworthy data can serve as evidence in the case of ex-post accountability. Thus, blockchain-based quality information management can meet traceability requirements.

In summary, in the context of Industry 4.0, current quality issues during the whole construction process could be tackled by the implementation of WRC teams and decentralized blockchains (Figure 1.1). We limited our research scope to these identified issues and aimed to proposed research solutions to facilitate the transition from current construction quality management to future construction methods.

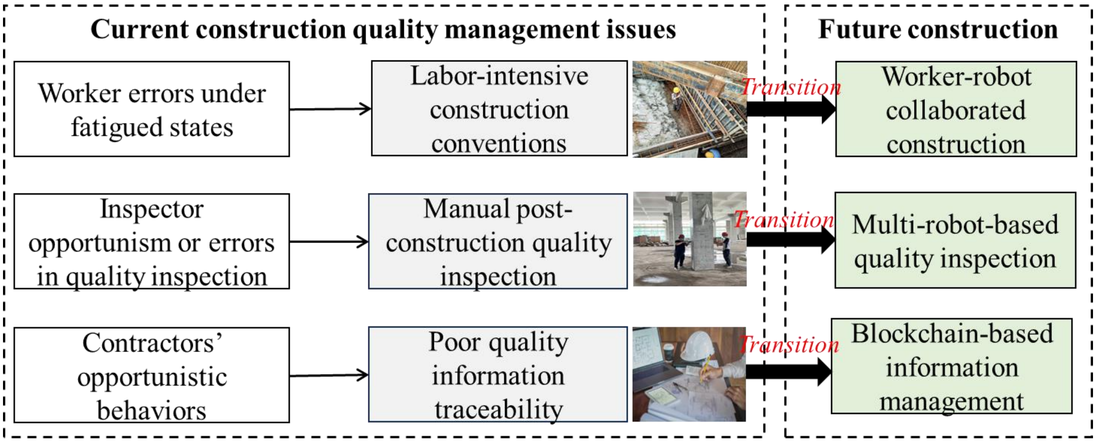


Figure 1.1. Current construction quality management issues and relevant technical solutions.

1.3 Research Problem Statement

Focusing on the potential of WRC and blockchain technologies in addressing the above quality management issues, several research problems in existing studies were identified.

Firstly, although WRC teams offer numerous benefits to construction, it also introduces unexpected safety concerns. Unlike manufacturing automation, construction robots are required to work closely with human workers. The implementation of WRC teams in unstructured and dynamic construction sites introduces collision risks (Cai et al., 2022). Note that collaboration is impossible until workers' safety is sufficiently guaranteed (Li et al., 2022a; Mazhar et al., 2019). Unfortunately, there is a lack of discussion on achieving safe and efficient interactions in the construction industry. Therefore, <u>a user-friendly and reliable communication method is essential for efficient interactions between on-site workers and robots</u>.

Secondly, although numerous DL models have been proposed to help robots detect quality defects, they neglect the data availability issue. In terms of quality and quantity, obtaining sufficient data to train DL models for robots is often expensive and complex (Zhong et al., 2019). Specifically, in the case of multi-robot-based quality defect inspection (QDI), a powerful DL model is required to help the robotic client efficiently detect various defects. In practice, developing a cross-project quality defect database is challenging. Quality defect information is considered private, and construction parties are hesitant to share such information. This is because the leakage of quality defect data (e.g., images) will bring negative reviews and potential damage to their image, resulting in a poor reputation in the market (Lee et al., 2016). Hence, useful data becomes fragmented as "data islands" that cannot be utilized for collaborative training for construction robots. Insufficient data leads to unsatisfactory performance of DL models (Li et al., 2021a). Existing methods fail to achieve ideal performance when construction robots are solely trained using their data. Therefore, <u>a novel model training approach</u>

that allows different robots to collaboratively train a power DL model is required for multi-robot based QDI.

Thirdly, blockchain technology has the potential to create a decentralized, transparent, and tamper-proof transaction ledge and act as a trustworthy platform for information exchange and quality traceability among different project actors. Existing studies also noticed its potential in quality information management (Zhong et al., 2020; Wu et al., 2021b; Lu et al., 2021a, b); however, they mainly focused on the recording of textual inspection information or construction supply chain information (Wu et al., 2023c). Very limited attempts have been made to explore blockchain-based construction activity traceability during construction processes. The lack of such traceability systems may induce contractors' opportunistic behaviors that usually negatively impact quality. Therefore, a decentralized blockchain-based construction activity information management method is required for process traceability.

Finally, we noticed that blockchain is more than a digital technology to the construction industry. Instead, blockchain is an institution technology for organizing economic activities and inter-organizational collaborations (Wu et al., 2023d). There is a key difference between blockchains and other digital technologies, e.g., robots, CV, and BIM. Specifically, blockchain acts as a self-contained and autonomous platform to handle business transactions (e.g., payments) in construction projects based on form rules. Interactions among project actors are governed by deployed smart contracts, and "once smart contracts are successfully deployed, the terms will be executed automatically" (Wu et al., 2022b; 2021a). Other digital technology mainly serves as a support tool for construction management rather than a governance mechanism per se (Lumineau et al., 2021). Hence, blockchain effects exist at the application level and in organizational collaborations among different firms. Its adoption requires the collective agreements of project actors and will encounter more resistances than other technologies (e.g., robots, BIM), including technical difficulties (Wu et al., 2021b), costs (Zhong et al., 2020), and policy and regulatory uncertainties (Li and Kassem, 2021). We have seen very few successful blockchain implementations in the industry practices. Most case studies remain in the pilot or planned use stage (Yang et al., 2020a). We must know blockchain adoption barriers to make this transformative technology real in the construction industry. Therefore, <u>it is crucial to understand the potential blockchain adoption barriers and identify key ones.</u>

1.4 Research Objectives

Against this backdrop, the primary objective of this research is to explore the feasibility of construction quality improvement through the utilization of worker-robot collaboration (WRC) teams and decentralized blockchains. We focused on the above research gaps and have tried to propose different research methods. This thesis is a compilation of several scientific manuscripts which illustrate these proposed research methods. Specifically, the thesis aims to achieve the following research objectives (RO):

- RO1: Develop a user-friendly and reliable interaction method to help workers control the robot assistant, propose a lightweight algorithm to efficiently recognize worker commands, and demonstrate its feasibility for safe WRC;
- RO2: Propose a federated learning scheme to help different robots collaboratively train the DL model without sharing the local data, develop a

defect detection algorithm, and test the performance of the proposed method in the case of crack detection;

- RO3: Investigate the suitable blockchain architecture to record construction process information for quality traceability, develop a blockchain prototype, and evaluate its performance;
- RO4: Identify blockchain adoption barriers with theoretical frameworks, analyze their interrelationships, determine key barriers based on expert evaluations, and propose policy suggestions for promoting blockchain implementation in the construction industry. Investigate the barriers that hinder blockchain adoption in the construction industry and identify key ones.

1.5 Overview of the Thesis

Figure 1.2 depicts the overall structure and the research path of this thesis. Note that this thesis is a compilation of peer-reviewed and under-reviewed scientific manuscripts. These manuscripts focused on the knowledge gaps mentioned above, aiming to promote the transition from traditional construction quality management to future construction supported by WRC and blockchains. The first two chapter aims to identify issues hindering the quality performance from the whole lifecycle of construction processes, state that adopting WRC and blockchains could tackle these issues, and then discuss existing gaps when utilizing WRC and blockchains to address these issues. These discussions allow us to understand existing research gaps. Then, several research studies were conducted to tackle these gaps. These proposed methods will lead to Chapter 3 to Chapter 6 of the thesis.

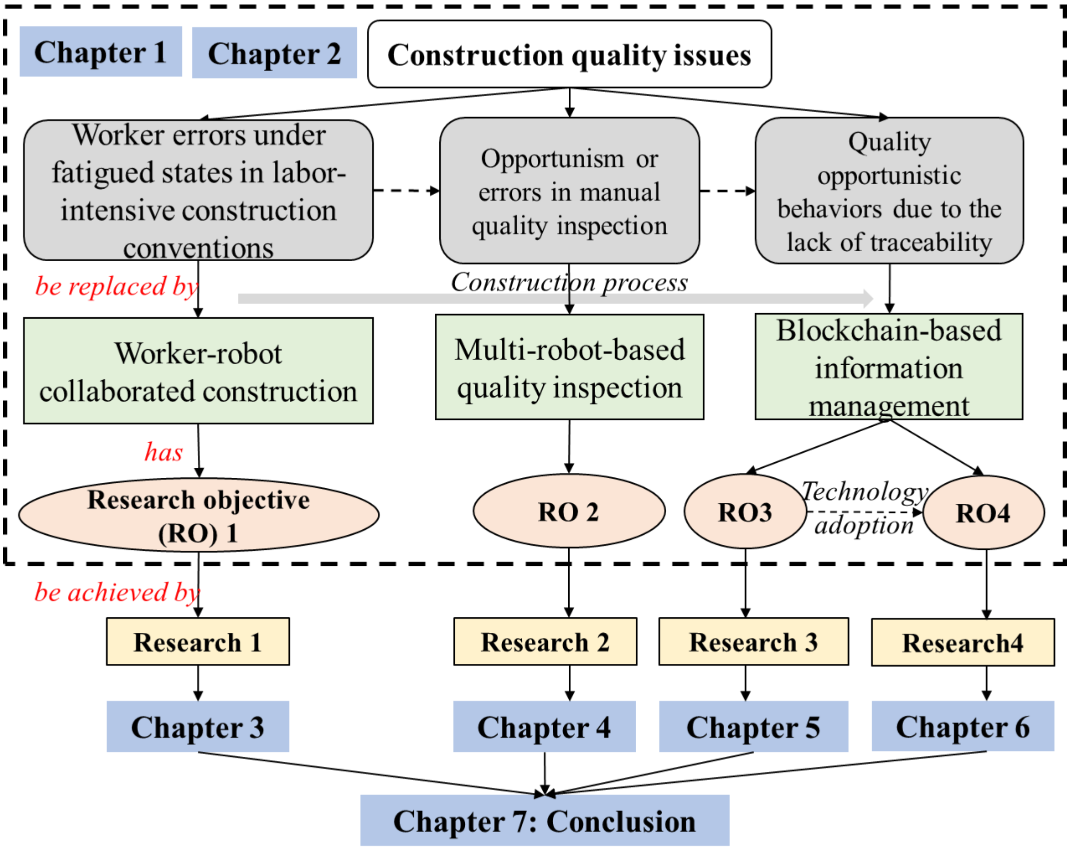


Figure 1.2. Research path of this thesis.

More specifically, Chapter 3 aims to address the challenges inherent in traditional human-based construction practices by developing a reliable WRC interaction method. We introduce a novel hand gesture recognition method that can accurately and quickly understand worker commands by identifying hand gestures from images. Several experiments are conducted in this research. Results show that the proposed method can reduce collision risks and achieve safe and efficient WRC, which will, in turn, promote the implementation of WRC teams in which the robotic assistant can reduce worker physical workloads and errors during construction.

Chapter 4 aims to propose a multi-robot-based method to reduce human opportunism and errors in post-construction quality defect inspections. We mainly focus on data availability and privacy concerns when training a powerful DL model for robotic clients in different construction projects. Crack detection is utilized as the evaluation case. Several comparative studies are performed to demonstrate the feasibility of the proposed methods. Experimental results indicate that the developed method allows robots to train the DL algorithm collaboratively without sharing the local data. Hence, the proposed method has the potential to facilitate the implementation of a multi-robot quality inspection system since it tackles data privacy concerns.

Chapter 5 focuses on the poor traceability of construction process information and introduces a blockchain-based solution. The design science method is used to guide the whole research process. We develop a conceptual framework integrating computer vision and blockchain techniques for worker activity recording during construction processes. A consortium blockchain prototype is developed, and its performance is evaluated in a laboratory environment. Experimental results indicate the feasibility. The proposed method can guarantee the reliability and traceability of construction process information, support ex-post quality accountability, and, in turn, mitigate contractors' opportunistic behaviors that usually have significant effects on quality performance.

After the above research, we notice that blockchains go beyond other digital technologies (e.g., robots, BIM) since they make it possible for collective agreements to be automatically executed based on smart contracts. It may induce an institutional revolution to project collaborations. Hence, promoting blockchain implementation in construction practices is important. In Chapter 6, we identify adoption barriers based on a literature review, analyze the interrelationships among these barriers, and identify key ones. This research can improve the comprehension of blockchain adoption barriers and then facilitate the diffusion of blockchains in real practices.

Finally, Chapter 7 provides a comprehensive summary of this study's key findings, theoretical and practical contributions, and significance. The limitations and recommendations for future works are discussed.

1.6 Chapter Summary

This chapter discusses issues affecting construction quality, including labor-intensive construction conventions, manual post-construction quality inspections, and the lack of quality information traceability. Digital technologies that could address these quality issues were identified, termly WRC teams and decentralized blockchains. Then, this chapter introduces the knowledge gaps when implementing WRC and blockchain solutions. Subsequently, the research objectives of the thesis are outlined, followed by an overview of the overall structure of the thesis.

CHAPTER 2 Literature Review[1]

2.1 Introduction

This chapter provides a comprehensive literature review of the research problems identified in this study. It begins by examining recent studies on robotic applications in the construction industry (Section 2.2). Next, the chapter investigates current practices related to quality information management in construction, introduces key concepts and technologies of the blockchain, and reviews blockchain studies in construction (Section 2.3). Finally, blockchain adoption barriers are discussed (Section 2.4). The main content of this chapter is presented in Figure 2.1.

[1] This chapter is based on a published study and being reproduced with the permission of Elsevier, ASCE publishers.
Wu, H., Li, H., Fang, X., & Luo, X. (2022). A Survey on teaching workplace skills to construction robots. *Expert Systems with Applications*, 117658. https://doi.org/10.1016/j.eswa.2022.117658.
Wu, H., Zhang, P., Li, H., Zhong, B., Fung, I. W., & Lee, Y. Y. R. (2022). Blockchain technology in the construction industry: Current status, challenges, and future directions. *Journal of Construction Engineering and Management*. 148(10), 03122007. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002380.

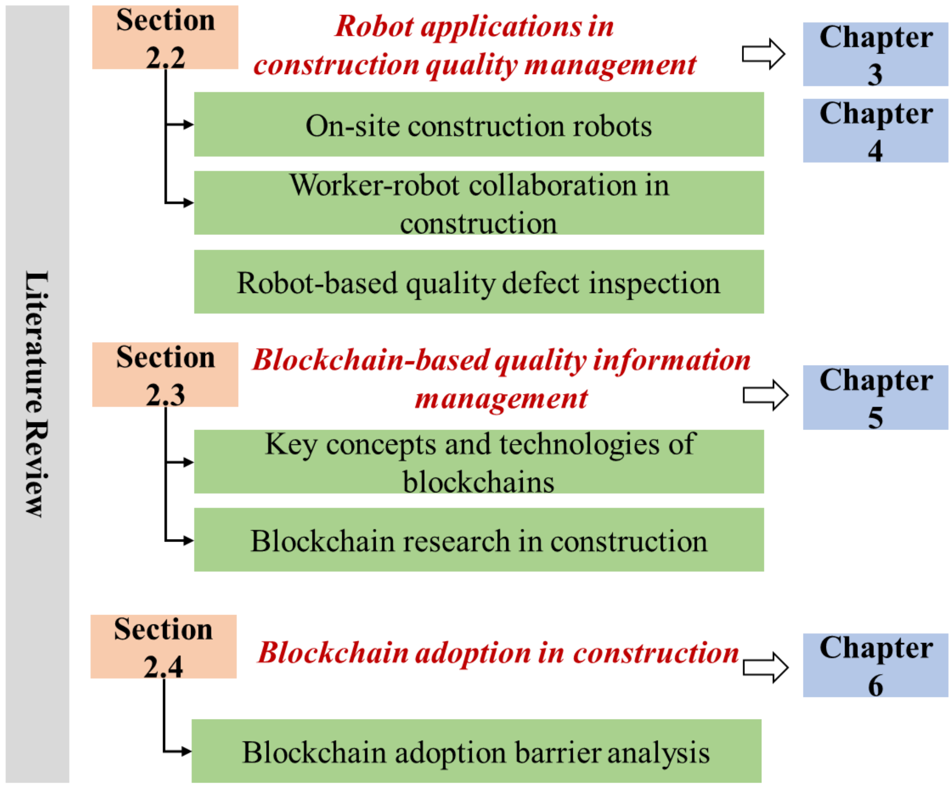


Figure 2.1. Structure of the literature review chapter.

2.2 Robot Applications in Construction Quality Management

Previous works have developed numerous digital methods to tackle these two problems, including on-site robots, computer vision (CV) techniques, and modular integrated construction (MiC) methods. In particular, robotics is regarded as a promising solution to address inherent challenges in conventional construction works, such as low productivity, errors in work, high injury rates, and labor shortages. For example, Brosque and Fischer (2022) quantified the impacts of ten on-site construction robots on quality, safety, progress, and cost in 12 projects. Their findings revealed a reduction of over 50% in rework and a 55% improvement in accuracy on average with the adoption of robots. Brosque et al. (2023) also found on-site robots minimized the 3% traditional rework to 0.15% in framing and drywall installation tasks. Moreover, various types of robotic devices have been proposed and applied in detecting defects due to their advantages of ease to use, high mobility, and capability of capturing images of hard-to-access areas (Tian et al., 2022). In summary, construction robots can reduce human errors in the construction process and support postconstruction quality inspections. Hence, we reviewed recent robotic works in the construction industry in following subsections.

2.2.1 On-site Construction Robots

Existing works primarily focuses on: (1) designing various robotic systems for construction tasks, and (2) enhancing robot automation capabilities. Recent studies can be categorized into three types based on their application scenarios: (1) automation of heavy construction equipment, such as autonomous excavator (Zhang et al., 2021) and bulldozer (You et al., 2022), with the aim of replacing operators who work in extreme conditions and hazardous environments; (2) special construction robots designed for specific tasks, such as wall climbing (Hu et al., 2022), cleaning (Do et al., 2022), and pipe inspections (Zhu et al., 2022). These robots usually have unique mechanical structures that enable them to operate effectively in challenging environments. Thus, research in this group mainly focused on the structure designing of robots; and (3) on-site general robots, which feature a general structure consisting of a mobile platform, robotic arms, and end-effectors. In this group, researchers mainly focused on the robot perception at dynamic construction sites and the decision-making abilities.

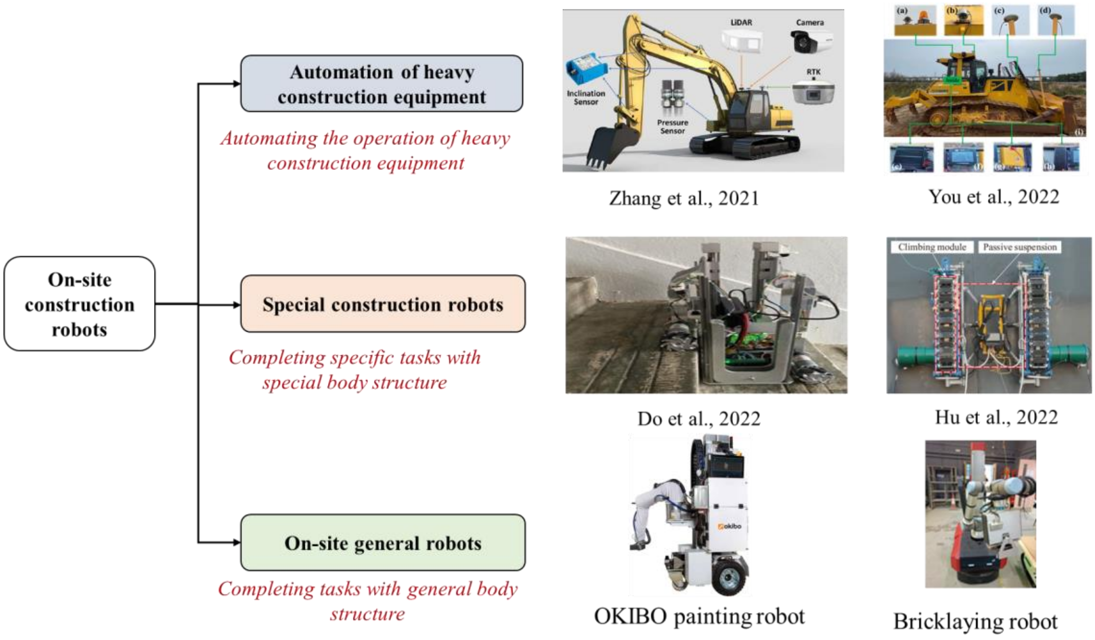


Figure 2.2. On-site construction robot classification.

Construction robots can also be divided into three categories based on the controlling mechanism: fully autonomous robots, teleoperated systems, and programmable construction robots (Gharbia et al., 2020). Autonomous robots are attractive for automating construction processes. According to Olivares-Alarcos et al. (2019), robot autonomy is defined as: "the extent to which a robot can sense its environment, plan based on that environment, and act upon that environment with the intent of reaching some task-specific goal without external control." Based on the Level of Autonomy (LoA) provided by the Society of Automotive Engineers, Melenbrink et al. (2020) classified present construction robots into five classes ranging from LoA 1 to LoA 5 and concluded that none of the current robots are capable of autonomously completing construction tasks under all site conditions.

Most current construction robots are pre-programmed for specific tasks such as drilling, painting, and excavating (Liang et al., 2020). These robots are designed to conduct certain actions in highly controlled environments using pre-programmed instructions (Kim et al., 2021a). For robots to be widely deployed on construction sites, they need to be able to handle differences and variations between the designed and built versions of structures. However, current construction robots do not have such ability. Completely replacing human workers with fully autonomous robots is not currently feasible. Current artificial intelligence struggles to effectively address the complexities and uncertainties present in real-world construction environments. Reinforcement learning and imitation learning algorithms were regarded as potential approaches to help robots learn new skills (Manuel Davila Delgado and Oyedele, 2022). Nevertheless, human reasoning remains crucial, particularly for complex tasks (Brosque et al., 2020; Ma et al., 2022). Moreover, the sole pursuit of full automation raises concerns about job loss, which can lead to resistance against such technologies.

2.2.2 Worker-robot collaboration (WRC) in Construction

Worker-robot collaboration (WRC) emerges as a crucial aspect of future construction practices (Ma et al., 2022; Wu et al., 2022a; 2022f), which could be defined as “workers cooperated with robots for accomplishing a specific construction task, and each role must be capable of making contributions to the task.” Wu et al. (2022f) stated that WRC is important for conducting complex construction tasks and developed an agent-based method to simulate WRC influences. Ma et al. (2022) also discussed the economic and technical feasibility of construction robots and stated that WRC would remain for a long time in the construction industry. A recent WRC review can be found in the works of Liang et al. (2021), Brosque et al. (2020; 2021), and Zhang et al. (2023). Specifically, Liang et al. (2021) categorized WRC applications into six groups based on the level of robot autonomy, with human workers transitioning from being “planners and executors” to “supervisors” as robot autonomy increases. Brosque et al. (2021) developed a haptic-based collaboration interface for complex tasks that require precise human teleoperation, surpassing the capabilities of pre-programmed robots. In summary, WRC enables human workers to transition from performing physical tasks to engaging in task planning and supervision, benefiting from the capabilities of robots (Zhang et al., 2023). In WRC teams, robots usually have two types of roles (Kim et al., 2022): (1) (sub)task executing role; and (2) assistive role. Specifically, some robots replace a part of human work and perform (sub)tasks, e.g., painting, while others are used to help workers in task execution, such as preparation and handling materials.

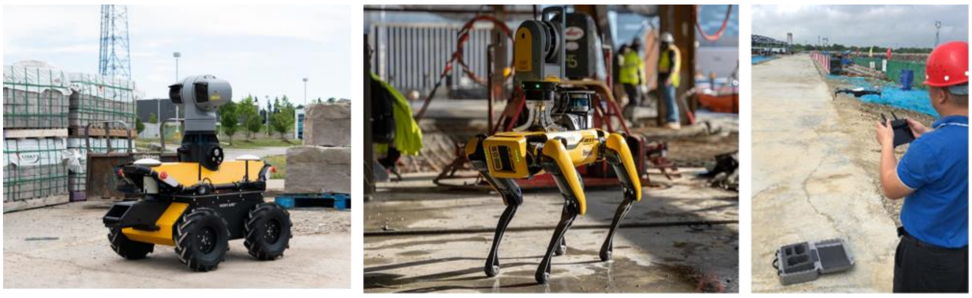
However, there is a lack of discussions on how to achieve safe and efficient interactions in the construction industry. For example, WRC has collision risks because the robot and the worker share the same physical space on the dynamic construction site (Cai et al., 2022; You et al., 2018). Workers often feel unsafe when working alongside robots. To address this issue, Cai et al. (2022) employed an uncertainty-aware long short-term memory (LSTM) network to predict worker trajectories and avoid collision risks. Liu et al. (2021a) formulated worker safety as a Markov decision process, utilizing deep reinforcement learning algorithms to learn collision avoidance policies. In addition to safety concerns, WRC can lead to mental stress and excessive cognitive workload due to potential “misunderstandings” (Liu et al., 2021b). Safety and health concerns in WRC make it necessary to design a user-friendly communication manner to support efficient interactions between human workers and robots (Czarnowski et al., 2018). Specifically, the robotic teammate should be capable of quickly and accurately understanding workers' commands, even in dynamic site conditions.

2.2.3 Robot-based Quality Defect Inspection (QDI)

Quality defects, including cracks, rebar exposure, and wall deformation, usually lead to reworks, project delays, disputes, and cost overruns during the construction process (Love and Matthews, 2020). Quality defect inspection (QDI) is a crucial component of quality control in construction projects. The objective of QDI is to identify unqualified products and defects in a timely manner and ensure the final quality of construction products in accordance with regulations and contracts. Various standards have been established to ensure the quality performance of a project, emphasizing the necessity of conducting inspections after major construction procedures for compliance checking and defect inspection (Ma et al., 2018a). Typically, quality inspectors of the contractor should develop a quality inspection plan containing inspection lots, checking items, and corresponding target objects. Following the quality inspection plan, the contractor's quality inspectors need to conduct a self-check first and record the inspection result on paper-based forms after construction procedures are completed. Subsequently, the inspectors would complete an inspection lot checklist and sign on it for submitting a re-check request to the inspectors or supervisors. For essential inspection lots, the owner may conduct double re-checks. However, manual QDI is characterized as time-consuming, error-prone, and low reliability. For example, manual inspectors may get tired, and the inspection accuracy may decrease over time (Yan et al., 2018). Robots equipped with various sensors were proposed to detect detections, including cracks, rebar corrosion, and degradation. In this research, we limited the research scope to cracks since crack is the most common damage and would cause severe problems with the integrity and safety of civil structures (Jiang and Zhang, 2020). Existing robot-based crack detection mainly focused on two aspects: (1) how to design a proper robot mechanism for efficiently collecting defect data; and (2) how to automatically detect defects from the raw data. In this research, we limited the literature review to crack defects since cracks will significantly affect the whole structure's safety.

Industry and academia have developed various types of robots for crack detection, which can be broadly divided into climbing robots, underwater robots, unmanned aerial vehicles (UAVs), and ground mobile robots. Climbing robots have been proposed for detecting defects in bridges and concrete walls. For instance, Jiang and Zhang (2020) developed a ring-type climbing robot to detect cracks in bridge piers. Xu et al. (2021) designed a climbing robot to test and maintain cables on cable-stayed bridges. Liu et al. (2013) created a wall-climbing robot with a negative-pressure adhesion mechanism for the automatic crack identification of bridge towers. Underwater robots have been used to inspect underwater infrastructures, such as dams (Li et al., 2022b). The critical research content for climbing and underwater robots is to design proper robotic mechanisms to help the robot collect data from challenging environments. For example, wall-climbing robots can be classified into two types based on their climbing mechanisms: pneumatic robots or magnetic robots (Tian et al., 2022).

In contrast to climbing robots, ground mobile robots, and UAVs have similar structures. Ground mobile robots can be classified into three categories: wheel, tracked, and quadruped. Although ground mobile robots have limited operation space since they are required to be contacted with the ground, they can usually offer comparative payloads (Lee et al., 2023). Therefore, they have been deployed for quality inspections of paved roads, bridge decks, and tunnels. For example, Halder et al. (2023) utilized a quadruped robot to assist human inspectors in completing on-site inspections. Several industrial robots have been created, such as the Husky UGV (Unmanned Ground Vehicle), Boston Dynamics Spot, and UAVs (shown in Figure 2.4). Compared with ground mobile robots, UAVs have a higher degree of freedom and perform well in construction scenarios with high headroom and/or poor ground mobility (Song et al., 2022b). Hence, UAVs have been used to support QDI in bridges (Liu et al., 2020a), building walls (Tan et al., 2022), and roads (Zhang and Elaksher, 2012). It is reasonable to state that, in the future, a multi-robot-based system can be developed for quality defect inspections, in which various types of robots are used to collect different types of defect data.



(a) Husky UGV (b) Boston Dynamics Spot (c) UAV

Figure 2.3. Example of industrial robots for quality defect inspection.

2.3 Blockchain Technology and Applications in Construction

2.3.2 Key Concepts and Technologies of Blockchains

Blockchain, as one type of distributed ledger technology (DLT), is a decentralized system that maintains transactional data or other information in chronological order, controlled by the consensus algorithm and secured by cryptography (Wu et al., 2022b). It consists of blocks chained together and secured by cryptography techniques. Figure 2.4 introduces the structure of the block, consisting of two parts: (1) a block header; and (2) a list of transactions. More specifically, information was transferred into the transaction (Tx) that will be packed into the block. As shown in Figure 2.4, the block header represents the basic information of a block, including the version number (the version of block validation rules), previous hash value (the hash of the previous block header), timestamp (the time of block generating), and Merkle root (the hierarchical hash results of recorded transactions). Note that each block has two hash values, and blocks are chained together via these values. The hashing algorithm has two main characteristics: 1) the encrypted content is difficult to reason through the hash value; 2) the hash value of each block will always be different even if there is a small change in the inputs (Farouk et al., 2020). Hence, through the connection of hashing values, blocks are chained together and even impossible to be tampered with.

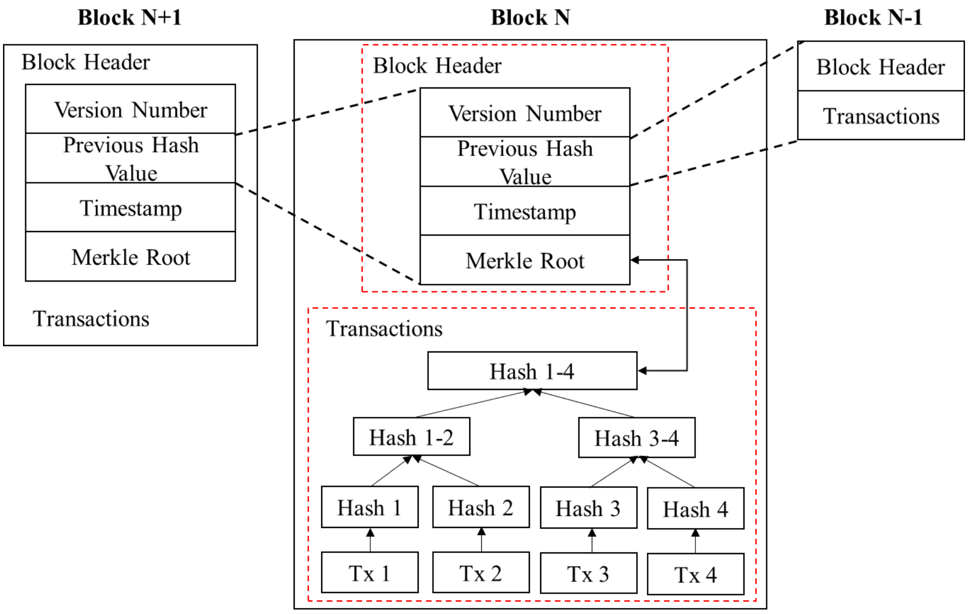


Figure 2.4. Typical structure of blocks.

Moreover, transactions recorded in the block are controlled by multiple parties in the Peer to Peer (P2P) network according to a decentralized consensus, which can guarantee transparency and avoid single-point attacks. Smart contracts enable the automatic execution of collective agreements, bypassing human actors' opportunism and errors. (Wu et al., 2022b; Zhong et al., 2022). All the nodes in the blockchain system are connected on a flat topology without a hierarchy, central authority, or main server, making the network purely decentralized. Therefore, a consensus mechanism is used to ensure that the block is valid before it is recorded on the ledger. In the blockchain, consensus algorithms are used to approve and confirm transactions in the distributed environment through a series of procedures, such as Proof of Work (PoW), Proof of Stake (PoS), Practical Byzantine Fault Tolerance (PBFT), Delegated Proof of Stake (DPoS), and so on (Wu et al., 2021b). That is, information is controlled and verified by several independent parties instead of the signal one in the centralized system. Figure 2.5 summarizes the technology components of a blockchain and corresponding technical features in terms of information management.

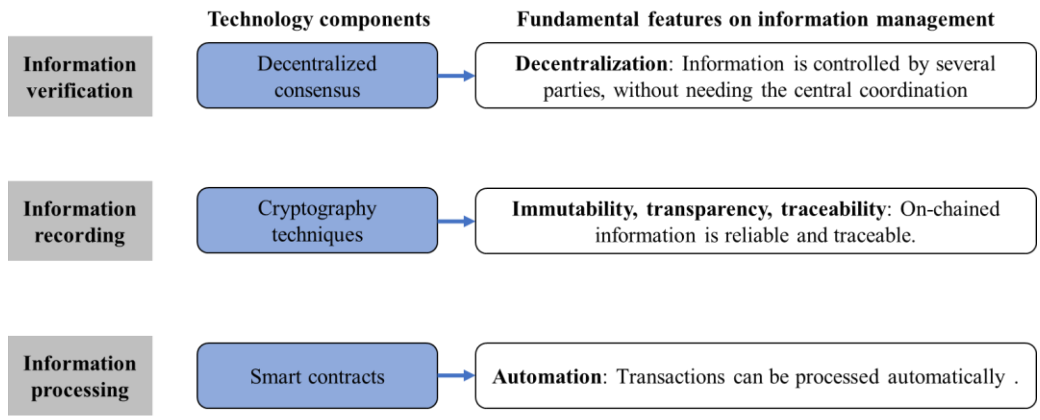


Figure 2.5. Blockchain technical components and fundamental features.

The development of blockchain technology has gone through three stages: 1.0, 2.0, and 3.0 (Jiang et al., 2021a). Blockchain 1.0 brought about cryptocurrency widely used in financial applications; an example is Bitcoin. The adoption of smart contracts promoted blockchain technology to enter the 2.0 era with the representative application Ethereum (Chen et al., 2020). Smart contracts, a computerized transaction protocol that executes the terms of a contract, enable the blockchain to be a self-enforcement platform that automatically executes transactions (Zheng et al., 2017). Since then, blockchain research has dramatically increased attention from different domains, and enterprises have tried to propose blockchain-based solutions. The enterprise-customized blockchain solutions termed the 3.0 era, in which Hyperledger Fabric (HLF) was the representative project (Androulaki et al., 2018). Blockchain 3.0 has the following fundamental properties: immutability, transparency, traceability, and automated business transactions. With the popularity of blockchain technology, the concept of Blockchain as a Service (BaaS) was proposed by technology giants (e.g., IBM, Microsoft, Amazon, and Oracle) to reduce blockchain implementation complexities. BaaS refers to cloud-based blockchain infrastructure developed by a vendor, allowing users to develop their blockchain applications even without enough hardware. That's why BaaS was regarded as a promising solution for facilitating blockchain implementation. For example, Microsoft provided Ethereum BaaS (EBassS) on Microsoft Azure which allows financial customers to quickly build private, public, or consortium blockchain applications.

According to the openness level of the participants ("*Who can join the network*?") and governance ("*Who is responsible for the consensus process*?"), blockchain can be divided into three categories: public, private, and consortium blockchains (Zhong et al., 2020). The public blockchain (also referred to as the permissionless blockchain) is open to anyone, which means that anyone can read transactions and write into the ledger without any control. It is fully decentralized, and all members are anonymous. Bitcoin is an example of a public blockchain. In contrast to the public, private and consortium blockchains can only be accessed by authorized participants. Therefore, artificial incentives are not required to guarantee the system's operation because validator nodes are known. The private blockchain (e.g., R3's Corda) is applied to a specific organization, while the consortium blockchain (e.g., IBM's HLF) is usually governed by a set of organizations (Zhong et al., 2020). The characteristics of different blockchain types are shown in Table 2.1.

Table 2.1 Comparison of different blockchain types

	Public blockchain	**Consortium blockchain**	**Private blockchain**
Decentralized degree	Complete decentralization	Partial decentralization	Centralized
Management principals	All participants	Pre-agreed participants in a consortium consisting of several organizations	Participants in a specific organization
Data access	Anyone	Only authorized users	Only authorized users
Transaction speed	Low	Medium	High
Identity	Anonymous	Identifiable	Identifiable
Examples	Bitcoin	IBM's HLF	R3's Corda

2.3.3 Blockchain Research in the Construction Industry

Blockchain technical features enable this technology to have the potential to bring a paradigm shift in the construction industry toward trust, coordination, and cooperation. The construction industry is becoming increasingly interested in blockchains, and relevant publications have blossomed in recent years. As shown in Figure 2.6, blockchain research in construction can be divided into three stages: (1) conceptual analysis; (2) blockchain applications in specific scenarios; and (3) the integration with other digital technologies, e.g., BIM.

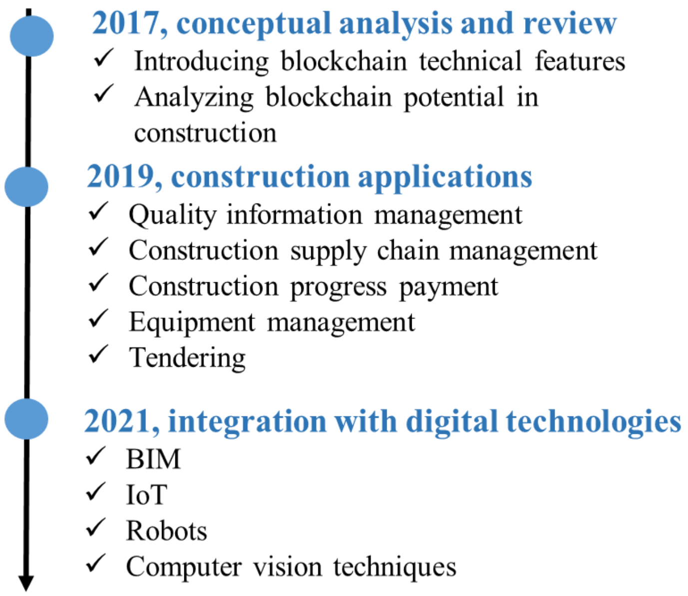


Figure 2.6. Blockchian research in the construction industry.

Specifically, early research concentrated on qualitatively illustrating blockchain potential. For example, Wang et al. (2017) discussed three types of blockchain-enabled applications in the construction sector: contract management, supply chain management, and equipment leasing. After reviewing policy papers from China and Europe, Belle (2017) highlighted how the architecture, engineering, and construction industry may benefit from blockchain technology and found several issues impeding the digitization process. According to Heiskanen (2017), combining blockchain with the Internet of Things (IoT) might increase the productivity of construction projects. These studies contribute to a better understanding of blockchains, and more scholars are becoming interested in this game-changing technology.

Various studies try to provide a comprehensive analysis of blockchains in the construction industry. Li et al. (2019) identified seven types of blockchain applications in the construction industry and studied three use cases, including automated project bank accounts, compliance checking, and a single shared-access BIM model. Perera et al. (2020) explored whether blockchain is just hype in the construction business or has real-world uses, such as property administration, asset management, and construction management, among others. Hunhevicz and Hall (2020) classified use cases of blockchain described in the literature into many categories based on the specific value propositions of blockchain technology. Scott et al. (2021) claimed that an expansive literature review has only recently been possible since 2021, as there is now a substantial body of study on the blockchain. In Scott et al. (2021), 31 application categories of blockchain technology were identified from 121 publications. Nevertheless, as the author pointed out, only one scientific database (Scopus) was used, which may have impacted the sample's comprehensiveness. In our previous study (Wu et al., 2022e), we conduct a systematic blockchain review to clearly show blockchain research status, challenges, and future directs. Table 2.2 displays these reviews.

Table 2.2. Summarization of blockchain reviews in the construction industry.

Reference	Study design	Research focus	Research outcome
Li et al. (2019)	A coherent approach integrating systematic review, focus group discussions, interviews, and the socio-technical theory.	Identify the state of distributed ledger technologies (DLTs) in the built environment	Three specific use cases were appraised, and two conceptual models were proposed to show DLT challenges and involved participants in its development.
Perera et al. (2020)	A qualitative review	Examine whether blockchain will create just hype or real disruption in the construction industry.	Applications of Blockchain 1.0, 2.0, and 3.0 were introduced from different domains, such as healthcare, food and architecture, and the construction industry.
Hunhevicz and Hall (2020)	A qualitative review	Review DLT use cases proposed in the construction industry and propose a design framework for DLT design options.	DLT use cases were summarized based on the technical properties; An integrated framework was presented to help select proper design options of DLTs.
Scott et al. (2021)	A systematic review integrating qualitative and quantitative analysis	Investigate the expansion of the blockchain in the construction industry	Blockchain research was classified into seven topics.
Wu et al. (2022e)	A systematic review contain qualitative and quantitative analysis	Understand blockchain research states, challenges, and future trends	Blockchain research mainly focused on the construction stage

Previous research has demonstrated several blockchain applications across the lifecycle of building projects. Figure 2.7 summarizes blockchain application across the whole lifecycle of building projects. In particular, the majority of the work concentrated on potential use cases of blockchains in the construction stage, in which numerous enterprises (e.g., the owner, contractors, designers, and supervisors) with varying motives must interact over long-time horizons. Most blockchain applications rely on two functions provided by blockchain technology: (1) recording evidence information in an immutable, transparent, and traceable way, and (2) boosting the efficiency and credibility of business processes using smart contracts. For example, blockchain facilitates information sharing among different stakeholders of modular construction projects through decentralized data recording (Wu et al., 2021b; Jiang et al., 2021b) and enhances the management efficiency of construction payment (Hamledari and Fischer, 2021).

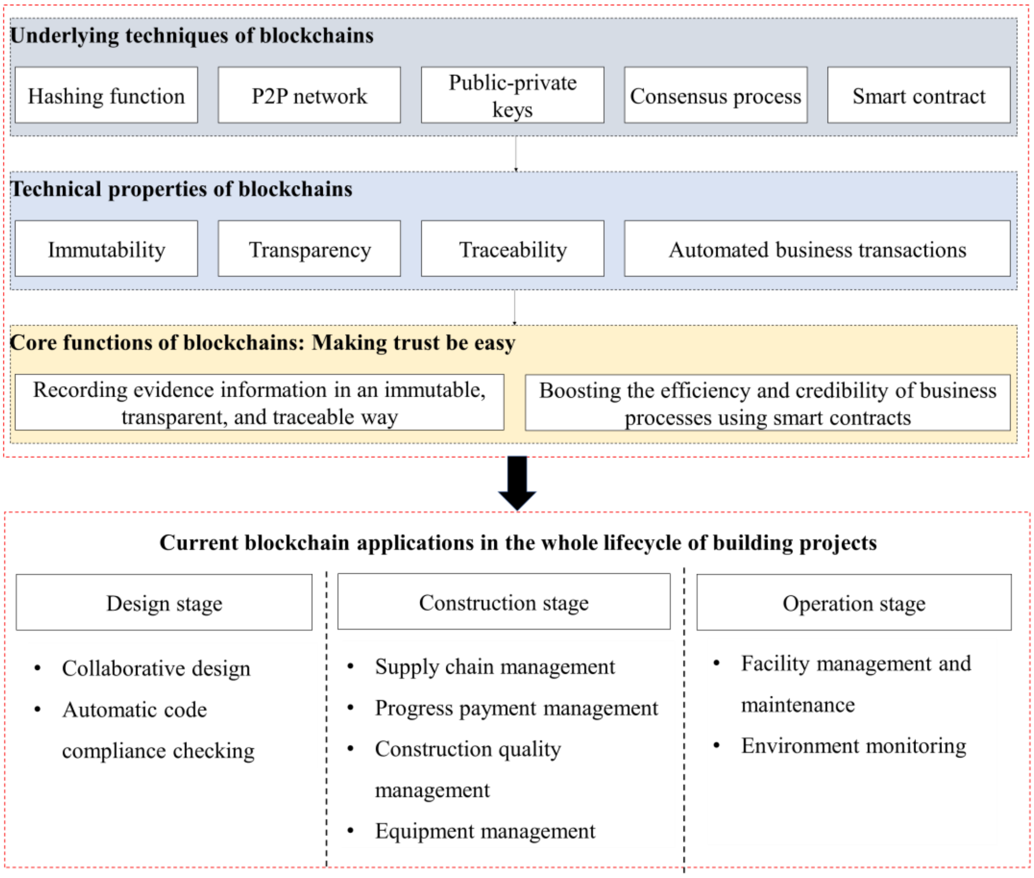


Figure 2.7. Blockchain-based applications in the whole lifecycle of building projects.

Concerning specific applications in construction quality management, a consortium blockchain was developed in our previous studies to record quality inspection information for future accountability (Zhong et al., 2020; Wu et al., 2021b). Several amazing works related to the construction supply chain come from the team of Lu Weisheng (Wu et al., 2022c, 2022d; Lu et al., 2021a, 2021b). For example, Wu et al. (2022c) indicated blockchain applicability to improving the information-sharing accuracy in the onsite assembly of modular construction. Considering that the execution of smart contracts usually requires an exchange of real-world data, Lu et al. (2021a) proposed a smart construction object (SCO)-enabled blockchain oracle framework to guarantee data authenticity. SCO represents a robust IoT model with sensing, processing, and communicating capacities. Recently, the integration of IoT, BIM, and blockchain was further investigated by Wu et al. (2022d), in which sensors like RFID collected material or product information of prefabricated modules. The IoT system can help blockchain tackle the "first mile/last mile" problem of the blockchain (Zhong et al., 2022). Additionally, the efficient integration of BIM and blockchain got increasing attention from the construction industry (Xue and Lu, 2020; Tao et al., 2022).

2.4 Blockchain Adoption Barrier Analysis in Construction

Despite the anticipated benefits of pilot cases, we have seen very few successful blockchain implementations in the construction industry. This paucity of practical applications indicates that most construction firms still hesitate to adopt blockchain technology. Blockchain adaption may face several resistances from various dimensions. For example, one significant challenge is to simultaneously satisfy the properties of "decentralization," "security," and "scalability" for current blockchain systems (Lee et al., 2021a). Existing studies have employed different architectures in different applications, such as the Hyperledger Fabric (Wu et al., 2021b; 2022b) and Ethereum (Das et al., 2020, Elghaish et al., 2023). However, lacking technical standards has led to interoperability issues (Choi et al., 2020). In addition, the security of smart contracts is another critical factor that affects blockchain reputations (Li and Kassem, 2021). Wu et al. (2022b) suggested that smart contracts may not be suitable for high-complexity construction projects with unexpected possibilities, while Sheng et al. (2020) argue that blockchain adoption needs to consider scalability issues, referring to the ability of participants in the blockchain system to process and store a large number of transactions efficiently. 60% of business executives stated that implementing blockchain was more complicated than expected owing to scalability concerns (Pawczuk et al., 2018).

Moreover, blockchain adoption may face resistance from organizations, as the technology has the potential to eliminate intermediaries and change how people work, which could lead to opposition from those resistant to change (Walsh et al., 2021). Additionally, the high financial costs of blockchain implementation, including development, deployment, and maintenance costs, can be a significant barrier (Zhang et al., 2023). However, limited attempts have been made to examine the cost-benefit of real-world blockchain projects (Yang et al., 2020a). Furthermore, there is a shortage of trained and skilled workers who can develop and maintain blockchain systems (Sheng et al., 2020). Regulatory ambiguity is also seen as an essential barrier that exacerbates stakeholders' reluctance to use blockchains (Wu et al., 2021b). Given these challenges, construction firms may be hesitant to adopt blockchain technology, despite its potential benefits. Thus, it is crucial to investigate and analyze blockchain adoption barriers systematically.

Several works have aimed to systematically illustrate the barriers to adopting blockchain technology and examine their relationships. For example, Olawumi et al. (2020) used a system dynamics approach to illustrate the causal relationships between these barriers, although this analysis lacked data validation. Sadeghi et al. (2021) listed 32 barriers affecting the adoption of distributed ledger technology (DLT) across four levels (e.g., project, organization, market, and industry) and then used the ordinal priority technique to identify critical barriers. It is important to note that blockchain and DLT are not synonymous, as blockchain is a subset of DLT (Li and Kassem, 2021). Similarly, Xu et al. (2023) reviewed 11 barriers and identified key ones, but these barriers lack insightful examinations and theoretical foundations. Recently, Wang et al. (2022b) conducted an empirical analysis to illustrate how external factors affect construction practitioners' intention to adopt blockchain technology. Li et al. (2022c) used the partial least squares structural equation model (PLS-SEM) to identify critical barriers and then adopted the fuzzy-set qualitative comparative analysis (fsQCA) to explore their synergistic effects. The game theory has also been used to investigate blockchain adoption decisions (Zhang et al., 2023; Ding et al., 2023). These studies greatly facilitate the understanding of blockchain adoption barriers.

2.5 Chapter Summary

This chapter reviews recent works related to the identified research problem respectively. Section 2.2 introduces research regarding robot applications in construction quality management, while the following part (Section 2.3) describes recent progress related to blockchain studies in construction. Additionally, Section 2.4 introduces recent works discussing blockchain adoption barriers.

CHAPTER 3 A Reliable Interaction Method for Safe WRC in Construction[2]

3.1 Introduction

We state that even with the assistance of robots, the construction industry cannot currently be totally automated. Construction tasks are complicated, extremely nonlinear, and unpredictable, and construction environments are dynamic and unstructured. The ever-changing nature of on-site environments presents great challenges to robot-based automation. Human workers can quickly improvise a new plan to adapt to substantial variations in task or environment based on domain knowledge, historical experiences, and perceptions. Hence, worker-robot collaboration (WRC) applications will be a critical part of the construction process. WRC can integrate the robots' advantages in strength and accuracy with human ability in intuitive decision-making and adaptability; thus, it can significantly reduce workers' physical fatigue and avoid relevant quality errors. However, since robots and works share the same workplace, WRC requires a reliable interaction method to help workers control the robots and then avoid collision risks.

[2] This chapter is based on a published study and being reproduced with the permission of Elsevier.

Wu, H, Li, H, Chi, H., Peng, Z, Chang, S, & Wu, Y. (2023). Thermal Image-based Hand Signal Recognition for Worker-Robot Collaboration in the Construction Industry: A Feasible Study. *Advanced Engineering Informatics*. 56, 101939. https://doi.org/10.1016/j.aei.2023.101939.

Vision-based hand gesture recognition (HGR) is a simple but effective solution for WRC interactions. Although vision based HGR methods have been proposed in various domains, they are not appropriate for on-site WRC due to the following challenges. First, existing methods mainly relied on 3-channel RGB inputs, and their effectiveness was greatly affected by environmental light conditions, such as darkness, fog, and mist (Zhang et al., 2018). Unlike manufacturing robots typically placed at stationary locations, construction robots in WRC work at complex, unstructured, and dynamic sites with different lighting conditions. For example, night construction without sufficient lights is typical in our industry. Previous RGB-based methods would fail to recognize workers' hand signals in almost total darkness accurately. The depth modality, which stores the Euclidean distance between the sensor and points in the scene, was used to provide complementary information to RGB images. However, depth sensors only allow measurement ranges of a limited distance (e.g., 0.5-4.5m of Kinect V2), and depth images usually have much noise at the edge of objects. For example, the hand region on the depth map usually has holes and cracks (Qin et al., 2014). Moreover, it is challenging to ensure real-time performance due to the significant amount of point clouds generated by the depth sensor, especially for resource-constrained mobile construction robots.

Second, WRC's safety demand requires the algorithm to recognize hand gestures accurately and quickly on mobile construction robots with limited computational resources. Although many DNN models were developed for HGR, they usually strive for higher accuracy and ignore the computational efficiency (e.g., model size and inference speed). Existing models have heavy architectures and require high computational resources beyond the capabilities of many mobile applications (Maaz et al., 2023). Thus, existing methods are challenging to be implemented in WRC scenarios. Although cloud computing enables the robot to offload most of the computational and storage works to the cloud (Du et al., 2017; Wang et al., 2022e), it may fail in WRC applications characterized by fast processing and quick response time. Specifically, cloud-based methods may incur low scalability, high latency, and bandwidth congestion due to the massive data transmission among numerous robots and the central cloud server. Construction projects (e.g., tunnels and bridges) may sometimes be located in undeveloped or rural areas with limited or no internet connectivity. 5G networks have not been implemented in some remote areas. Moreover, robots may experience downtime in cloud-based methods (Bello et al., 2021), leading to collision risks. Hence, it is necessary to design a lightweight algorithm for construction robots to recognize gestures with computing power.

<u>Against this backdrop, this chapter aims to develop a reliable method to support worker-robot interactions in WRC based on the thermal modality</u>. Unlike visible cameras that work in the visible light spectrum from 0.4μm to 0.7μm, thermal cameras capture the heat humans radiate (Civilibal et al., 2023). Hence, thermal images are not sensitive to background lighting since they do not require lighting. In addition, thermal images highlight only the warmer/colder objects and do not detect objects with many details (e.g., cloth colors). Hence, thermal images can not only protect privacy but also reduce the effect caused by complex backgrounds on construction sites. However, few studies have discussed the potential of thermal-based HGR in on-site WRC applications. The objectives of this research were twofold: (1) to investigate the benefits of the thermal modality based HGR in WRC applications, and (2) to propose an efficient and

lightweight deep learning model for on-site construction robots.

The contributions of this research are presented as follows:

- To the author's best knowledge, this is one of the first attempts to explore the feasibility of thermal modality in on-site WRC applications. The safety performance of WRC could be significantly enhanced because the proposed method can get accurate results when lighting conditions are not satisfied, e.g., dim light and total darkness, which is an advantage over the typical RGB-based methods.
- We developed a lightweight DL model using structural re-parameterization, which can achieve comparable accuracy and latency with fewer parameters, even in resource-constrained edge devices like mobile construction robots.
- We developed a thermal dataset containing seven types of hand signals in WRC-based bricklaying tasks, evaluated our method, and conducted a comparative study with advanced lightweight models. Experimental results indicate the superiority of our method in optimizing the trade-off between accuracy and latency.

The remainder of this chapter is organized as follows. Firstly, this chapter reviews recent works related to vision based HGR (Section 3.2). Then, research methods are presented in Section 3.3, followed by the implementation and training details (Section 3.4). Section 3.5 discusses contributions and limitations. Finally, Section 3.6 shows the summary and future works.

3.2 Research Background

Several communication methods were proposed in existing works, including voice-based methods (Nikolaidis et al., 2018), neurophysiological signal-based methods (Liu et al., 2021b), gesture-based methods (Wang and Zhu, 2021a), and so on. Among these approaches, hand gestures are considered natural and intuitive ways to interact with robots (Liu and Wang, 2018). Hand gestures are simple and effective; for instance, on-site workers with different cultural backgrounds can easily communicate using hand signals (Bust et al., 2008). Consequently, hand gesture recognition emerges as one of the most effective communication methods for WRC.

Existing studies on hand gesture recognition can be broadly categorized into two classes based on the input data type: (1) vision-based methods that detect hand signals from images (Mazhar et al., 2019); and (2) sensor-based methods that identify hand gestures using wearable sensors (Ovur et al., 2021; Wang et al., 2022a). Despite the excellent performance of sensor-based recognition, these methods are usually intrusive and inconvenient. Specifically, humans usually need to wear special sensing equipment like surface electromyography (sEMG) sensors (Ovur et al., 2021). Workers may reject these sensors in real-world applications. Instead, vision-based methods are more user-friendly. Therefore, this research adopts a vision-based hand gesture recognition (HGR) method, given its advantages in WRC scenarios.

As shown in Figure 3.1, a brief review of previous works on vision based HGR was introduced from two aspects: (1) data inputs; and (2) processing algorithms. Regarding data inputs, existing studies can be primarily classified into two categories: (1) single-modality methods, including RGB-based, depth (D)-based, skeleton-based, and thermal

(T)-based approaches; and (2) multi-modality methods, such as RGB+D fusion. While integrating multiple modalities may enhance performance, it also introduces training challenges and potential latency issues, particularly for resource-constrained mobile construction robots. Among single-modality methods, RGB and depth (RGB-D) data have been widely utilized in HGR.

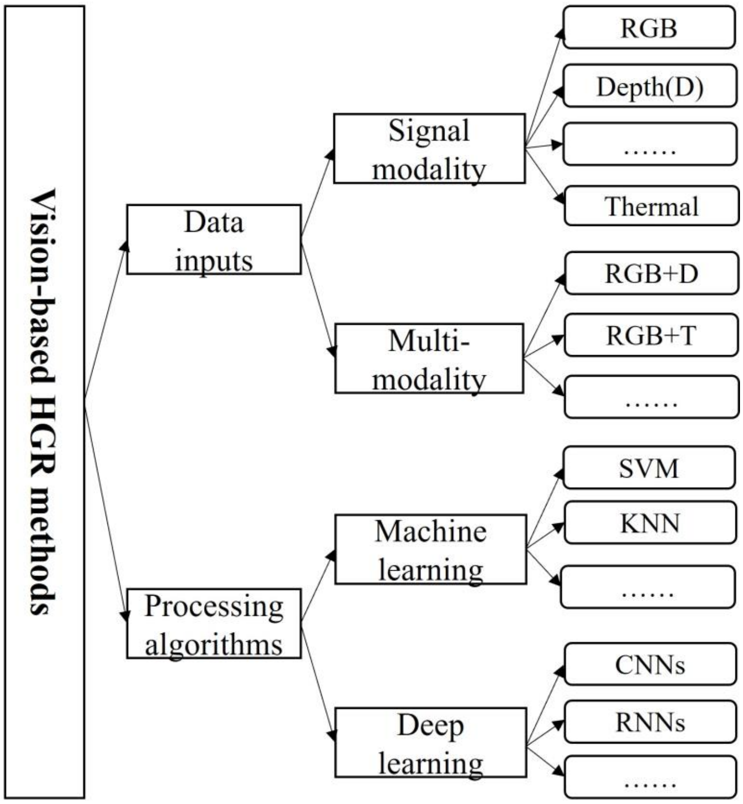


Figure 3.1. Classification of vision-based hand gesture recognition methods.

The performance of RGB studies will greatly degrade when the light is insufficient, as shown in Figure 3.2(a). In contrast, RGB-D-based HGR has gained considerable attention due to the availability of affordable depth cameras (e.g., Microsoft Kinect, Leap Motion). RGB-D data exhibits robustness against illumination variations and contains valuable 3D structural information (Wang et al., 2018). Nevertheless, real-time performance remains challenging due to the computational burden of processing massive point clouds generated by depth sensors, particularly for mobile construction robots with limited computational resources. Additionally, RGB-D introduces unwanted distractions from cluttered backgrounds, as exemplified in Figure 3.2(b). Moreover, depth data struggles to identify small objects accurately.

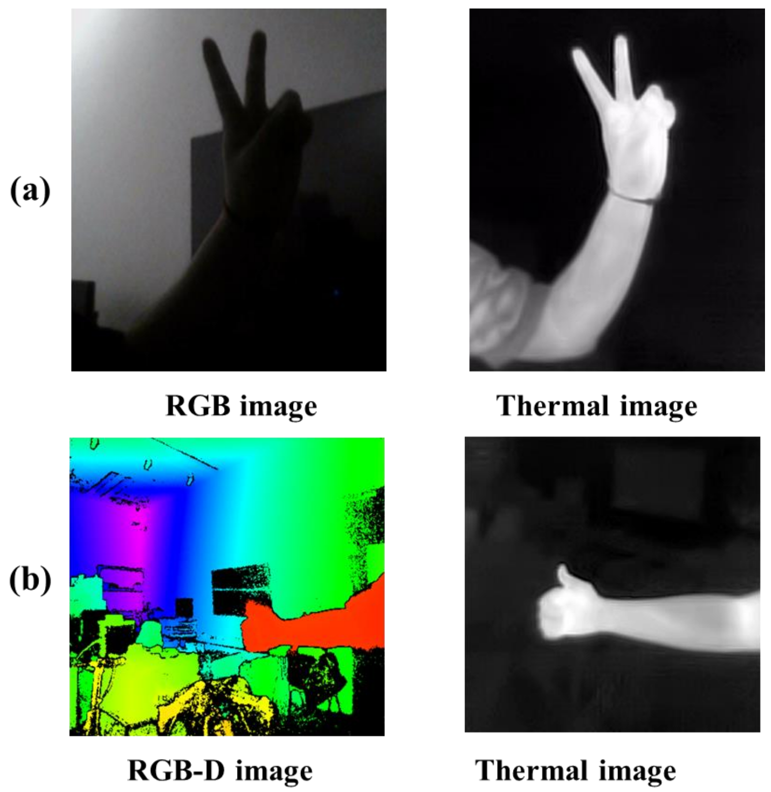


Figure 3.2. Differences among RGB, RGB-D, and thermal images.

Thermal imaging has recently got attention due to its ability to maintain high imaging quality even under poor illumination and occlusion conditions (Breland et al., 2021; Song et al., 2022a; Wang et al., 2023). For instance, Song et al. (2022a) leveraged the compensatory effect of thermal images on RGB images and curated an RGB-T dataset comprising images captured under diverse illumination conditions. Unlike visible cameras that operate in the 0.4μm to 0.7μm visible light spectrum, thermal cameras capture images based on thermal radiations emitted by objects with temperatures above absolute zero. This characteristic makes thermal data suitable for human action recognition (Akula et al., 2018), salient object detection (Song et al., 2022a), and robotic scene understanding (Sun et al., 2021). However, limited research has explored thermal image based-HGR in the construction industry.

In terms of data processing algorithms in HGR, previous works can be broadly categorized into two groups: (1) machine learning methods; and (2) deep learning methods. Conventional methods include feature extraction algorithms such as Histogram of Oriented Gradients (HOG) and classification techniques such as Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). However, these methods are constrained by the extensive workload associated with feature engineering and lengthy training times. DL eliminates the need for manual feature extraction by leveraging neural networks and can achieve higher accuracy with large-scale data samples. For instance, convolutional neural networks (CNNs) and their variants have been widely employed in image-based safety monitoring, encompassing tasks such as non-hardhat detection (Fang et al., 2018) and fall risk detection from heights (Wu et al., 2021a). In the domain of WRC, Mazhar et al. (2019) proposed a transfer learning-based CNN approach to ensure robustness and background independence in hand gesture detection from RGB-D images. Adithya and Rajesh (2020) developed a deep CNN architecture for hand signal recognition. Avola et al. (2022) introduced a keypoint-based framework to estimate the 3D pose of a hand from an RGB image. In the construction industry, Wang and Zhu (2021a) conducted a feasibility study to explore the potential of hand signals in construction WRC, followed by the proposal of a You-Only-Look-Once (YOLO) v3-based framework for interpreting signalmen's hand gestures in tower crane operations (Wang and Zhu, 2021b).

The above-discussed works highlight the significance of hand signal recognition in WRC, and while numerous image-based HGR approaches have been explored, they are not specifically tailored for WRC applications. Nonetheless, several challenges persist in on-site WRC scenarios. Firstly, existing methods predominantly rely on RGB images, which are sensitive to background lighting conditions. Construction sites are dynamic and characterized by various machinery, materials, and tools. Therefore, mobile construction robots must possess the capability to comprehend worker commands (e.g., move backward) while ensuring worker safety in diverse environments, including low-light conditions during night construction or even completely dark environments. Consequently, the limitations of previous approaches prevent them from fulfilling such requirements. Thermal sensors present a promising solution to address these challenges, as they detect thermal radiation and provide temperature values represented in human-readable colors. Unfortunately, thermal image based HGR has not been investigated by existing studies in the construction industry. Second, although deep CNNs (e.g., ResNet, ResNeXt) have been widely used in image classification tasks in the construction industry, these models have evolved towards deeper architectures and increased network layers to enhance feature extraction capabilities and achieve higher accuracy. However, such complex architectures (e.g., residual addition in ResNet) with a multitude of parameters impose substantial computational requirements on hardware resources, such as graphic processing units (Mehta et al., 2021). Consequently, deploying these models on mobile construction robots with limited computational power is challenging. Previous DL models often incorporated intricate multi-branch architectures to optimize for accuracy while neglecting computational efficiency. As a result, they may not exhibit fast performance, particularly on edge devices. In actual WRC applications, it is crucial for the robot to recognize workers' hand gestures accurately and rapidly (Maaz et al., 2023).

3.3 Research Method

This study presented a feasibility study to explore thermal image potential in supporting worker-robot collaboration (WRC) applications in construction, which has not been introduced before in our research community. Figure 3.3 presents the workflow of this research. Relevant tasks are the hand signal design in WRC, thermal image capturing, recognition algorithm development, and implementation, which are introduced in the following sections.

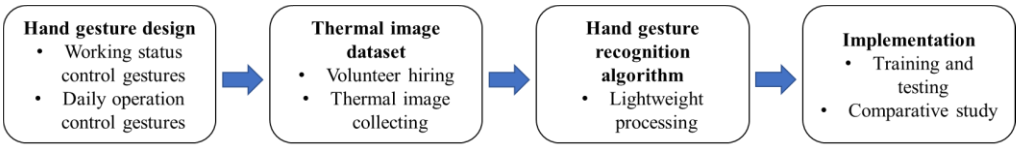


Figure 3.3. Workflow of the proposed methodology.

3.3.1 Hand Gesture Design

On-site construction tasks (e.g., bricklaying) can be conducted like WRC, where the worker plays the critical role of task planning and supervising while the robotic assistant performs relevant work. Notably, the robot was equipped with a mobile platform and a robotic arm because robotic arms can offer greater degrees of freedom and adaptability to the complexities of construction tasks (Belousov et al., 2022; Liang et al., 2020). Such hardware architecture can support various construction tasks. As shown in Figure 3.4, the mobile bricklaying robot was required to understand the worker's hand signals (e.g., stopping, leaving away, picking a brick) in the WRC-based bricklaying task even under extreme environments (e.g., cloudy, haze, dust, or poor lighting condition during the night construction). Hence, hand gestures should be pre-defined to represent different commands. That is, each of the categories of hand gestures was assigned a specific command related to robotic actions in a specific task.

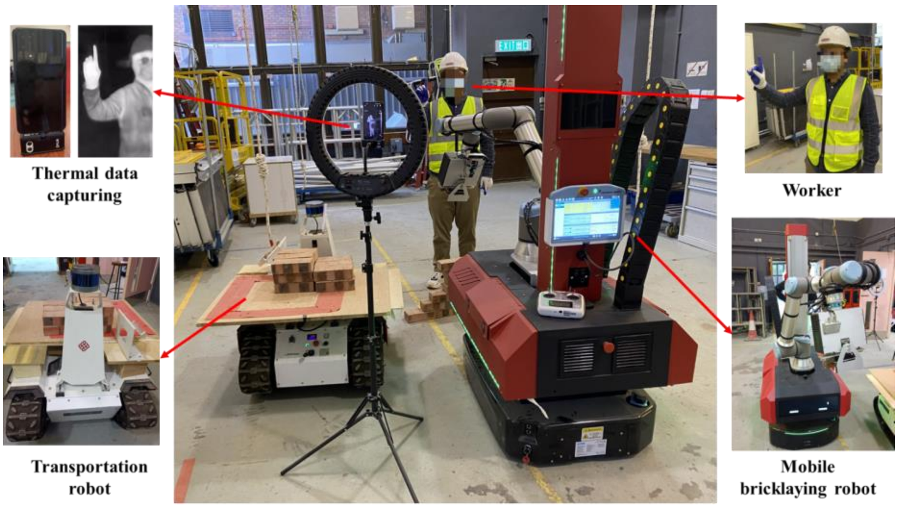


Figure 3.4. WRC-based bricklaying using hand gestures.

Currently, gestures representing manipulation commands have two types: (1) gestures with common semantics. For example, the Code of Practice for Safe Use of Tower Cranes was issued in Hong Kong, where 25 types of hand gestures were introduced for tower crane operations. In this case, the users, e.g., tower crane signalmen and operators, should have to learn such gestures; and (2) self-defined gestures. That is, the user designs a gesture to trigger a predefined event. For example, Wang et al. (2020b) defined ten types of gestures to guide the movement of a quadruped robot, while Mazhar et al.

(2019) used nine letters/numbers taken from American Sign Language to communicate with robots. To date, there is a lack of discussions on gestures guiding construction robot actions. Giving the bricklaying task as the case, we designed seven types of gestures that represent different collaboration commands in WRC. The designed gestures (C1 to C7) and their semantics are illustrated in Figure 3.5. More specifically, we introduced three types of gestures for controlling the robot's working status, including C1-*starting and following the worker*, C2-*emergency stop*, and C3-*stopping and leaving away*. In addition, we used four numbers taken from the Hong Kong sign language to represent manipulation commands in practical construction. Previous studies widely adopted these gestures (Mazhar et al., 2019; Sharma and Singh, 2021). Notably, the semantics of the designed gesture can be modified to accommodate the users' operation habits in practical applications. The author also acknowledges that it could be beneficial to determine a unified gesture dictionary that defines various gestures and corresponding semantics for different WRC applications. Nevertheless, developing such a gesture dictionary or designing gestures for different construction tasks was out of the scope of this research. Instead, we investigated the feasibility of thermal data-based hand gesture recognition and designed a lightweight recognition algorithm.

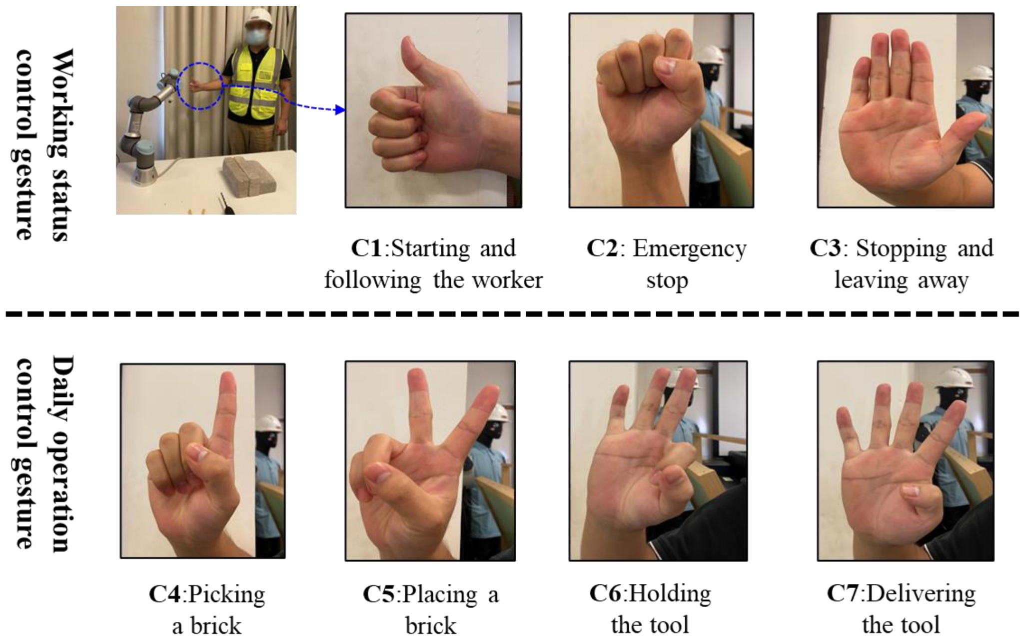


Figure 3.5. Designed hand gestures to represent WRC commands.

3.3.2 Thermal Image Capturing

The advancement of thermographic imaging technologies enables hand signals to be visible in different conditions, such as poor illumination or severe weather (e.g., under fog). To the author’s best knowledge, seldom research in the construction domain has discussed thermal image-based hand gesture recognition. Hence, we created our own datasets using the commercial thermal imaging camera, termly, FLIR ONE PRO. Figure 3.6 shows the FLIR ONE PRO-based thermal image-capturing equipment. This equipment has a sensitivity that detects temperature differences down to 70 mK. The sensing temperature range of FLIR ONE PRO is between −20℃ to 120℃, while its operating temperature is from 0℃ to 35℃. Notably, thermal cameras are different from Near-Infra-Red cameras. The latter uses short-wavelength infrared light to illuminate an interesting area, while the thermal camera use mid- or long-wavelength energy and only sense differences in heat. The author also admits there are numerous types of thermal cameras that have higher resolution performance; however, such equipment is usually expensive. Instead, FLIR ONE PRO is cheap (around HKD 3200), and it is convenient to use since it can be combined with smartphones.

(a) FILR ONE PRO

(b) Thermal image capturing with smart phones

Figure 3.6. FLIR ONE PRO-based thermal image collection.

Ten volunteers (7 males and 3 females) were recruited from the Hong Kong Polytechnic University to develop the thermal image dataset in the indoor environment. The thermal camera was set in front of the subject at a short distance (e.g., around 1m). The author admits that the imaging distance may be longer in real applications. Notably, the focus of this research is to test the feasibility of thermal images in hand signal recognition. Moreover, the thermal radiation attenuation can be ignored in such a short distance, while it should be considered in long imaging distances. Subjects were required to perform pre-designed hand gestures. Static thermal images of hand signals were collected. Notably, the FLIR ONE PRO camera provides five types of color maps: iron, gray, rainbow, saturation, and blue-red blended. In this research, we collected both grayscale and iron color images for each gesture to double the size of the dataset (Breland et al., 2021). Figure 3.7 describes gesture examples of thermal images collected by the FLIR ONE PRO.

Figure 3.7.Gesture examples of collected thermal images.

3.3.3 A Lightweight Model Recognizing Thermal Hand Gestures

In this research, we proposed a lightweight and efficient deep learning model to help construction robots recognize hand signals from thermal images, which was termed as ThermalNet. The main goal is to optimize the trade-off between accuracy and speed in robots with limited computation resources.

We first designed a computationally efficient network in ThermalNet, which consists of a 3×3 convolution (Conv) layer, a rectified linear unit (ReLU) layer, and a 1×1 Conv (Wang et al., 2022c). Moreover, we adopted the structural re-parameterization technique to improve accuracy since the plain model is challenging to reach a comparable level of accuracy performance as the complicated models. Structural re-parameterization aims to modify the structure of CNNs to reduce the number of model parameters and required computational resources while preserving the accuracy of the network. Several re-parameterization methods were proposed, including network pruning, network compression, network expansion, and so on. We adopted the re-parameterization technique proposed by Ding et al. (2021) because it has been shown to result in improved accuracy and is memory economical. Specifically, the main principle is to design a multi-branch architecture for training and a plain architecture for inference and then merge the multi-branch into a single network for inference via parameter transformation. As shown in Figure 3.8, we added a parallel 1×1 Conv branch to enrich the feature space and added batch normalization (BN) operations in the training block. Within the simple algebra, parameters in the training block can be transformed into the inference block. Hence, the re-parameterization operation can lead to improved accuracy while reducing the computational cost and memory footprint, which makes the ThermalNet more practical to be deployed on construction robots and meet the high accuracy and low latency demands in WRC applications.

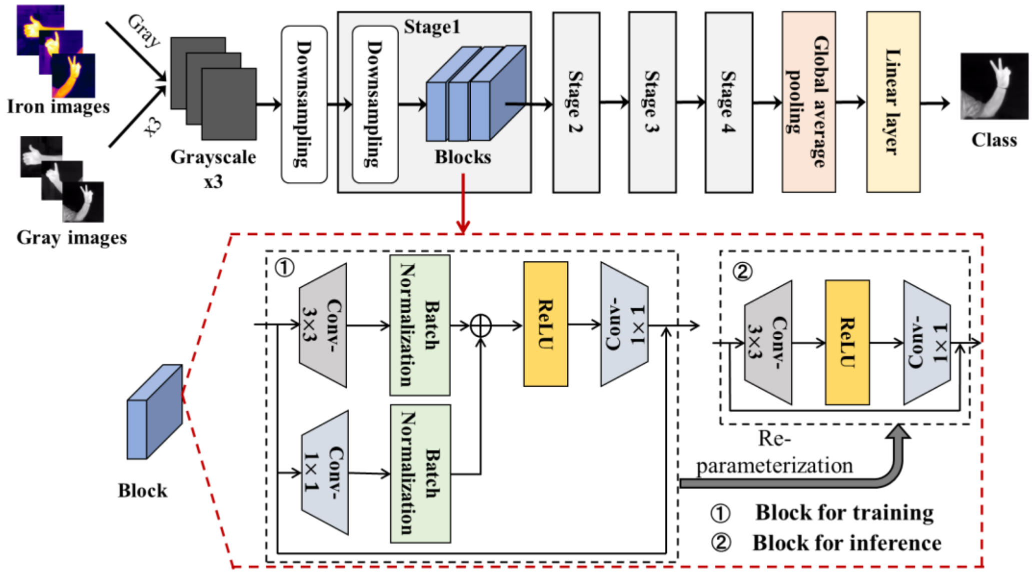


Figure 3.8. The overall architecture of the proposed ThermalNet.

As shown in Figure 3.8, collected iron and gray images were transferred to 3-channel gray images in ThermalNet since the hand shape is more important than the color in our classification tasks. These images with a resolution of 224×224 were firstly changed to images with the 112×112 resolution using the down-sampling module, followed by four stages with the same architecture. Each stage starts at the down-sampling module, followed by several blocks. Specifically, the inference block used the proposed architecture that contains the 3×3 Conv layer, ReLu, and the 1×1 Conv layer. A residual connection was also employed to improve network stability in the inference block. As shown in Figure 3.6, these two branches are integrated together by summing before the ReLU layer. The training block can be represented in Eq.(3.1), where x is the input and y is the output. Conv11 and Conv33 represents the 1×1 Conv and 3×3 Conv respectively.

$$y = x + Conv11(\mathrm{ReLU}(\mathrm{BN}(\mathrm{Conv33}(x)) + \mathrm{BN}(Conv11(x)))) \tag{3.1}$$

The 3×3 Conv can be represented in Eq.(3.2), in which i and j refer to the coordinate number of elements in feature maps respectively. C is the channel number of feature maps. Similarly, the 1×1 Conv was expressed with Eq.(3.3).

$$y^{33}_{(i,j)} = \sum_{i-1}^{i+1}\sum_{j-1}^{j+1}\sum_{c=0}^{c-1} w^{33}_{i,j,c} x_{i,j,c} \tag{3.2}$$

$$y^{11}_{(i,j)} = \sum_{i}^{i}\sum_{j}^{j}\sum_{c=0}^{c-1} w^{11}_{i,j,c} x_{i,j,c} \tag{3.3}$$

As to the parameter transformation process, weights of 1×1 Conv can be transferred into 3×3 Conv by zero-padding positions of i -1 or j -1. That is, we add the 1×1 kernels onto the central point of 3×3 kernel and make other positions of the 3×3 Conv kernel to be zero. The parameter transformation process was represented as follows:

$$w^{\ 33}_{rei,j,c} = \begin{cases} 0, & otherwise \\ w^{11}_{i,j,c}, & \text{if}\,(i,\,j)\ at\ the\ central\ of\ \ 3\times 3\ kernel \end{cases} \tag{3.4}$$

Hence, we combine the 3×3 Conv with 1×1 Conv during the inference process, which can be represented by Eq.(3-5) and Eq.(3.6). In this way, the proposed method can utilize multiple branches in training to enhance the accuracy and ensure the low latency requirement by merging multiple branches into the plain architecture during the inference.

$$y^{11}_{(i,j)} = \sum_{i-1}^{i+1}\sum_{j-1}^{j+1}\sum_{c=0}^{c-1} w^{\ 33}_{rei,j,c} x_{i,j,c} \tag{3.5}$$

$$y^{33}_{(i,j)} + y^{11}_{(i,j)} = \sum_{i-1}^{i+1}\sum_{j-1}^{j+1}\sum_{c=0}^{c-1} (w^{33}_{i,j,c} + w^{\ 33}_{rei,j,c}) x_{i,j,c} \tag{3.6}$$

$$y = x + Conv11(\mathrm{ReLU}(Conv33(x))) \tag{3.7}$$

Finally, the global average pooling (GAP) layer was used to generate the feature map, followed by the linear layer as the head for the classification task. Table 3.1 introduces the description of ThermalNet network with respect to stages, layers, feature size, channel, expand size, and blocks, where k represents kernels and s represents stride.

Table 3.1. ThermalNet architecture specification.

Stages	**Layer**	**Feature size**	**Channel**	**Expand size**	**# Blocks**
Downsampling	Conv k=3 s=2	112×112	8		
Stage 1	Downsampling	56×56	16		
	Block			4	2
Stage 2	Downsampling	28×28	32		
	Block			4	2
Stage 3	Downsampling	14×14	64		
	Block			4	2
Stage 4	Downsampling	7×7	128		
	Block			4	2
GAP		1×1	128		

3.4 Implementation and Experimental Results

3.4.1 Implementation and Training Details

The training and validation process of the recognition algorithms was implemented on an Ubuntu Linux 64-bit operating system. The proposed and benchmark models were coded in Python 3.7 environment with the support of the PyTorch framework and PyCharm IDE. The hardware configuration was listed as follows: an Intel 9700 CPU, 32 G memory, and a single NVIDIA GeForce RTX 3090 GPU.

We hired ten volunteers to develop our own dataset in the classification experiment. The dataset contains thermal hand gestures in different environments and different lighting conditions. As shown in Figure 3.9, thermal images are robust to poor illuminations and complex backgrounds (e.g., different objects). In particular, the thermal camera can still collect human gestures in complete darkness. Moreover, several data augment steps were also used in this study, including gray scaling, flipping, sharpening, and RandAugment (Cubuk et al., 2020). Finally, a total of 19,418 thermal images were collected in the database, in which each person provides images for each gesture under different environment backgrounds, hand orientations, and illumination conditions (e.g., normal lighting, low lighting, complete darkness).

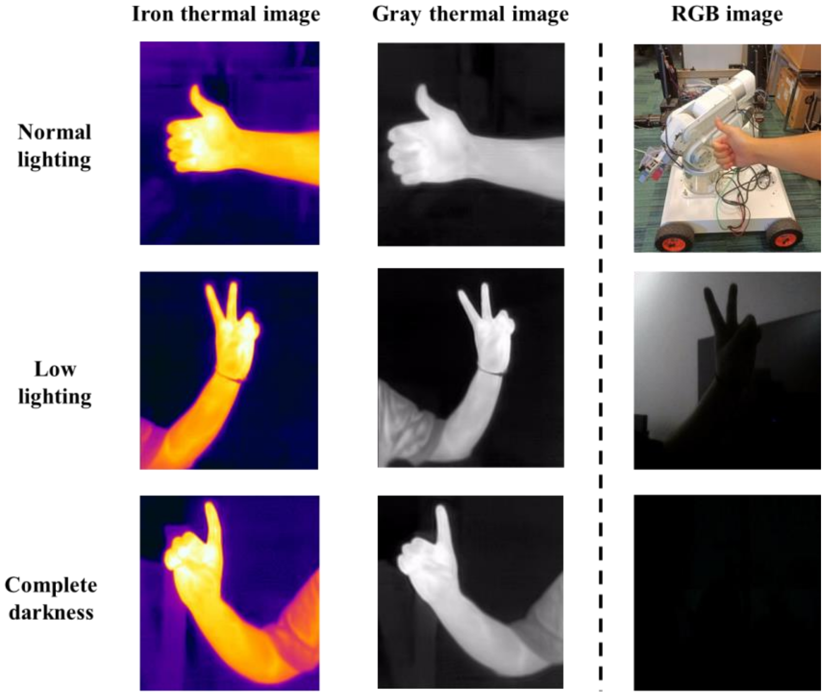


Figure 3.9. An example of collected thermal images in different conditions.

The thermal dataset was divided into the training subset and the test subset. Specifically, images collected from 7 subjects were used as the training data, while images from the other three subjects were used as the test dataset. Some unsatisfied images were removed. Finally, Table 3.2 summarizes the number of samples for each hand signal class in the train and test dataset. Such a strategy can test the generalization ability of the trained model since different people have different body temperatures that may lead to different characteristics in collected thermal data.

Table 3.2. Images of each class in the train and test datasets.

Hand signal class	Train dataset	Test dataset
C1	3382	180
C2	2689	180
C3	3557	180
C4	2354	180
C5	2426	180
C6	2585	180
C7	2425	180
All	19418	1260

During the training process, the learning rate and the batch size are initially set as 0.01 and 256, respectively. Step decay was used as the learning rate scheduler, which drops the learning rate by 0.1 every 30 epochs. Stochastic gradient descent (SGD) with a Nesterov momentum of 0.9 and weight decay of 1e-4 is employed as the optimizer. Figure 3.10 shows the loss reduction along with the training progress. The training for ThermalNet was completed after 90 epochs.

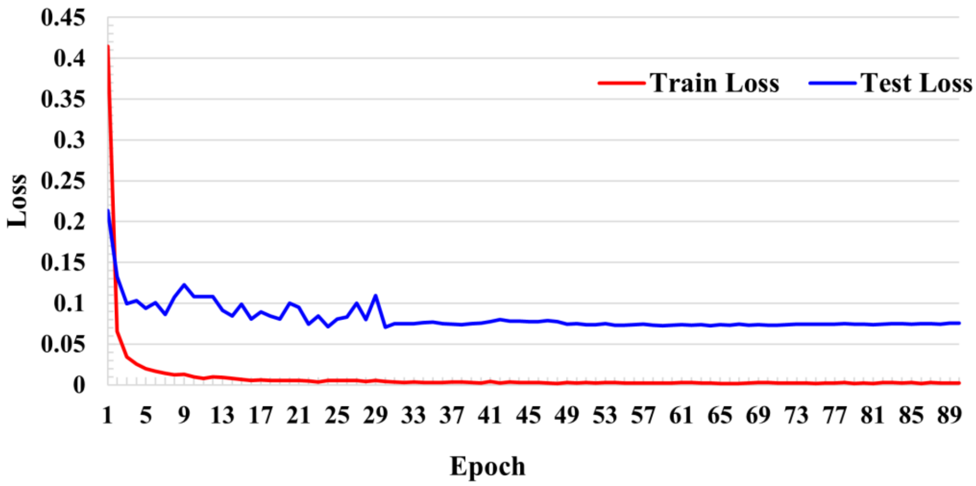


Figure 3.10. The loss reduction along with the training progress.

3.4.2 Experimental Results

The proposed lightweight achieves an average classification accuracy of 97.54% on the test dataset. Figure 3.11 presents the confusion matrix of the proposed model. As shown in Figure 3.11, the ThermalNet obtained the highest accuracy (100%) on the hand signal of C1 (*Starting and following the worker*) and C2 (*Emergency stop*) and got 98% accuracy on gestures of C3 (*Stopping and leaving away*) and C7 (*Delivering the tool*). The lowest classification accuracy of the ThermalNet is 94% on the gesture of C3 (*Holding the tool*).

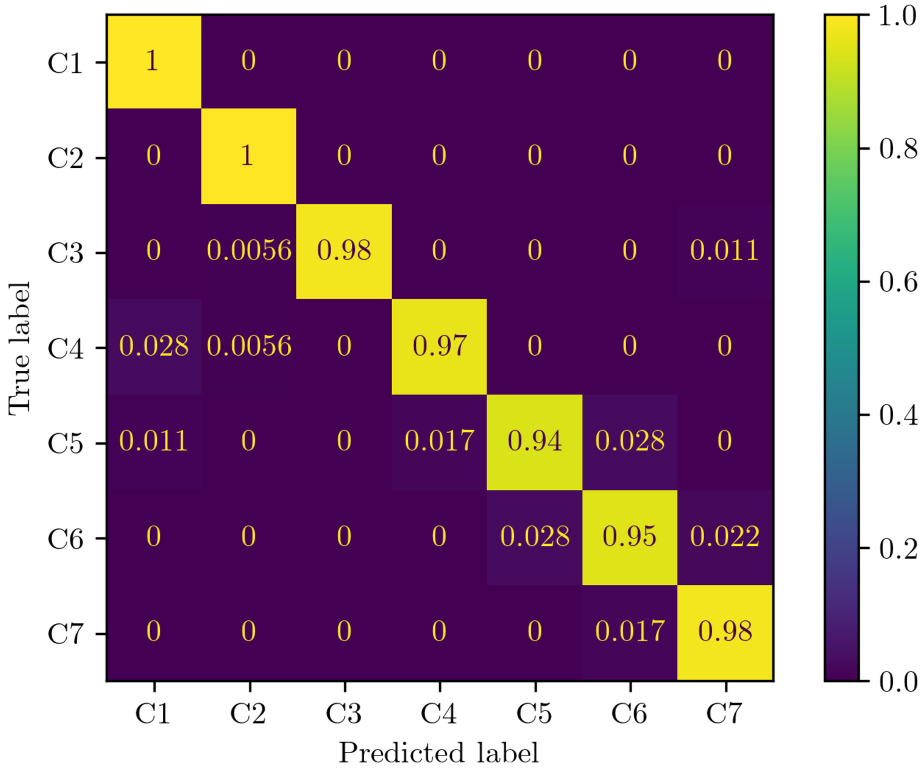


Figure 3.11. Confusion matrix of the proposed ThermalNet.

Moreover, we created heat maps for producing visual explanations of the ThermalNet based on the gradient-weighted class activation mapping technique (Selvaraju et al., 2017). Heat maps help us to know what regions of an image are important to the trained network. As shown in Figure 3.12, the ThermalNet model focused on figure shapes during the hand gesture classifying task. This is consistent with the human perception logic.

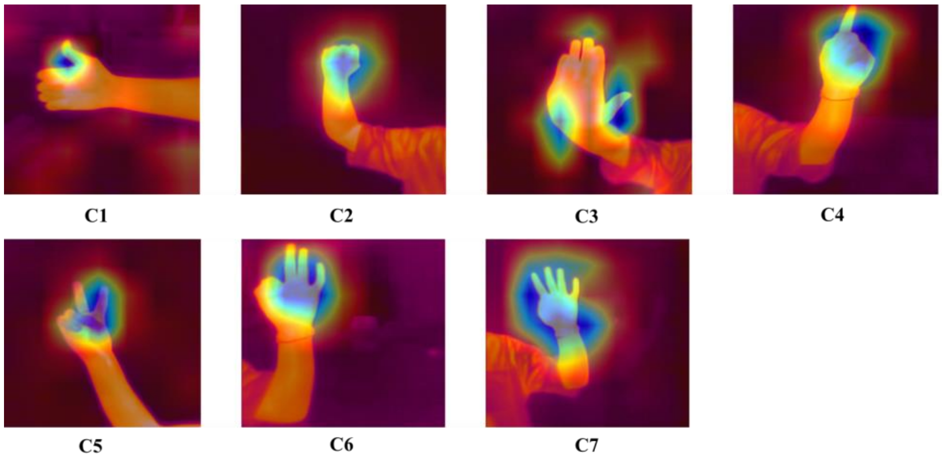
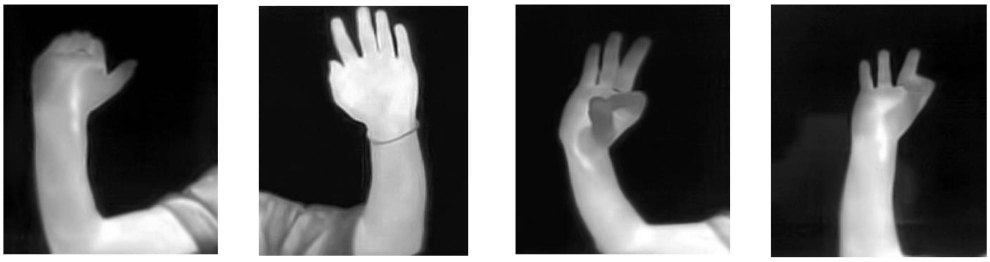


Figure 3.12. Heat map of the proposed ThermalNet.

There were also some inadequacies in the experiment. As shown in Figure 3.13(a), the gesture of C1 was recognized as C2 due to the challenging viewpoints. The shape of the gesture may also affect the result accuracy. For instance, the gesture of C3 was recognized as C7 in Figure 3.13(b). Similarly, the gesture of C6 was wrongly classified as C5 and C7 in Figure 3.13(c) and (d). These failures can be attributed to the following causes: (1) the lightweight backbone has a smaller number of parameters; therefore, the calculation and extraction of features may be insufficient; (2) the same gesture may have different characteristics at different imaging orientations. For example, imaging viewpoints in Figure 3.13(a) affected the classification accuracy.



(a) True:C3; Predict: C2 **(b)** True:C3; Predict: C7 **(c)** True:C6; Predict: C5 **(d)** True:C6; Predict: C7

Figure 3.13. Bad cases of the ThermalNet in hand gesture classification.

3.4.3 Comparative Studies

An ablation study was conducted to evaluate the effectiveness of the re-parameterization technique. Specifically, comparison among the ThermalNet and its counterpart (without the re-parameterization). Table 3.3 presents the results in terms of the Top 1 accuracy among these two networks on ImageNet and our own dataset. As indicated in Table 3.3, results show that the ThermalNet (with the re-parameterization) obtains higher accuracy on these two datasets than its counterpart, which validates the effectiveness of the re-parameterization.

Table 3.3. Ablation study result in terms of Top 1 accuracy.

Method		**Top 1 accuracy on ImageNet**	**Top 1 accuracy on our dataset**
ThermalNet	With the re-parameterization	46.25%	97.54%
	Without the re-parameterization	45.57%	96.43%

Furthermore, we compared our model with state-of-the-art lightweight models to further demonstrate the performance of the proposed model. Currently, MobileNet and ShuffleNet are the most lightweight architectures in mobile applications, including MobileNetV2 (Sandler et al., 2018), MobileNetV3 (Howard et al., 2019), and ShuffleNetV2 (Ma et al., 2018b). Specifically, MobileNetV1 and MobileNetV2 used depth-wise separable convolutions to reduce the needed number of operations and memory. Similarly, ShuffleNetV2 utilized group convolution and channel shuffle operation to reduce parameters. These structures are designed by human experts, while MobileNetV3 adopted the network architecture search method to automatically design the network architecture (Howard et al., 2019). Hence, these three prevailing models were considered due to their excellent performance on the accuracy and latency in mobile applications. All these benchmark methods were trained and tested with the same dataset in the proposed model. Three types of metrics were used to compare the performance of the proposed model with current prevailing lightweight models, termly, Top1 accuracy, latency, and parameters. Notably, we tested the latency performance in two devices, termly, the NVIDIA GeForce RTX 3090 GPU and Raspberry Pi 3 Model B+, because mobile construction robots usually have computational limits in real-world applications. Additionally, the proposed ThermalNet used the structural re-parameterization method and has different architectures in the training and inference model. In real-world applications, we considered the performance of the inference model.

Table 3.4 demonstrates the accuracy and parameters of the proposed ThermalNet with other models. As shown in Table 3.4, our model has fewer parameters (1.8 million), higher accuracy (97.54%), and minimum latency (7.98ms in GPU and 72.31ms in Raspberry Pi). The comparative results demonstrate the supervisory of the proposed ThermalNet to state-of-art lightweight models. Specifically, our model achieved the highest accuracy with the lowest latency in HGR. Hence, our model can facilitate the safety performance of real-world WRC applications by optimizing the trade-off between accuracy and latency, achieving low-latency classification even in mobile platforms with limited computational resources.

Table 3.4. Comparative results on accuracy, latency, and parameters.

Methods	Parameters/M	Top 1 Accuracy	NVIDIA 3090	Raspberry Pi
MobileNetV2	2.3M	95.87%	8.50ms	119.06ms
MobileNetV3	4.2M	95.95%	12.40ms	88.87ms
ShuffleNetV2	1.3M	97.06%	11.98ms	86.52ms
ThermalNet (Training)	2.0M	97.54%	8.53ms	95.77ms
ThermalNet (Inference)	**1.8M↓**	**97.54%↑**	**7.98ms↓**	**72.31ms↓**

3.5 Discussion

In this research, we proposed robust hand gesture recognition methods for on-site WRC applications using the thermal image. A lightweight model was designed to detect hand signals with high accuracy and speed on resource-constrained mobile platforms, e.g., the mobile robot. Experimental results demonstrate the feasibility and superiority of the proposed method.

3.5.1 Contributions

This research has several theoretical contributions. First, this could be one of the first studies that discuss workers' intentions in WRC by recognizing hand signals from thermal images. A new imperative objective for real-world WRC is to assure the safety of human co-workers even in extreme environments (e.g., cloudy, dusty, poor lighting) as construction robots are gradually adopted to job sites to work with humans. Our attempts can provide a robust method to obtain workers' commands and then enhance the safety performance in real WRC applications. For example, even in completely dark conditions, the robot can avoid potential safety issues (e.g., collisions) by robustly understanding worker hand signals (e.g., stopping).

Second, the designed ThermalNet model provides a lightweight and efficient algorithm for construction stakeholders to implement in real-world applications. Most existing studies focused on enhancing the accuracy performance, making the network architecture deeper and more sophisticated. These works neglected the computational efficiency that is important to operate on low-powered mobile devices. High latency was not allowed in actual WRC applications in the perspective of guaranteeing workers' safety. Our proposed model utilized the structural re-parameter method to enhance the accuracy performance and reduce the latency. Experimental results indicate that our inference model only has 1.8M and achieves 97.54% accuracy with a latency of 7.98ms on GPU and 72.31ms on Raspberry Pi. The comparative study demonstrates the superiority of the proposed model to state-of-the-art lightweight models.

3.5.2 Limitations

This research also has some limitations. First, the proposed method was designed to recognize static gestures because the main aim of this research is to test the feasibility of thermal image-based hand gesture recognition. In real-world applications, workers' hand signals may exist for several seconds, which are termed dynamic gestures. Compared with static gestures, dynamic gestures are closer to human expression habits. For the recognition of dynamic gestures, not only hand postures and shapes but also spatial displacement and spatiotemporal correlation should be considered. Future studies can design methods to recognize consecutive gestures from thermal videos. Moreover, we only designed 7 simple gestures in this research. Future studies can investigate how to design natural gestures as well as corresponding semantics for different WRC tasks.

Second, experiments are conducted in the laboratory environment to test the feasibility. The proposed methods may meet some technical difficulties in practical construction sites. For example, thermal radiation may reduce significantly under the long imaging distance or traversing obstacles such as glass and foil. Moreover, it is challenging to recognize accurate signals when there are other workers. Although thermal images are resistant to environmental disturbances, they usually have low resolution and poor texture, lack visual color patterns, and have blurry contours. The fusion of RGB and thermal data could be a possible solution to tackle this limitation.

Third, this research limits our research scope to the hand signal understanding that acts as the first step in WRC applications, neglecting the robotic execution and control. Future studies combine our method with robotic execution modules to further test the feasibility of the proposed thermal-based method and the ThermalNet in real-world WRC experiments.

3.6 Chapter Summery

This chapter reports a novel framework for on-site WRC applications that integrates thermal imaging information to achieve robust hand gesture recognition even in challenging environments (e.g., dim light). Specifically, seven classes of hand gestures are designed to represent normal instructions of workers. A thermal dataset is developed under different lighting conditions. Additionally, a lightweight model for resource-constrained mobile construction robots is designed in this chapter. Experimental results demonstrate that thermal-based solutions can still capture human hand signals in complete darkness, while the developed model can achieve higher accuracy with fewer parameters. Notably, the comparative study indicated the superiority of our model on the accuracy, latency, and model size over the widely used lightweight algorithms, termly, MobileNetV2, ShuffleNetV2, and MobileNetV3.

CHAPTER 4 Multi-robot Collaborated QDI Using A Hierarchical Federated Learning (FL) Method

4.1 Introduction

Robotics is seen as a promising paradigm for bypassing human unpredictability and inability in quality defect inspection (QDI) tasks. Specifically, robots can extend the reach of human inspectors to confined and risky spaces, such as bridge decks, while protecting them from associated safety risks (Tian et al., 2022). For example, remotely operated vehicles were used to collect underwater cracks in dams (Li et al., 2022b), and quadruped robots are suitable for data collection tasks in construction environments (Halder et al., 2023). These robots, integrated with powerful deep learning (DL) algorithms, should have the mobility ability to perform quality inspection in specific areas and extract potential defects from the raw data.

However, due to data leakage and privacy concerns, quality defect data usually exists as isolated "data islands" and cannot be utilized to support the training of DL networks for robotic devices. Some studies used the transfer learning (TL) technique to reduce the dependency on vast amounts of training data (Dais et al., 2021; Hou et al., 2020). However, the performance of TL is usually limited due to the significant difference between the prevailing image dataset (ImageNet) and quality defect images. Moreover, different types of projects may have different defect types. Even with the same defect, different projects may have different characteristics. For example, cracks in the dataset of (Chun et al., 2021) are transverse and cross cracks with rough backgrounds and holes, while the crack data in (Xu et al., 2019) contains linear and alligator cracks with a clean background. Previous DL models adopting the centralized training strategy may suffer from the generalization problem in practical applications, especially in a data-scarce environment.

Against this backdrop, this chapter introduces a hierarchical FL framework for QDI, which allows various construction robots from different projects collaboratively train the DL model via parameter aggregation instead of dataset aggregation. The proposed method allows robots to utilize the power of big data while preventing potential data security and leakage risks. Three objectives are designed accordingly: (1) to design a three-fold federated learning (FL) framework for construction robot-enabled QDI; (2) to develop a lightweight model for federated training at robot devices; and (3) to test and validate the feasibility of the proposed framework within the case of image-based crack segmentation.

The remainder of this chapter is organized as follows: Section 4.2 introduces the recent works of deep learning-based defect detection and describes basic knowledge of FL. Section 4.3 presents the proposed hierarchical FL framework, followed by the implementation details with a case study (Section 4.4). Section 4.5 shows experimental results, while section 4.6 highlights the differences between this research and previous works to showcase its novelty and discusses its limitations. Section 4.7 summarizes this chapter and outlines future research directions.

Two challenges must be considered when developing a construction robot-enabled quality inspection system. First, current deep learning (DL) models tend to develop deeper and more sophisticated networks in pursuit of ever-increasing accuracy (Li et al., 2022b). These models with heavy architectures and massive parameters require high computational resources on hardware (e.g., graphics processing units). However, mobile construction robots usually have limited computational resources and cannot efficiently (low latency) execute the defect recognition task (Wu et al., 2023a).

4.2 Research Background

4.2.1 Prevailing Deep Learning Algorithms for QDI

The breakthrough of deep learning (DL) algorithms enables robots to automatically extract defects from the raw data. Different types of sensors were used in defect detection, such as ground-penetrating radar (Zhang et al., 2022), laser scanning (Guo et al., 2020), and visual cameras (Ma et al., 2021). Among these modalities, visual images are widely used in defect detection, including cracks (Ai et al., 2023; Dung and Anh, 2019), leakage (Li et al., 2021b), and steel damage (Kim et al., 2021b). Hence, this section reviews the prevailing DL algorithms for image-based crack detection.

Convolutional neural networks (CNNs) have significantly improved the performance of several computer vision tasks, including defect recognition, detection, and segmentation (Zhong et al., 2019). CNN architectures typically consist of several blocks and a linear layer, with each block containing a conventional layer, an activation layer, and a pooling layer. For example, Cha et al. (2017) developed a CNN-based classifier to detect concrete cracks from images, achieving an accuracy of 98%. Faster Region-based CNN

(Fast R-CNN) was proposed to enhance the accuracy of R-CNN, and Faster R-CNN was developed further to improve the accuracy performance of Fast R-CNN by introducing the region proposal network (RPN) to generate object proposals. Cha et al. (2018) utilized the Faster R-CNN method to detect concrete cracks and steel corrosion. Kong et al. (2021) used dual-scale CNN to detect cracks from images and match the same cracks according to measured crack parameters. Some other studies used the transfer learning strategy to enhance training efficiency and accuracy (Li et al., 2022b; Savino and Tondolo, 2021).

Previous works mainly focused on detecting cracks from images. However, engineering practices require crack features such as length, width, and branches. Hence, recent works have focused on pixel-wise crack segmentation (Hsieh and Tsai, 2020). For example, encoder-decoder fully convolutional networks (FCNs) were widely used to measure diverse cracks at the pixel level (Dung and Anh, 2019). FCN uses the same feature extraction backbone as traditional CNN models, but the fully connected layers are replaced with fully convolutional layers to provide a spatial map for each class. VGG16, VGG19, and ResNet50 were frequently used as backbone networks. U-Net was another prevailing segmentation network in which the encoder extracts features by convolution and pooling operations, and the decoder repairs the detailed features by multi-scale feature fusion, up-sampling, etc. (Liu et al., 2019). To further enhance the segmentation performance of tiny cracks, Chu et al. (2022) introduced a dual attention module to separate the tiny cracks from the background. Recently, the Transformer architecture obtained excellent results on computer vision applications since it can capture global semantic information. For example, Shamsabadi et al. (2022) employed the vision transformer(ViT) framework in the crack detection task. Wang and Su (2022) proposed a crack segmentation algorithm that use a hierarchical Transformer as the encoder and a top-down pathway with lateral connections as the decoder. Zhou et al. (2023) integrated Swin Transformer and CNN in tunnel lining crack identification. In summary, numerous DL models were proposed for crack detection and segmentation, which achieved outstanding accuracy performance.

4.2.2 FL Knowledge and Related Works in the Construction Industry

Federated learning (FL) is a trendy technology that alleviates the constraints of data availability and data privacy, fully discovering and amplifying the big data's value (McMahan et al., 2017). FL is first proposed by Google (Konečný et al., 2016), and it provides a promising method to collaboratively train the model without averaging data (Banabilah et al., 2022). Figure 4.1 introduces training procedures of the cloud-based FL, including three steps: (1) local model calculation, (2) model aggregation, and (3) model update. Specifically, the central server sends a global machine learning model to all connected devices as the initial model. Then, each client trains the initial model with the local data. Once the local model is trained, the updated parameters of each model will be sent to the central server for aggregation and updating of the global model. A training round of FL is completed when the global model is updated. The training will end when the model achieves a certain desired performance.

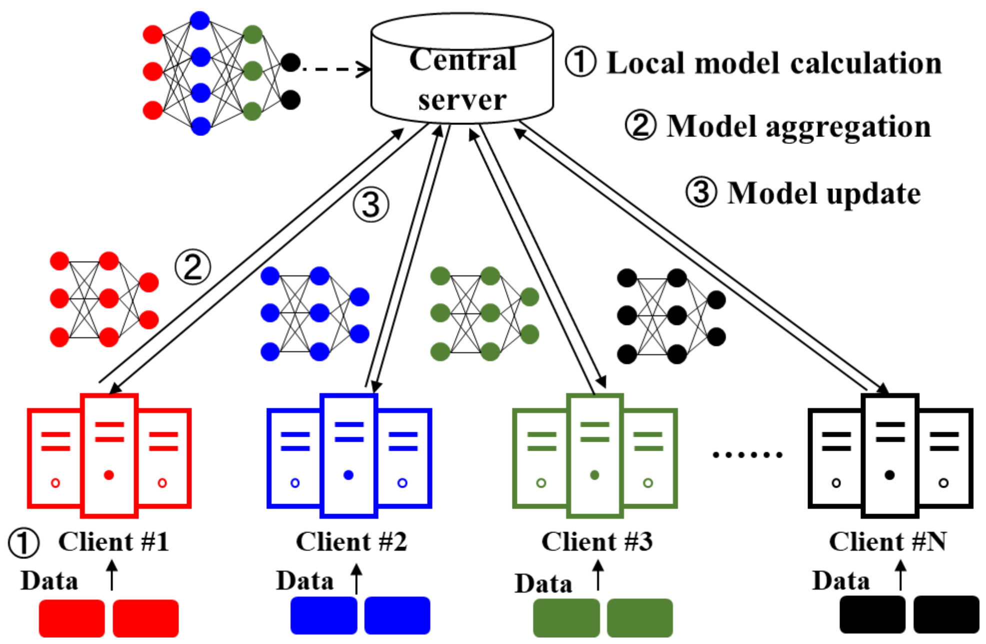


Figure 4.1. Cloud-client FL and its training procedure.

FL procedures can protect users' privacy, which has been widely used in scenarios involving confidential data (Li et al., 2020). The construction industry also involves private data, such as neurophysiological signals (Xing et al., 2020), facial features, and workers' body postures (Yu et al., 2019). Construction quality defect is also private information, and stakeholders may refuse to share the defect data. In this case, FL enables construction robots from different projects to collaboratively train the quality defect detection/segmentation model without data aggregation. However, very few attempts have been made to explore FL potential in the construction domain.

Li et al. (2021a) first used FL to monitor workers' safety and health without generating data privacy concerns. Then, considering that finding a robust central server may be difficult, the author combined the blockchain with FL, in which parameters were aggregated in a peer-to-peer network (Li et al., 2023). These two works provide insightful findings and can inspire more discussions on FL-based construction applications. Unfortunately, existing works adopt the typical server-client architecture, in which the communication between clients and the cloud server is very slow, especially when there are vast amounts of clients involved in the FL system (Liu et al., 2020b). Some studies proposed edge-based FL methods in which a server was placed at the proximate edge to avoid network congestion issues and reduce latency (Wang et al., 2019a; Wang et al., 2022d). However, edge-based FL has a limited number of clients and cannot provide the massive datasets needed for a high-performance deep learning model. Hence, this study proposes a hierarchical FL framework to help construction robots train the defect detection model collaboratively.

4.3 Proposed Framework

This study considers a construction robot enabled quality inspection system consisting of a cloud server, I edge servers deployed at different construction projects, and J on-site construction robots (shown in Figure 4.2). Giving a specific task, e.g., crack segmentation from images, we aim to train a deep learning (DL) model with the abundant data $\left(D_{11}, D_{12}, ..., D_{1j}, ..., D_{i1}, D_{i2}, ..., D_{ij}\right)$ collected by all robots in I construction projects. Traditional methods need to put all data together to train the model in a centralized manner, suffering from data privacy and security concerns. Thus, we propose a three-fold hierarchical FL framework to help multi-construction robots collaboratively train the DL model without compromising user data privacy via leveraging the merits of federated learning (FL) and edge computing. The FL training details, as well as the proposed DL model, were introduced in the following sections.

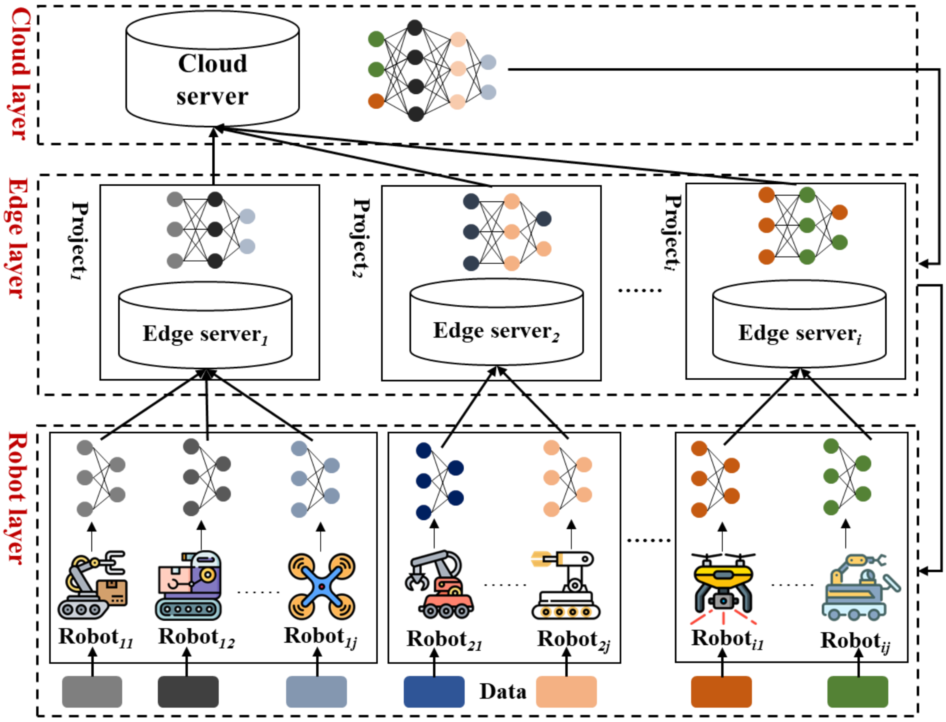


Figure 4.2. Hierarchical FL framework for multi-robot based QDI.

4.3.1 Cloud-Edge-Robot FL Process

As shown in Figure 4.3, the proposed hierarchical FL method contains three stages: (1) Construction robot initialization; (2) edge FL; and (3) cloud FL.

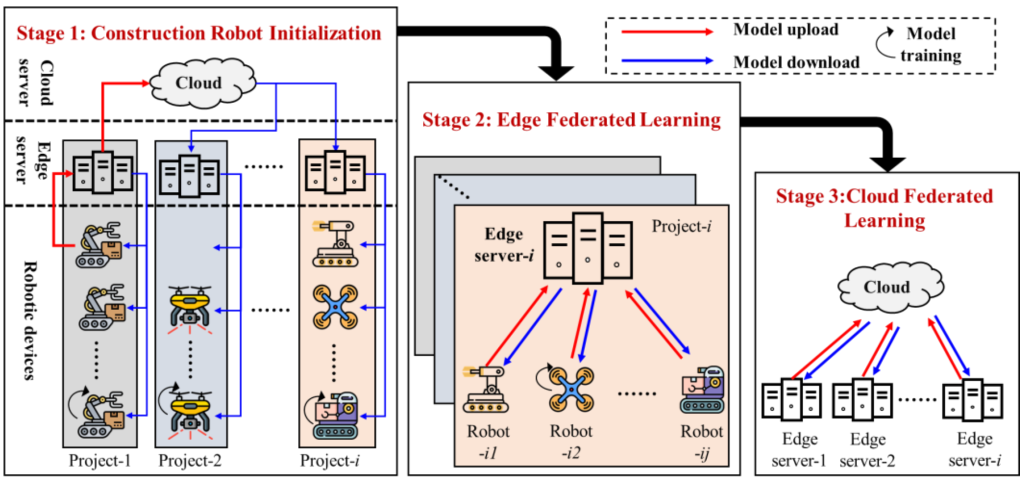


Figure 4.3. Cloud-Edge-Robot FL process.

Details of these three stages were introduced as follows:

- **Stage 1: Construction Robot Initialization.** In a standard FL scenario, the central server broadcasts a randomly initialized model to each client. However, the random initialization strategy usually led to slow convergence. In this research, we adopted the transfer learning strategy to avoid the above issue. Specifically, the aforementioned randomly initialized model (e.g., W_{11}) can be set by the pretrained model of one of the robot devices (e.g., R_{11}) which would be transported to the cloud server and the other robot devices (e.g., R_{12} … , R_{1j}) within the same project via its connected edge server (e.g., E_1). The cloud server will further send W_{11} to all robotic devices (e.g., R_{21}, … , R_{2j} , …, R_{i1}, …, R_{ij}) via their correspondingly connected edge servers (e.g., E_2, E_3, …., E_i) to initialize their local model. Finally, all having been initialized robots will update their local model $\omega_{t,ij}$ based on the local dataset.

- **Stage 2: Edge Federated Learning.** Edge server (E_i) gets its local model by aggregating model parameters of the corresponding set of robotic clients (e.g., R_{i1}, R_{i2}, … , R_{ij}), and then broadcasts the updated model to all connected robots through wireless communication. With a few rounds of parameters exchange, the edge server develops an edge local DL model that has good performance of quality defects in the local project. The federated averaging algorithm (FedAvg) was used to update the edge local model in each round, which combines local stochastic gradient descent (SGD) on each robotic client with the edge server that performs iterative model averaging (McMahan et al., 2017). The model aggregation process in edge servers can be represented in Eq. (4.1), in which J_i represents the number of connected robots of the edge server. Loss of each client's model are monitored at the end of each round.

$$\omega_{e,i} = \frac{1}{J}\sum_{j=0}^{J_i}\omega_{t,ij} \tag{4.1}$$

- **Stage 3: Cloud Federated Learning.** The cloud server obtains the global model by aggregating model parameters still based on FedAvg policy from all connected edge servers, which can be represented by following Eq. (4.2), where *I* means the total number of edge servers connected to the cloud server.

$$\omega_g = \frac{1}{I}\sum_{i=0}^{I}\omega_{e,i} \tag{4.2}$$

Additionally, Algorithm 1 depicts the holistic mechanism of the proposed hierarchical FL, in which different construction robots train the model for quality defect detection with the coordination of edge servers and a cloud server by leveraging FL.

Algorithm 1: Hierarchical FL

Input: $\mathbf{D}_{ij}$, where i = $1, 2, \cdots, I$, and j = $1, 2, \cdots, J_i$

Output: cloud model parameters ω_g

initialize client randomly $\omega_{t,11} = \omega^{\mathrm{rdm}}$

for *epoch* $k = 1, \cdots, K_{\max}$ **do**

  model updates: $\omega_{t,11} \leftarrow \{\mathrm{D}_{11}\}$

end

initialize devices: $\omega_{t,12}=\cdots=\omega_{t,IJ_I}=\omega_{e,1}=\cdots=\omega_{e,I}=\omega_g=\omega_{t,11}$

for *epoch* $n = 1, \cdots, N_{\max}$ **do**

  for *edge* $i = 1, \cdots, I$ ***in parallel*** **do**

    for *agent* $J = 1, \cdots, J_I$ ***in parallel*** **do**

      for *round* $\tau = 1, \cdots, edge\_fed\_interval$ **do**

        model updates: $\omega_{t,ij} \leftarrow \{\mathrm{D}_{ij}\}$

        if $\tau == edge\_fed\_interval$ **then**

          return $\omega_{t,ij}$ to the edge server

        end

      end

    end

    executes $\omega_{e,i} = \frac{1}{J_I}\sum_{j=1}^{J_I} \omega_{t,ij}$

  end

  if $i \ \% \ cloud\_fed\_interval == 0$ **then**

    cloud server executes $\omega_g = \omega_{e,1} = \cdots = \omega_{e,I} = \omega_{t,11} = \cdots = \omega_{t,IJ_I} = \frac{1}{J_I}\sum_{i=1}^{I} \omega_{e,i}$

  end

  else

    executes $\omega_{e,i} = \cdots = \omega_{e,iJ_i} = \omega_{e,i}$, where i = $1, 2, \cdots, I$

  end

end

4.3.2 Crack Segmentation Network Design

This section shows a lightweight crack segmentation model termed CrackNet. The principle of the CrackNet design is to significantly reduce network parameters and inference time without compromising accuracy, aiming for reduce the communication cost of the federated training process. Figure 4.4 describes the architecture of the proposed crack segmentation network. Specifically, we built our model based on the bilateral segmentation network (BiSeNetV2) (Yu et al., 2021). BiSeNetV2 can optimize the trade-off between the accuracy and inference speed by treating spatial details and categorical semantics separately with two branches: (1) the Detail Branch (DB), and (2) the Semantic Branch (SB). To further reduce the model size, we replace the DB with the Landmark Branch (LB). The design principle of LB is to extract salient features or landmark features of crack images though using max pooling (kernel=2, stride=2) and convolutional (Conv) operations, which consists of the human perception process. Specifically, human experts mainly concentrate on salient features (e.g., crack sizes, types, colors) in visual inspections.

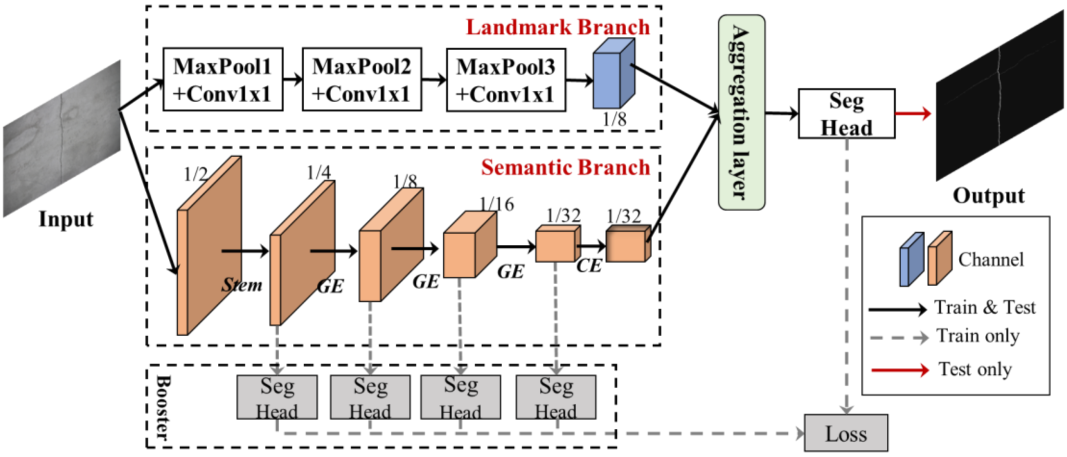


Figure 4.4. Architecture of the proposed CrackNet for crack segmentation.

The instantiation of the proposed crack segmentation network is introduced in Table 4.1. The instantiation of the LB contains three stages, and each stage contains the MaxPool2d and Conv2d operations. Each stage has numerous operations that contain a kernel size k, stride s and output channels c, repeated times r. e is the expansion factor for expanding the channel number of the operation. The SB was used to obtain the large receptive field, including the Stem blocks, gather-and-expansion (GE) layers, and the context embedding (CE) layer. Details of SB components as well as the aggregation layer can be found in (Yu et al., 2021).

Table 4.1. Instantiation detail of the proposed crack segmentation network.

Stage	Landmark Branch					Semantic Branch						Output
	operations	***k***	***c***	***s***	***r***	***operations***	***k***	***c***	***e***	***s***	***r***	
Input	-	-	-	-	-	-	-	-	-	-	-	320×320
S1	MaxPool	2	3	2	1							160×160
	Conv	1	32	1	1	*Stem*	3	16	-	4	1	160×160
S2	MaxPool	2	32	2	1							80×80
	Conv	1	64	1	1							80×80
S3	MaxPool	2	64	2	1	*GE*	3	32	6	2	1	40×40
	Conv	1	128	1	1	*GE*	3	32	6	1	1	40×40
S4	-					*GE*	3	64	6	2	1	20×20
						GE	3	64	6	1	1	20×20
S5	-					*GE*	3	128	6	2	1	10×10
						GE	3	128	6	1	3	10×10
						CE	3	128	-	1	1	10×10

4.4 Implementation with the Case of Crack Segmentation

4.4.1 Crack Dataset Development

We used seven open-access crack datasets for testing the feasibility of the hierarchical federated learning (FL) framework. These datasets include crack images from civil engineering projects, such as bridges, concrete walls, pavements, and tunnels, and have pixel-wise annotations (segmentation masks) for each image. Table 4.2 presents detailed information on used open-access crack datasets.

Table 4.2. Open-access crack segmentation datasets used in this research.

Dataset	**Reference**	**Building type**	**Size**
3_Ren	Ren et al. (2020)	Tunnels	919 images with 512 × 512 pixels
5_Yang	Yang et al. (2018)	Pavements and walls	776 images with different pixels
DeepCrack	Liu et al. (2019b)	Asphalt and concrete buildings	443 images with 544 × 384 pixels
Sylvie	Amhaz et al. (2016)	Pavements	157 images with 256 × 256 pixels
Eugen	Yang et al. (2020b)	Asphalt walls	47 images with different pixels
Volker		Walls	842 images with different pixels
Forest	Shi et al. (2016)	Pavements	90 images with different pixels

In order to demonstrate the proposed FL method, we assume that there are seven construction robot clients, three edge servers, and one cloud server. Table 4.3 introduces the data allocation among the seven clients. Crack data within each client is similar; however, no client can be representative of all datasets. Such non-Independently

Identically Distribution (IID) and unbalanced data distribution are consistent with QDI practices because different building projects are likely to suffer different types of crack defects. For example, there are micro-cracks and linear cracks in Ren et al. (2020), while cracks in Yang et al. (2020b) tend to be horizontal, longitudinal, and crocodile ones. Implementation details are presented in the following section.

Table 4.3. Data allocation in the FL experiment.

Edge server	**Robotic clients**	**Dataset**	**Training Samples**	**Testing Samples**
Edge #1	#1	3_Ren	735 images	184 images
	#2	5_Yang	622 images	154 images
Edge #2	#3	DeepCrack	370 images	73 images
	#5	Eugen	40 images	7 images
	#7	Forest	84 images	16 images
Edge #3	#4	Sylvie	131 images	26 images
	#6	Volker	702 images	140 images

4.4.2 Implementation Setting and Training Details

The experimental environment was conducted in Ubuntu 20.04.1 system. The configurations of the computing machine and development tools are presented in Table 4.4.

Table 4.4. Experimental configurations of this research.

Configurations	Specifications
CPU	AMD Ryzen 9 3900X 12-Core Processor
GPU	NVIDIA GeForce 3090
RAM	Kingston 32G
Deep learning framework	PyTorch @ 1.13.0
CUDA	11.6
CUDNN	8302

In FL, each robot client trains the crack segmentation model locally and then weighted model averaging was conducted at edge servers and the cloud server. The Adaptive Moment Estimation (Adam) was chosen as the optimizer. Related hyperparameters are presented in Table 4.5. Moreover, data augmentation techniques were used to make the training datasets richer, such as flip, translation, and rotation. Moreover, all images were adjusted to the fixed size 320×320 to make it possible to train or test together.

Table 4.5. Hyperparameters used in different training strategies.

Hyperparameters	Centralized learning	FL
Learning rate	1e-5	0.003
Batch size	32	32
Pretraining epoch	-	100
Epoch	500	500
Edge Fed interval	-	1

Cloud fed interval	-	1
Adam betas	(0.9, 0.999)	(0.9, 0.999)
Adam Weight Decay	0	1e-4

4.4.3 Evaluation Metrics

The intersection over union (IoU), Precision, Recall, F1 and Area Under Curve (AUC) of the Precision-Recall (P-R) curve are used to evaluate the model's segmentation performance on test dataset. IoU calculates the percentage overlap between the actual and predicted segmentation masks. As a result, the higher the IoU value, the better the proposed model's crack segmentation ability. Considering that the Precision and Recall travel in opposite directions in some circumstances, we used the F1 score to properly evaluate the model's performance. Moreover, AUC (Area Under the Curve) of the PR-curve was also adopted as the evaluation metric since the positive class (crack) and the negative class (background) are significantly imbalanced in the crack segmentation task. Furthermore, the inference time and model parameters were used to assess the proposed model's lightweight degree.

$$\text{IoU} = \frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{FP_i + TP_i + FN_i} \tag{4.3}$$

$$\text{Precison} = \frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{FP_i + TP_i} \tag{4.4}$$

$$\text{Recall} = \frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{FN_i + TP_i} \tag{4.5}$$

$$\text{F1} = \frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{FN_i + TP_i} \tag{4.6}$$

Adopted metrics were measured by the Eq. (4.3, 4.4, 4.5, 4.6), in which FP is the number of background pixels recognized as a crack, TP represents the number of crack pixels predicted as a crack, TN represents the number of background pixels detected as the background, and FN is the number of crack pixels recognized as the background. In our research, background is labelled as 0 and crack is labelled as 1 in masks included in both training and test datasets. N represents the total number of samples in the test dataset.

4.5 Experimental Results

Based on above configurations, several experiments were conducted to evaluate the performance of the proposed hierarchical federated learning (FL) method, including (1) the comparation between the designed CrackNet and other prevailing segmentation models; (2) the comparation with the individual learning strategy; and (3) the comparison with typical FL methods.

4.5.1 Comparison between CrackNet and other segmentation models

Aiming to demonstrate the lightweight performance of the proposed model, we compare the CrackNet with other state-of-the-art crack segmentation algorithms, including the SegNet (Badrinarayanan et al., 2017), DeepLabv3 (Chen et al., 2017), and BiSeNetV2 (Yu et al., 2021). These networks were implemented with the same dataset and environment. Table 4-5 shows the comparison results based on IoU, precision, recall, F1, inference time, and model parameters. As indicated in Table 4-6, our model obtains comparative performance on IoU (35.64%), precision (40.30%), recall (78.19%), F1

(50.34), and inference time (0.04862s), while it has clear advantages in terms of model parameters (14.8 M).

Table 4.6. Comparison with the prevailing crack segmentation algorithms.

Method	**IoU(%)**	**Precision(%)**	**Recall(%)**	**F1**	**Inference time (s)**	**Parameters (M)**
SegNet	43.04	47.15	85.31	58.32	0.05931	117.9
DeepLabv3	32.49	38.51	70.78	46.87	0.05406	134.3
BiSeNetV2	24.78	33.70	55.80	36.93	0.05521	21.0
CrackNet	35.64	40.30	78.19	50.34	0.04862	14.8

The P-R curve with AUC results also shows the outstanding performance of CrackNet (shown in Figure 4.5). The higher AUC value indicates a better model performance. Although the performance of our proposed model is a little worse than SegNet, our model parameters are just one-tenth of it. This is important for deploying the model in mobile construction robots with limited computational resources. Moreover, the reduction of model parameters also decreases communication costs in FL training processes. Huge model sizes can result in slower training times and may prevent the model from converging to an optimal solution. BiSeNetV2 has a similar model size to our model; however, our model (AUC=0.6254) obtains better performance than BiSeNetV2 (AUC=0. 4371).

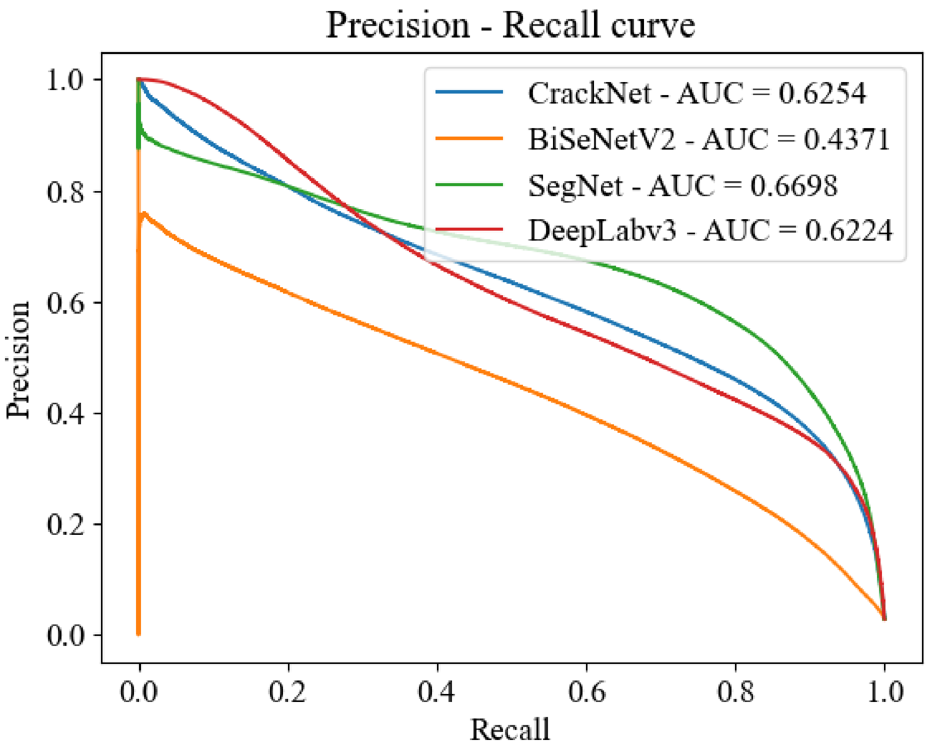
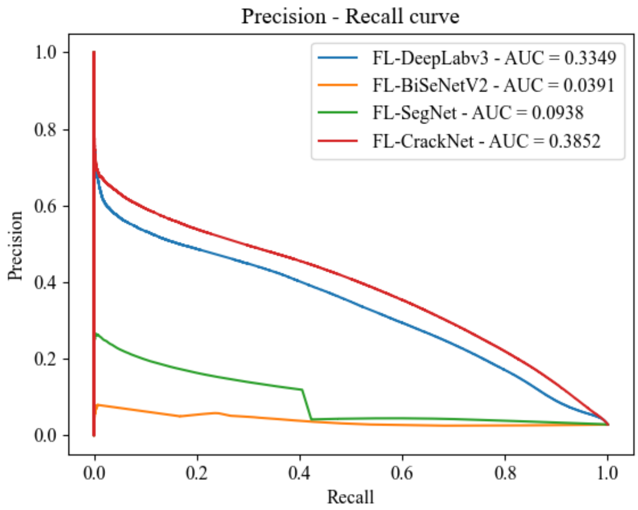
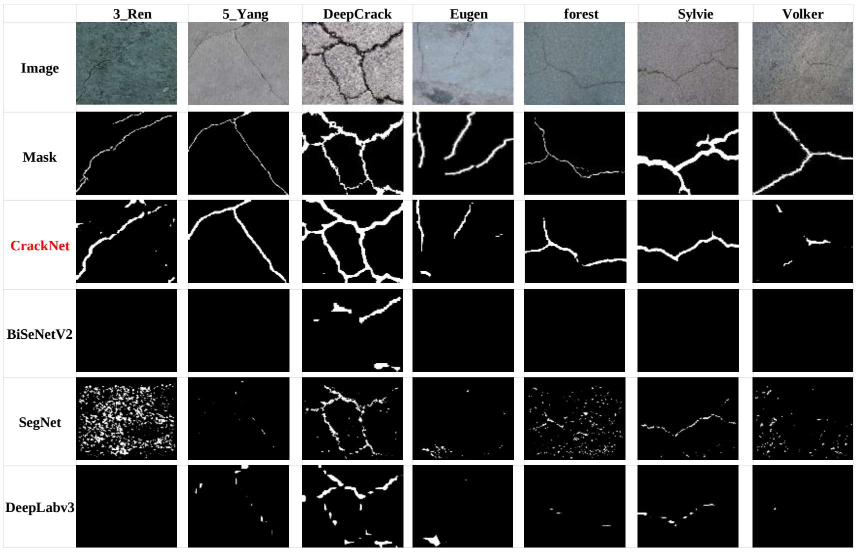


Figure 4.5. PR-curve of the CrackNet and other segmentation models.

We also compared their performance in FL environments. For example, FL-CrackNet means that CrackNet was adopted as models in the hierarchical FL training process. Figure 4.6 presents the AUC results of these four models in FL environments. As shown in Figure 4.6 (a), our model achieved the best performance with AUC=0.3852 compared with all other benchmarks. Figure 4.6 (b) also presents some representative results of different segmentation models.



(a) PR-curve



(b) representative results of different models

Figure 4.6. Segmentation results of different models in the FL environment.

4.5.2 Comparison between Individual Learning and FL

In this section, we use CrackNet as the baseline to compare federated learning (FL) with individual learning (IL) strategies. In this case, we assumed that there are seven robotic clients coming from three projects. Notably, robots in the same project can share their data, while robots in different projects will not share the data, which is consistent with construction practices. Hence, IL represents that each project was required to train the model based on its own data. That is, the crack segmentation model should be trained at the edge level in IL, while FL means that all clients participate in training. Figure 4.7 shows the comparison results between FL and IL. As shown in Figure 4.7, the proposed hierarchical FL achieved high IoU and F1 score than IL using data from the edge #1, #2, #3. This is because cloud server meets the feature of datasets of all robotic clients while edge servers just involve datasets of part of robotic clients.

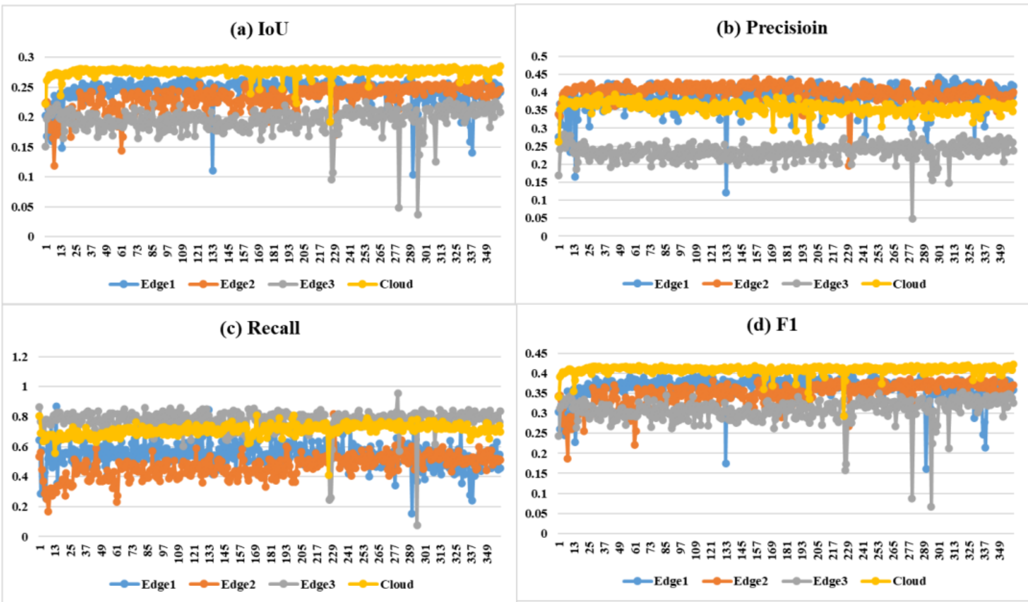


Figure 4.7. Comparison between IL and FL.

4.5.3 Comparison between the Proposed FL and Traditional FL

In this experiment, we compared the proposed cloud-edge-device federated learning (FL) framework with the traditional cloud-device FL method based on the CrackNet. More specifically, Figure 4.8 presents the performance of these two types of methods in terms of IoU, precision, recall, and F1. As shown in Figure 4.8, the proposed FL and traditional FL methods achieve almost the same performance. Notably, our method converges faster than the traditional method. This is because we used the transfer learning strategy rather than random initialization.

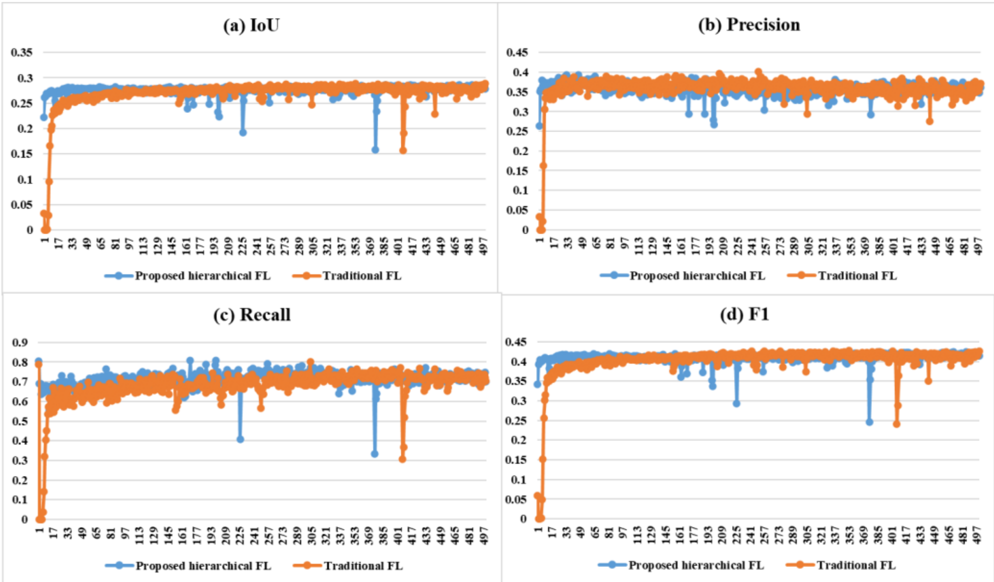


Figure 4.8. Comparison between the proposed FL and cloud-client FL.

Moreover, we compared the communication overheads in the federated training process. Specifically, Figure 4.9 lists the total communication overheads of the proposed hierarchical FL and traditional cloud-client FL. FL(4,1) means that we set the cloud aggregation interval as 1 and the edge aggregation interval as 4. As shown in Figure 4.9, communication overheads decreases in the proposed three-layer FL method. For example, the communication overload of the proposed FL method was 888M when the edger federated interval is 4 and cloud federated interval is 1, which is less than the traditional FL.

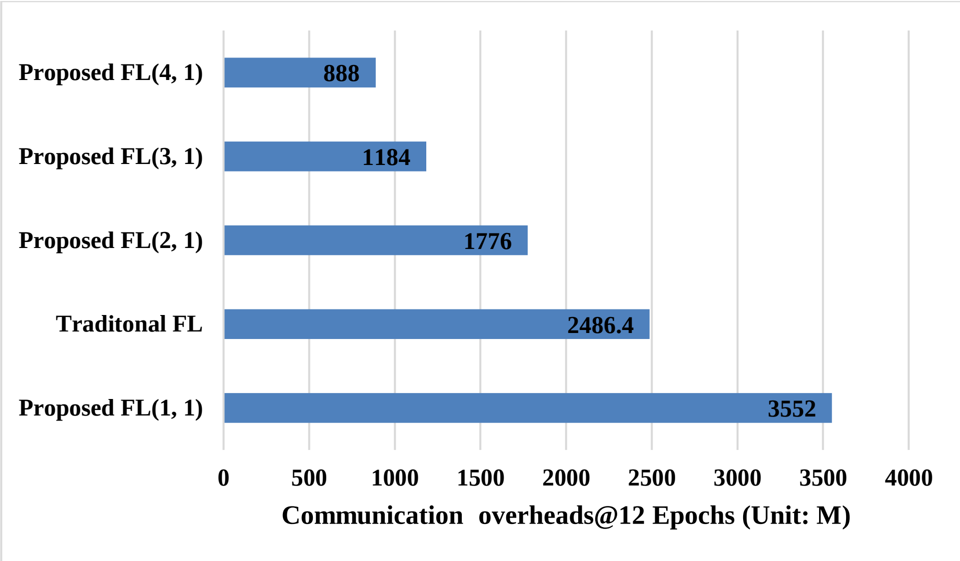


Figure 4.9. Communication overheads comparison.

4.6 Discussion

4.6.1 Theoretical Contributions and Managerial Implications

A lightweight segmentation algorithm was proposed to help construction robots recognize cracks from images. Specifically, several state-of-the-art deep learning (DL) algorithms have been proposed for crack detection, classification, and segmentation (Chu et al., 2022; Chun et al., 2021; Li et al., 2022b). However, centralized DL methods require large, high-quality datasets to train a robust model. In real-world scenarios, the amount of data from a single project may not suffice, and construction stakeholders may be hesitant to share sensitive quality defect data. As the construction industry endeavors to harness the potential of big data while ensuring data privacy, this research proposes a hierarchical FL framework for multi-robot-based quality defect inspection (QDI). The proposed approach offers a privacy-preserving mechanism for utilizing the knowledge of local data from different robotic devices without compromising data privacy. This is achieved by avoiding the sharing of privacy-sensitive crack image data across different projects. Compared to existing studies, the proposed hierarchical FL framework provides the following contributions:

- Firstly, to the best of our knowledge, this study represents one of the earliest attempts to apply federated learning (FL) to support QDI tasks in the context of construction robots. Prior studies have explored crack detection using remote robots (Li et al., 2022b) or UAVs (Tan et al., 2022), but most of them rely on centralized training strategies that may raise concerns about data availability and privacy in practical applications. In contrast, our proposed FL framework enables construction robots from different projects to train defect detection models collaboratively without sharing their data. As depicted in Figure 4.7, the segmentation performance of FL is superior to the IL solution trained with its own data.
- Secondly, our proposed three-fold hierarchical FL framework is energy-efficient and aligns with quality inspection practices in the construction industry. Typically, existing FL methods adopt a cloud-client architecture (Li et al., 2021a; 2023), which may be slow due to network congestion when dealing with a large number of involved robot clients. For example, considering that construction workers' safety and health monitoring often involve personal private information, Li et al. (2021a) developed an FL-enabled smart working package method to preserve privacy and tested FL performance in three subjects. In this study, we assume that each project has an edge server connected to its construction robots, and there is a cloud server connected to all edge servers. Our proposed hierarchical framework, supplemented by edge-robot and client-edge updates,

can significantly reduce communication costs and accelerate the convergence of the global FL model. As shown in Figure 4.9, communication overloads in our proposed method are lower than in traditional FL methods.

- Thirdly, our proposed lightweight segmentation model has a relatively low number of parameters (14.8 M), making it ideal for implementation in construction robots and enhancing communication efficiency during parameter aggregation in FL model training processes. Previous DL models with numerous parameters are typically resource-intensive, require high computing power, and may necessitate long training and inference times. Our designed model optimizes the trade-off between accuracy and latency on computational resource-constrained construction robots. The comparative results in Figure 4.5 and Figure 4.6 show its superiority over other advanced segmentation algorithms.

In addition to theoretical contributions, this study has managerial implications to postconstruction quality assessment of buildings. Although different robotic devices and DL solutions have been proposed for QDI, construction practitioners may not be willing to utilize the robot based QDI scheme since preparing enough data to train the DL model is usually time-consuming and costly. The proposed FL method can address this issue since FL does not need robots to share the local data. Using the proposed FL method, numerous robots from different construction projects can collaboratively train a powerful DL model with excellent performance on defect identification. Robotic clients can easily utilize the benefit of big data analysis. Hence, the proposed method may facilitate multi-robot based QDI implementation by addressing data privacy and availability concerns. Note that the proposed FL method is a generative framework, and it can be used for any other applications involving data privacy issues, such as facial feature-based worker fatigue recognition.

4.6.2 Limitations

Despite the valuable contributions of this study, it is important to acknowledge its limitations.

- Firstly, the proposed hierarchical federated learning (FL) method was only tested on a merged dataset that contained one type of quality defect, termly cracks. However, in real-world applications, clients may encounter a variety of quality defects, and incorporating significantly different defect data may have negative impacts on an existing federation. Techniques such as multi-task learning, model regularization, and client clustering, which can address this issue, were not explored in this study.
- Secondly, FL clients are vulnerable to adversarial attacks, including data poisoning, data inference attacks, and submission of incorrect model parameters. Additionally, the central server may experience a single-point failure. Protecting client data privacy is critical, and techniques such as differential privacy, homomorphic encryption, and blockchain can be utilized. However, this study did not delve into such encryption algorithms or security analysis.
- Thirdly, all FL clients received the same updated model regardless of their contributions. Since data is a crucial asset in FL, clients with fewer data may benefit more compared to those with more data resources. Additionally, clients have varying computational capabilities, and personalized incentive mechanisms should be investigated in future FL studies.

4.7 Chapter Summary

This chapter develops a three-fold FL framework to enable multi-construction robots from different projects to collaboratively train a detection model without sharing local data. The proposed method was tested using a case study of crack segmentation. A lightweight model was developed specifically for the crack segmentation task in the FL experiment. The comparative study demonstrates the superiority of the proposed segmentation model over other prevailing segmentation algorithms. Notably, our model has fewer parameters and a faster inference speed. Moreover, FL experimental results show that the proposed FL is better than the centralized training strategy in terms of IoU and F1 scores and demonstrate the superiority of the proposed hierarchical FL to traditional cloud-client FL methods in terms of communication overloads.

CHAPTER 5 Blockchain-based Information Management for Construction Process Quality Traceability [3]

5.1 Introduction

The lack of traceability in construction processes is a crucial factor driving opportunistic behaviors and quality failures (Qi et al. 2021). It is difficult to trace back to the source of the quality problem, which leads to difficulties in subsequent quality management. Traceability refers to the fact that products with quality problems can be processed from downstream to upstream along the production and supply chain, which has been widely used in the manufacturing and food industries. Quality traceability could help construction stakeholders demonstrate their compliance with regulations, decrease disputes, and facilitate continuous improvement by learning lessons from history (Lee et al., 2021b). Different from products or food that can be manufactured by mass production within a limited period, the construction process is complex and spans long durations. Hence, the quality traceability of the construction process becomes more

[3] This chapter is based on a published study and being reproduced with the permission of ASCE, Elsevier, and IEEE publishers.
Wu, H., Li, H., Luo, X., and Jiang, S. (2023). Blockchain-based On-site Activity Management for Smart Construction Process Quality Traceability. *IEEE Internet of Things*. https://doi.org/10.1109/JIOT.2023.3300076.
Wu, H., Zhong, B., Li, H., Guo, J., & Wang, Y. (2021). On-site construction quality inspection using blockchain and smart contracts. *Journal of Management in Engineering*, 37(6), 04021065. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000967.
Wu, H., Zhong, B., Li, H., Chi, H. L., and Wang, Y. (2022). On-site safety inspection of tower cranes: A blockchain-enabled conceptual framework. *Safety Science*, 153, 105815. https://doi.org/10.1016/j.ssci.2022.105815.

complicated, time-consuming, and expensive.

Blockchain can ensure the recorded quality data be highly reliable since on-chained data is not only virtually impossible to tamper with but also easily traceable. Such credible data provides a solid base for traceability. However, existing studies mainly focused on recording supply chain information (Wu et al., 2022c; d) or post-construction inspection texts (Wu et al., 2021b; Sheng et al., 2020), while limited attempts have been made to explore the traceability of on-site construction activities (OCAs). OCA is an essential quality component of the construction process. Numerous regulations have been published to regulate the sequence of worker activities. For instance, according to GB 50202-2018 regulation, workers should clean the joints before pouring concrete into underground diaphragm wall projects. OCA traceability is crucial since it can mitigate project actors' opportunistic behaviors and improve the visibility of the construction process. Unlike inspection texts and sensory data of materials, OCAs were usually recorded by video with large memory and are unsuitable for being directly stored by blockchains. For example, a one-hour video in 1080p resolution requires around 2GB of digital storage space. The blockchain system will suffer excessive latency and network collapse in processing such large files. Fast-evolving deep learning algorithms could provide a solution by automatically detecting OCA information from videos or images. Nevertheless, current artificial intelligence (AI) algorithms cannot achieve accurate and explainable results. Potential disputes may arise when using AI-detected information as evidence for traceability. Most previous research explored the AI and the blockchain separately, with little effort providing a conceptual view for possible convergence in the traceability of OCAs.

Moreover, previous research tends to develop prototypes in the laboratory environment according to the application scenario. For example, several prototypes were proposed based on the hyperledger fabric (HLF) framework because HLF is energy-efficient and easily implementable compared with Ethereum [7]. However, regarding practical applications, it usually costs too much effort to configure, operate, and maintain a blockchain system. Additionally, experienced developers are in short supply for the construction industry. Thus, it is necessary to make blockchain more accessible for construction stakeholders to meet the increasing interest in blockchains. Blockchain as a Service (BaaS) could be an ideal solution by allowing users to create, develop, deploy, and operate blockchain applications on the cloud infrastructure. Nevertheless, seldom has noticed the potential of BaaS platforms in the construction industry. Such absence may hinder the adoption of this transformative technology in the construction industry.

Against this backdrop, this chapter develops a BaaS-based conceptual framework to support immutable, transparent, and traceable OCA information recording during construction processes. More specifically, the objectives are to: (1) determine the proper blockchain architecture for construction quality information management; (2) develop a blockchain prototype; and (3) test the performance of the prototype using a case of worker activity recording.

The remainder of this chapter is organized as follows: Section 5.2 introduces the research background. Section 5.3 presents the proposed conceptual framework. Section 5.4 shows implementation details and experimental results, while Section 5.5 discusses contributions and limitations. Section 5.6 summarizes this chapter and outlines future research directions.

5.2 Research Background

5.2.1 Current Practices of Quality Information Management

A traceability system involves three key modules (Dong et al., 2023): (1) the data collection module that captures required data (e.g., *what, where, who, when, and why*) from the physical world; (2) the data transmission module that moves the digital data from a local source to global systems/database; and (3) the data management module that provides access, sharing, and control to the data. Internet of Thing (IoT) technology advancement in past two decades has greatly facilitated the development of traceability modules. For example, embedded sensors, e.g., RFID (radio frequency identification) technology, was used to improve tracking and managing of building materials. The development of internet and communication technologies improved the efficiency of data transmission. Unfortunately, data management remained the bottleneck of traceability.

In construction practices, paper-based files are still the main mode of quality information preservation (Ma et al. 2018a), which are easy to lose and tamper with. Building information modeling (BIM) has been widely used to increase total project quality through efficient information collection and visualization (Bynum et al., 2013). For example, Chen and Luo (2014) developed a BIM-based construction quality model and explored the workflow when using this model in construction quality inspection. Ding et al. (2017) proposed an industrial foundation classes-based inspection process model to enable information exchange requirements for quality-related information to occur in real time during construction. Lee et al. (2016) proposed a defect query model that used BIM and linked data technologies, in which the data search time is reduced, and the accuracy of search results is improved. The true potential of BIM in construction quality management is that it can be an information platform to share information from various participants throughout the whole life cycle of construction projects and visualize the information. Although efficient and fast, BIM systems are controlled by a single party and is vulnerable to risks of data leakage, tampering, loss, and single point of failure (Wu et al., 2021b).

5.2.2 Blockchain-based Quality Traceability

Blockchain is an attractive solution for quality traceability. For example, Ho et al. (2021) built an hyperledger fabric-based blockchain prototype to accurately record traceability data of aircraft spare parts. Similarly, Wang et al. (2019b) established a blockchain system to realize the traceability of food products in supply chain scenarios. Garrard and Fielke (2020) conducted a case study of applying the blockchain to support the provenance of the aquaculture industry. However, compared with quality traceability in the manufacturing or food industry, quality traceability in the construction industry is more complicated because of construction complexities and the long duration of construction projects. Zhang et al. (2020) proposed a blockchain-based theoretical framework for the quality traceability of precast components. However, it is a conceptual discussion and has not established a prototype. In addition, Wu et al. (2021b) and Zhong et al. (2020) explored blockchain-based quality inspection text recording. Lu et al. (2021a) stated that IoT technologies could prevent false information from entering the blockchain system and developed a blockchain-based framework to support the supply chain management of prefabricated modules. Similarly, Wu et al. (2022c) indicated the applicability of blockchain to improve the information-sharing accuracy in the on-site assembly of modular components.

5.3 Proposed Conceptual Framework

As shown in Figure 5.1, the design science approach illustrated is adopted to guide the whole research progress (Peffers et al., 2007). Design science focuses on comprehending problems and proposing alternative solutions to describe, explain, and anticipate the current natural or social reality (Van Aken, 2005). Firstly, the technical characteristics of blockchains were identified through a systematic literature review. Secondly, after several group meetings, a blockchain-based conceptual framework was proposed to record quality-related information during the construction process. Thirdly, a prototype system was developed to implement the conceptual framework. Finally, a case study was conducted to test the latency and throughput performance of the developed prototype.

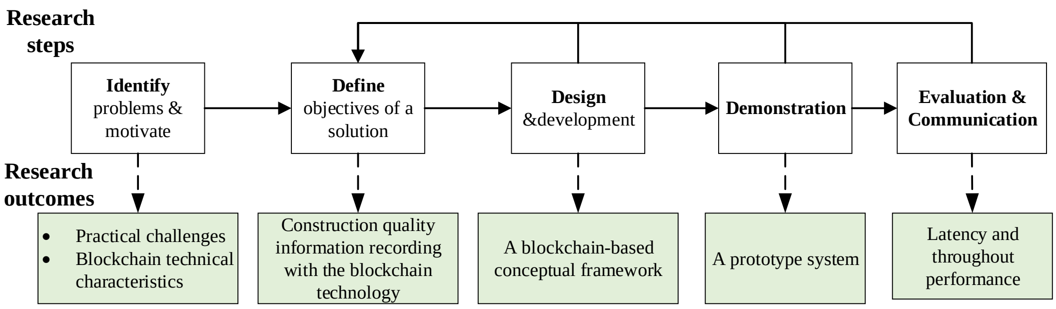


Figure 5.1. Research steps of the design science method and its outcomes.

As presented in Figure 5.2, a blockchain-driven framework was proposed to record quality-related information during the construction process, aiming to support future traceability and accountability. Such a framework contains two layers: (1) the information collection and processing layer; (2) the blockchain layer. In the first layer, cameras can be mounted at a high and remote position (e.g., in the operator cab of tower cranes) to obtain a broad view, reduce the deployment cost, and avoid frequent repairs in practical applications. Such videos were termed "far-field surveillance videos" and contain sufficient construction process information (Luo et al., 2019), in which the pixel size of workers is typically small (as small as 30 pixels tall). Fast-evolving DL algorithms were used to extract construction process information from the videos. The extracted information, as well as the encryption information of the raw data, would be recorded in the blockchain system for future checking.

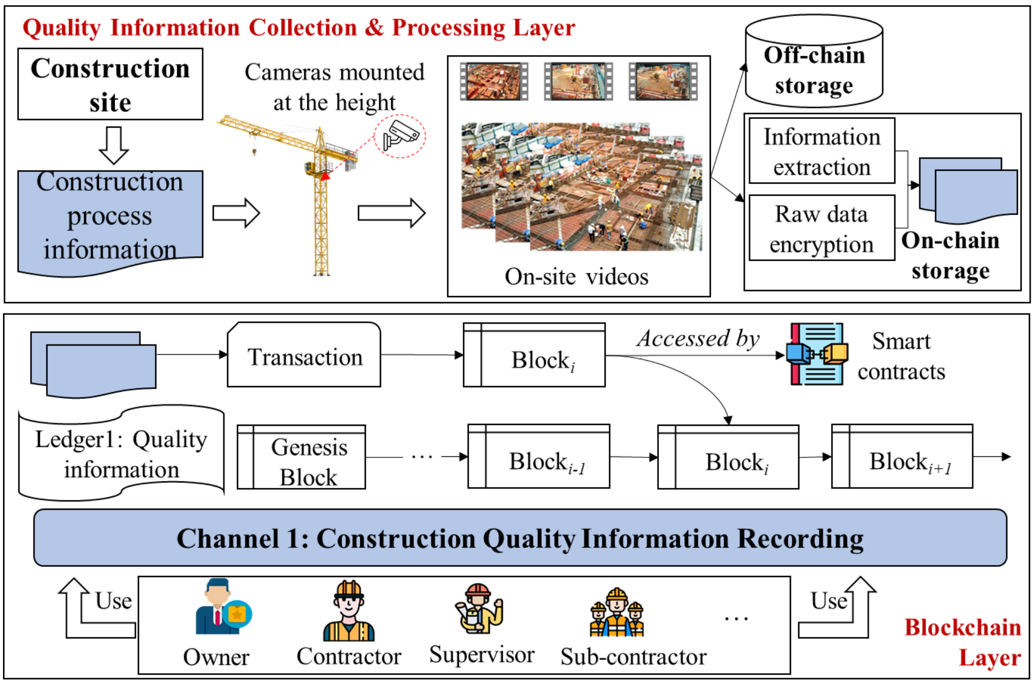


Figure 5.2. Blockchain-based framework for quality information management.

Additionally, the core part of the proposed framework is the blockchain-based layer for decentralized data recording. Specifically, the proper blockchain architecture was determined by considering the characteristics of construction projects and the demands of quality accountability. Then, a blockchain prototype was established based on a general blockchain as a service (BaaS) platform. Project actors (e.g., owners, contractors, sub-contractors, and supervisors) can join the prototype and mutually govern the system. With the blockchain layer, quality-related information can be translated into transactions and then packaged into on-chained blocks, in which the information is almost immutable, transparent, and traceable. The details of these two layers were introduced in the following sections.

5.3.1 Worker Activity Information Processing

Although some deep learning (DL) algorithms can attractive performance in extracting information from images or videos, just relying on the DL cannot meet the demands of process quality traceability since it cannot achieve complete accuracy. Stakeholders may deflect blames because they cannot fully believe the information extracted by the computer vision module. Therefore, the raw data should also be safely stored in off-chain datasets for re-checking. The extracted activity information, as well as the hash values of the raw data, would be uploaded to the blockchain system. The overall process is shown in Figure 5.3.

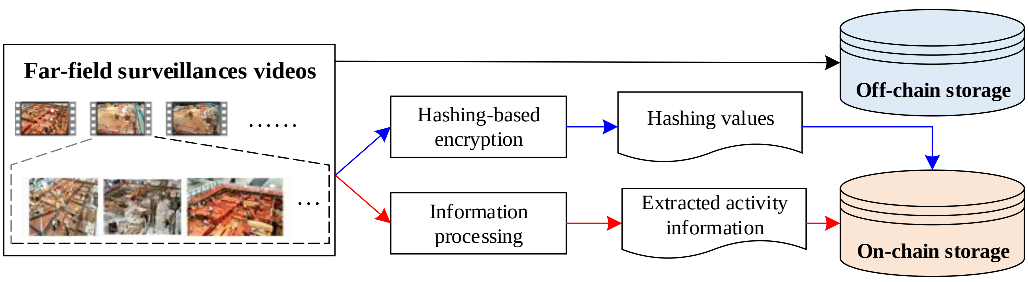


Figure 5.3. Video-based construction process information processing flow.

As shown in Figure 5.4, a cryptographic hash function termed secure hash algorithm (SHA) 256 was adopted to encrypt the videos, aiming to guarantee the security and integrity of the raw data and avoid potential disputes on the results extracted by DL algorithms. After SHA256-based encryption, the raw data associated with the extracted activity information would be translated into hashing values, and the values would also be stored in blockchains. Once there are disputes on the extracted activity information, participants can retrieve the on-chained hashing value *A* and recalculate the hash value *B* based on the raw data. Cryptographic hash functions have three main characteristics: (1) they translate the input into hashing values with a fixed length; (2) the encrypted content is difficult to be reasoned through the hash value; (3) the hash value will always be different even if there is a small change in the inputs. That is, these hashing values (e.g., *A* and *B*) would be different if the content of raw data was tampered with. Thus, the security and integrity of videos can be guaranteed using the SHA256 algorithm. The process can be shown in Figure 5.4.

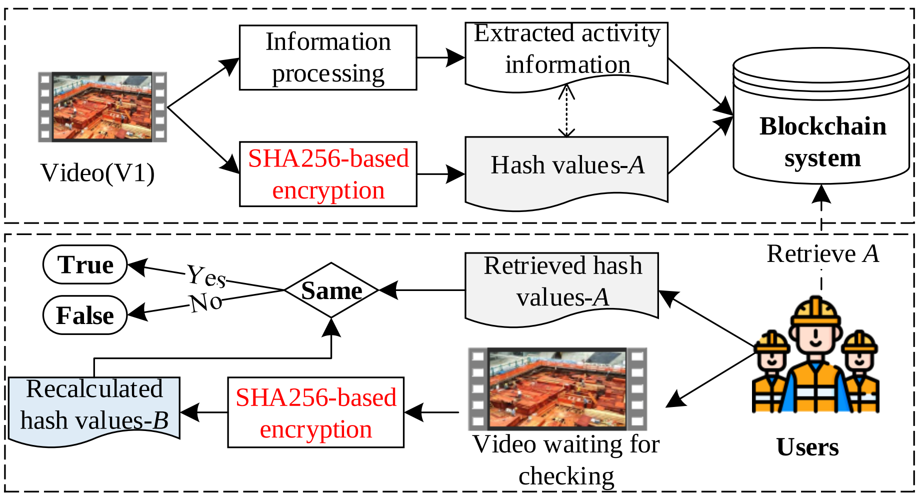


Figure 5.4. SHA 256 encryption-based integrity checking of the raw data.

5.3.2 Blockchain Architecture Selection

According to the theory of the Technology Life Cycle, blockchain technology is at the "fermentation" stage with technological uncertainty. There are thousands of blockchain projects worldwide under development. However, the following two questions need to be answered before the development of a blockchain system in order to avoid pointless blockchain projects, namely, "Q1: *do you need a blockchain in your application*?" and "Q2: *what types of blockchain network should be adopted*?".

Precious works have presented different decision frameworks for managers to answer these questions. For example, the White Paper published by the World Economic Forum developed a decision tree containing 11 questions for blockchain adoption (Mulligan, 2018). Turk and Klinc (2017) used eight questions to draw a conclusion that the consortium blockchain is suitable for the construction industry. Li et al. (2019) showed a path tree for blockchain's adoption and used three construction industry use cases to visualize the decision process. Hunhevicz and Hall (2020) summarized eight decision frameworks in previous works and then proposed an integrated framework. To summarize, previous decision frameworks aim to answer the Q1 from two aspects: (1) whether the traditional can solve your problem, such as "*Are there multiple writers*", "*Can you use an always online trusted third party*" from Li et al. (2019), and (2) whether the blockchain is suitable for your problem, such as "*Do you require rapid transactions*", "*Do you intend to store large amounts of non-transactional data*" from Hunhevicz and Hall, (2020), and "*are all participants interest aligned*" from Turk and Klinc (2017). Furthermore, blockchain architecture can be determined by two questions: (1) who can access the on-chained data , such as "*should transactions be public*" from Li et al. (2019);

(2) who manages the consensus process, such as "*do you need control functionality on protocol level*" from Turk and Klinc (2017). According to these decision frameworks, the Hyperledger Fabric (HLF)-based consortium blockchain network is selected for construction quality information management. The whole decision process is shown in Figure 5.5.

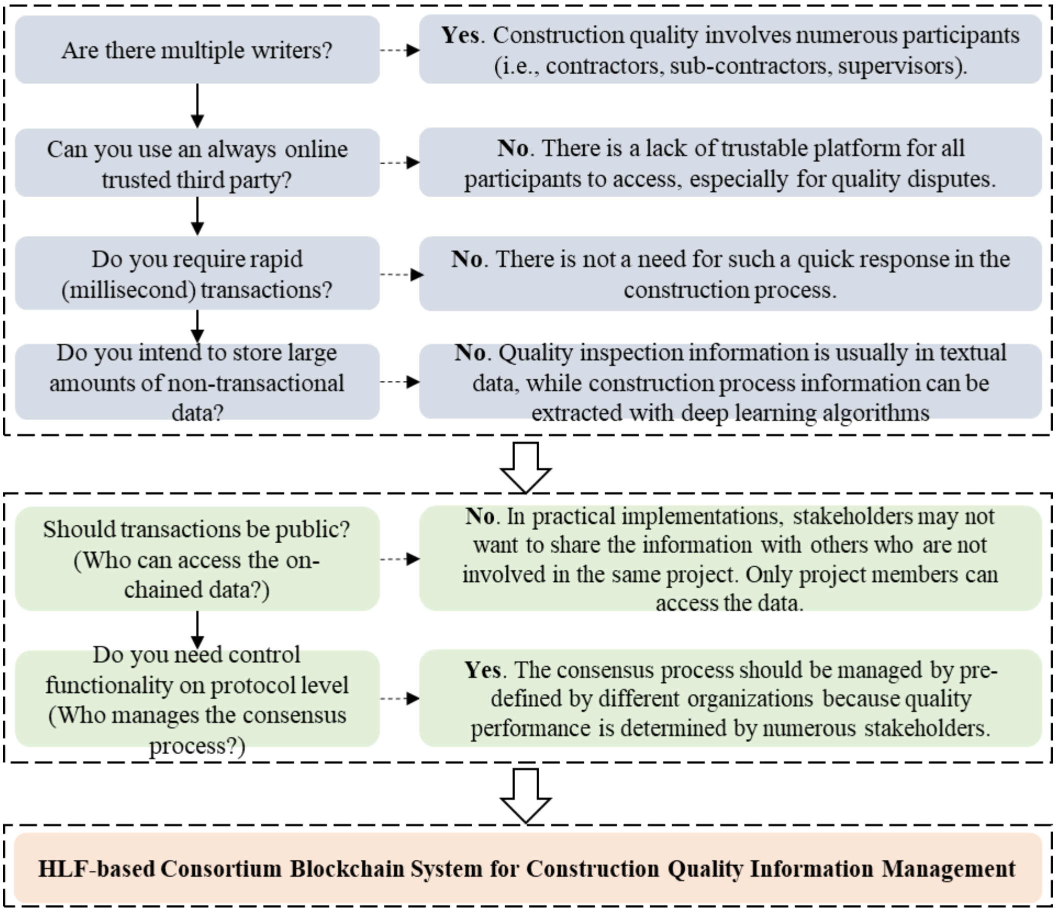


Figure 5.5. Decision process on the blockchain type.

In this study, HLF is selected as the development architecture of the consortium blockchain system. Public and permissionless architectures (e.g., Ethereum, Bitcoin), allowing unknown identities to participate, may not be suitable for the construction industry when considering business competitiveness and data privacy. Participants may not want to share sensitive data (e.g., pricing, financial data, quality data, etc.) with others who are not involved in the same project (Perera et al., 2020). HLF-based consortium blockchain allows participants to create their own channels in which information cannot be accessed by other participants who are not in the channel. As shown in Figure 5.6, different channels can be created to meet the demands of quality traceability. To illustrate, construction suppliers usually share building material information with the owner (who buys the materials), the owner (who manages the materials), the supervisor (who monitors the process), and the government (who monitors the process), but not sub-contractors. That is why HLF is regarded as a suitable platform for business requirements in the construction industry (Perera et al. 2020). In this research, we concentrated on the channel that records construction process information (Channel 1).

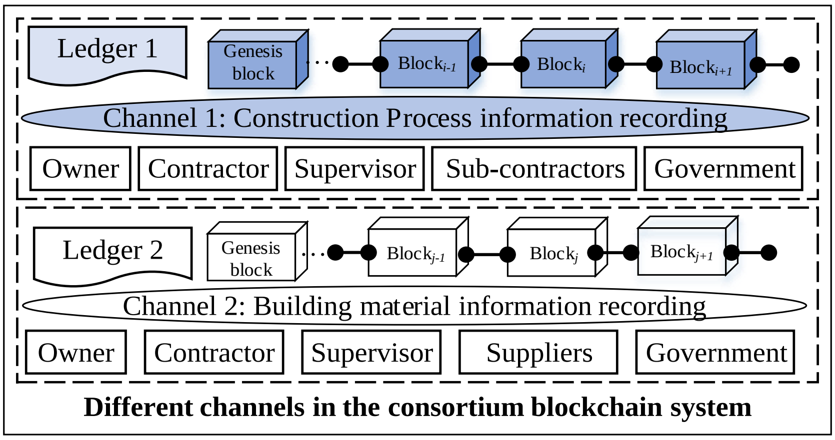


Figure 5.6. Channels in the consortium blockchain system.

We also acknowledge that HLF, as the architecture of “private and permissioned” distributed ledger technologies, makes compromises on decentralization, transparency, and equal rights of participants. Therefore, HLF cannot fully be equated to “blockchains” due to less decentralization and inherent security risks. Specifically, HLF architectures leave out decentralized consensus, and only authorized participants can create and view transactions. However, HLF is more energy-efficient and easily implementable compared to public blockchain architectures that allow anyone to participate in the network (Hang and Kim, 2021). It has good performance in transaction throughput and scalability (i.e., the ability to handle an increasing number of transactions at a time). A shorter time frame is needed to complete the consensus process for a new block; for instance, it can easily support 100,000 transactions at 200 tps (Kuzlu et al. 2019). Actually, it is difficult to satisfy the properties of "decentralization," "security," and "scalability" simultaneously in the development of blockchain projects, which is termed the "blockchain trilemma" (Lee et al. 2021a). In this study, HLF is used as the development architecture for the consortium blockchain prototype because it can ensure confidentiality for the sensitive data of construction projects and has high accessibility and good performance in scalability.

5.3.3 Consortium Blockchain System Development

Based on the Hyperledger Fabric (HLF) architecture, we develop a consortium blockchain system for construction process information (e.g., worker activities) management. As shown in Figure 5.7, system users contain the owner, the contractors, the supervisor, sub-contractors, and the government since they are highly related to construction process quality performance. Notably, the government is the regulatory node that can only query on-chained data, while others are federated members who are responsible for maintaining the blockchain system. Each node of federated members consists of four components: (1) application component that describes application logic interacting with the users; (2) consensus component that aims to package transactions into blocks; (3) storage component that manages the block data after confirming the block; and (4) network component that aims to interact with other nodes, such as synchronizing transactions and blocks. Notably, each of the four components concentrates on one dedicated group of functionalities, achieving modularity.

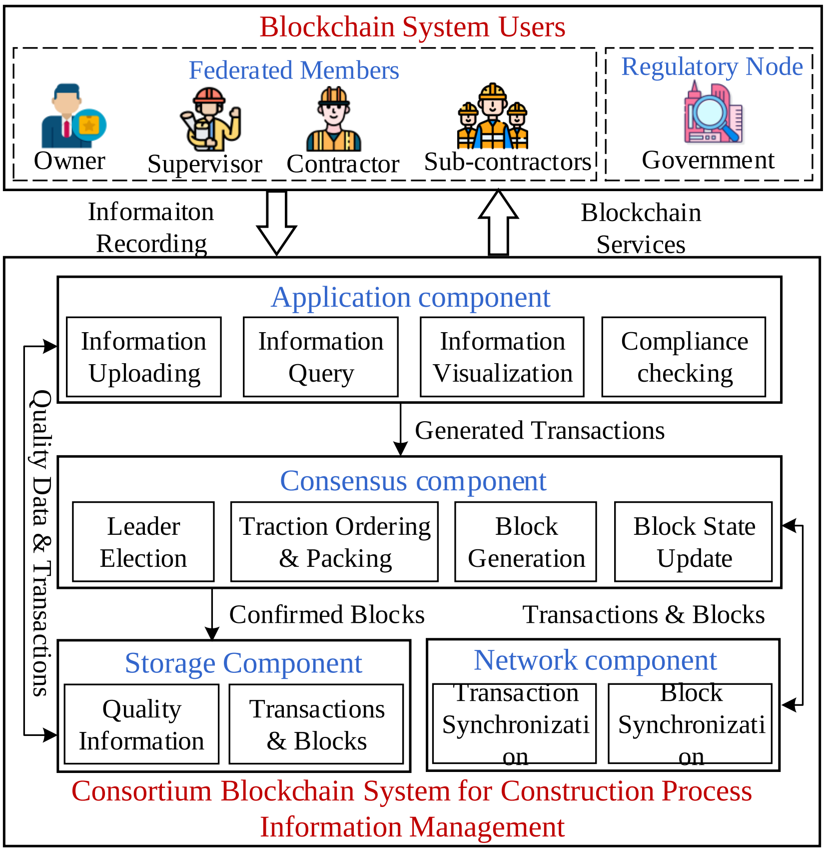


Figure 5.7. Consortium blockchain system for construction process information management.

5.4 Demonstration and Evaluation

5.4.1 Use Case

A high-rise office building located in Hong Kong was adopted to validate the theoretical feasibility of the proposed framework. During the construction process, a pan-tilt-zoom camera was mounted at the operator cab of the tower crane to collect far-filed surveillance videos and monitor the working floor in a square shape of 48.5×48.5 m. Such videos are continuously filmed with a resolution of 2048×1536 pixels at 25 frames per second, aiming to visually record construction process information. In this research, we focused on worker activities during the construction process since the construction industry is currently labor-intensive, in which the quality of final buildings is inseparable from on-site productive workers. There are numerous construction procedure constraints in quality regulations, which regulate the sequence of worker activities. For example, according to the regulation of GB 50202-2018, workers should clean the joints before pouring concrete in underground diaphragm wall projects. Recording such information can enhance the visibility of construction processes.

A surveillance video of approximately 30 minutes, filmed with a fixed field of view, was used as the validation case in this research. In this case, the conditional random field (CRF) method proposed by Luo et al., (2020) was used due to its amazing performance in identifying worker activity information from far-field surveillance videos. The author admits that there would be other deep learning (DL) algorithms for detecting construction activity information from on-site videos. However, developing a creative method or improving the performance of DL models has not been the focus of our research. Instead, we aim to develop a decentralized blockchain framework to record the worker activity information in a decentralized manner, considering the gap in the construction process traceability. Figure 5.8 shows an example of the CRF-based detection result of the video. The worker types, as well as specifications of action labels in Figure 5.8, were explained in Table 5.1. Such detected information will be uploaded to the blockchain system.

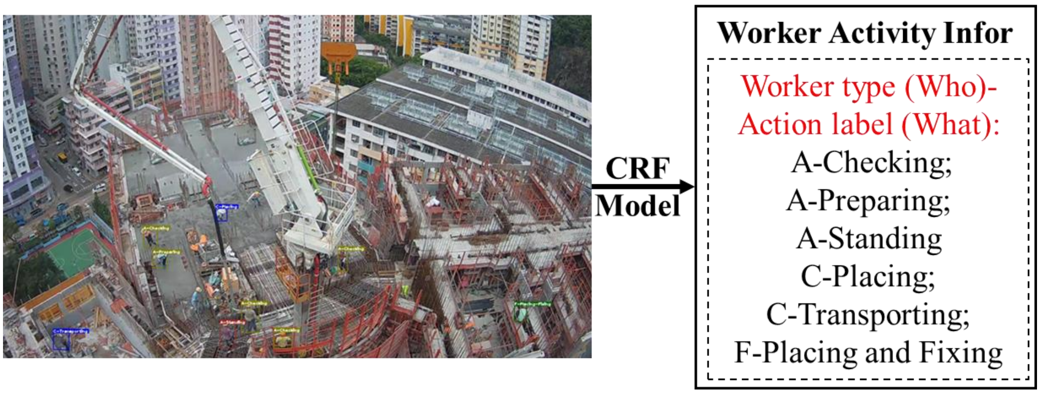


Figure 5.8. An example of extracted worker activity information.

Table 5.1. Activity taxonomy and specifications

Worker Trade	Activity label	Specification
All (A)	A-Checking	Checking site stations or measuring formwork, purlins, and rebar with a tape.
	A-Standing	Standing still, standing, and drinking water, or standing and wiping perspiration.
	A-Preparing	Preparing auxiliary materials or setting up equipment for subsequent tasks.
Concrete workers (C)	C-Placing	Placing concrete by moving the hose of a concrete placing boom.
	C-Transporting	Pulling a concrete placing boom.
Formwork workers (F)	F-Placing-Fixing	Placing and fixing formwork and purlins.

5.4.2 Implementation Details of Blockchain Prototype

Regarding practical applications, it usually costs too much effort to configure, operate, and maintain a blockchain system. For example, experienced blockchain developers are in short supply for the construction domain. Hence, it is necessary to make blockchain more accessible for construction stakeholders. Blockchain as a Service (BaaS) could be an ideal solution to reduce stakeholders' concerns about blockchain technical complexities, which allows users to create, develop, deploy, and operate blockchain applications on the cloud infrastructure (Song et al., 2021). In this research, we develop the prototype system of consortium blockchains based on the PolyChain BaaS platform. This is because PolyChain is a generic BaaS platform that can meet the requirements of modularity, flexibility, scalability, reliability, and security (Jiang et al., 2021a). Figure 5.9 (a) presents details of a block in the prototype system. As shown in Figure 5.9 (a), the hash value of the raw video data and extracted worker activity information will be recorded in a block after reaching a consensus. Figure 5.9 (b) presents the generated blocks of the use case in this research.

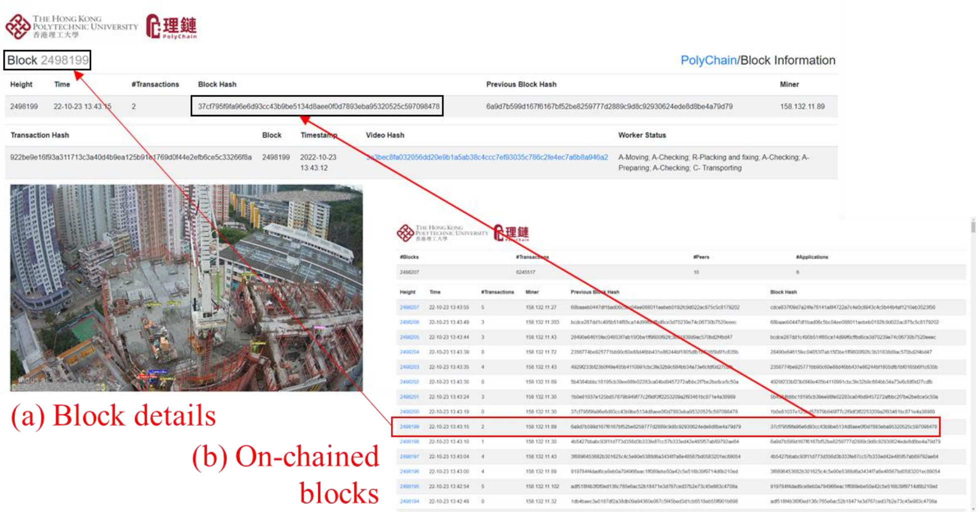


Figure 5.9. BaaS-based blockchain prototype: (a) Block details; (b) on-chained blocks.

5.4.3 Performance Analysis

Two metrics were selected to test the performance of the prototype, termly, latency, and system throughout, since they are regarded as the most prevailing performance metrics of the blockchain (Singh et al., 2022). Transaction throughput is the number of committed transactions per second (TPS), while latency refers to the difference between the start time and the end time of publishing an operation in a blockchain network. These metrics were related to several parameters, such as the block generation time, the block size, and the number of connected nodes. Specifically, the block size, which refers to the number of transactions in a block, was determined by dividing the block gas limit by the transaction gas limit. Gas is the measurement index of the computational resource for one transaction, and the gas limit is the maximum amount of gas that may be utilized to execute transactions. Aiming to ensure universality, we tested the TPS and latency performance of the developed prototype using differentiated connected nodes, different block generation times, and differentiated block sizes (ranging [500,5000] with a common difference of 500).

Figure 5.10 present the performance evaluation results for the blockchain prototype under different block generation time and block sizes. As shown in Figure 5.10(a) and (b), system throughput declined as block generation time increased and enhanced as block size increased, respectively. Figure 5.10(c) indicates that the longer the block is generated, the longer the delay. This is because as the time generated by the block rises, more requests are received during the time period, and the broadcast and verification time is longer, resulting in an increase in the transaction delay. Furthermore, the blockchain prototype can reach an acceptable throughput of around 750 with a blockchain size of 2500, and the number of nodes does not have an observable influence on the throughout. As shown in Figure 5.10(d), the average transaction latency ranged from 1s to 3s. The average latency increased when there were more nodes in the blockchain prototype; however, the maximum latency was still controlled in 3s with ten nodes, which is acceptable for practical construction applications (Jiang et al., 2021b).

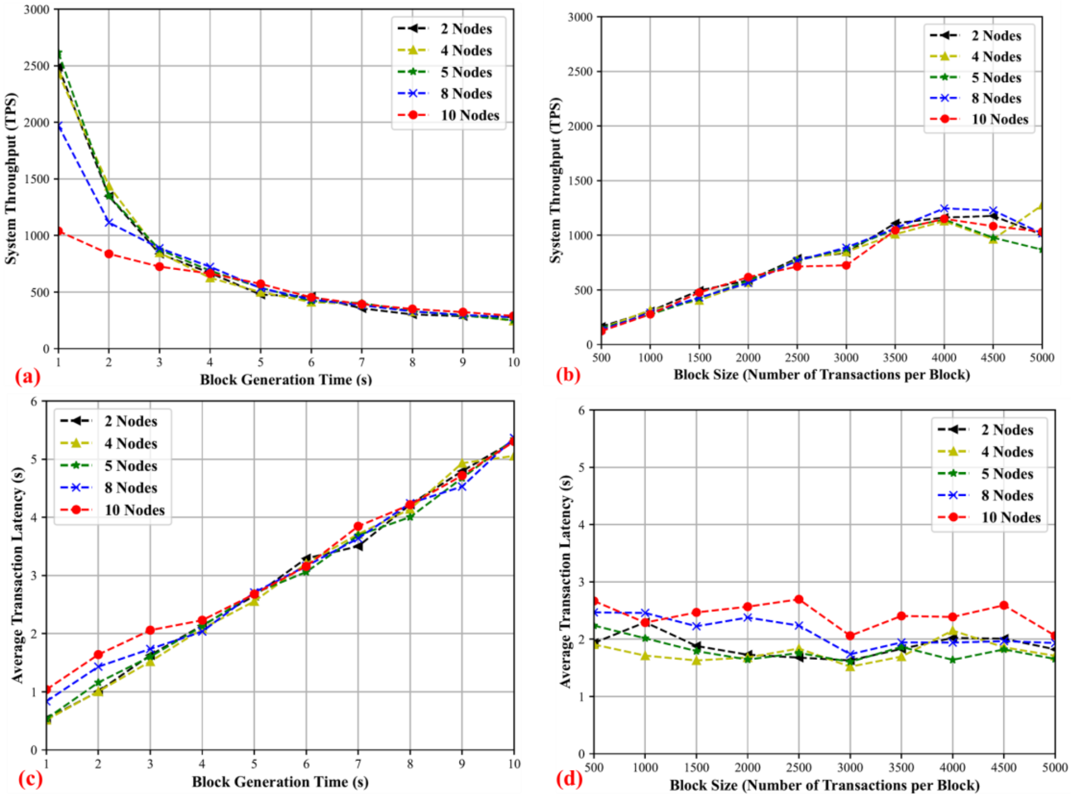


Figure 5.10. Throughput and latency results of the developed prototype under differentiated block generation time, block size, and nodes.

5.5 Discussion

5.5.1. Contributions

The following aspects of theoretical originality to the proposed method were outlined in comparison to previous studies: (1) a blockchain-enabled framework was proposed to record activity information of on-site workers in a group for traceability. Previous blockchain studies mainly focused on recording inspection texts and sensory data of materials, while limited attempts have been made to explore how to record worker activities during the construction process. That's because construction activities are typically recorded by videos with large memories that are not suitable for being directly stored in the distributed blockchain network. Thus, deep learning (DL) algorithms were integrated into the framework to efficiently extract worker activities from videos; (2) A cryptographic hash function was adopted to encrypt the raw data, aiming to ensure the integrity of on-site videos. It is necessary for the traceability application when the deep learning algorithms cannot obtain the full right results; (3) A consortium blockchain system was developed based on a general BaaS architecture, which can prevent the tampering of worker activity information and make the construction process traceable.

Furthermore, this study provides several significant implications for construction practice. First, this study may be a beneficial attempt to provide construction participators (e.g., quality inspectors and project managers) with a creative way of construction quality management. Second, it gives an easy-to-implement blockchain solution for construction quality traceability by using BaaS platforms. Seldom research noticed the potential of BaaS in the construction industry. Such absence may hinder the adoption of this transformative technology in the construction industry because experienced blockchain developers may be scared in the construction industry, and construction organizations may feel confused even if they want to adopt blockchain in their applications.

5.5.2. Limitations

However, there are still some limitations in this research. First, only three types of worker activity information, including time (when), worker type (who), and worker action label (what), were used to show the feasibility of the proposed framework. More types of information should be detected from the site to improve the granularity of quality traceability. For example, the location (where) information should be collected to meet traceability demands. Furthermore, although vision-based methods can enable worker monitoring on a large scale, their performance is often limited by the light and occlusions in the field. An effective framework integrating vision and sensing technologies, such as radio frequency identification, can be proposed to collect comprehensive construction process information, which is shown in Figure 5.11. Notably, whether collecting workers' identity information should be further discussed. In this research, we only detected the worker type due to the following reasons. Firstly, just relying on computer vision technology is challenging to detect the identity information from the far-filed surveillance video. More importantly, the author believes construction workers belong to the most vulnerable group in the whole world, and the responsibility should be tracked at the organizational level instead of the personal level. For example, they usually need to complete highly physically demanding tasks under various climatic conditions.

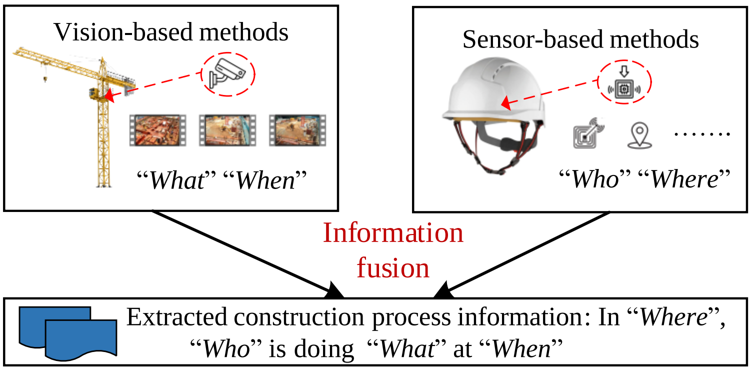


Figure 5.11. A conceptual framework for vision and sensor-integrated construction process information extraction.

Second, the prototype system is developed and evaluated in the laboratory environment. The performance of the prototype system in actual implementations should be evaluated with several metrics, such as storage cost, transaction latency, throughput, scalability, and resource utilization. In addition, a detailed analysis of blockchain's benefits, as well as its cost, within a pilot project should be conducted to promote its implementation in the construction industry. The development and operation costs can be quantitatively analyzed, while the practical benefits of blockchains to construction quality management can be qualitatively analyzed with workshops, questionnaires, or structured interviews.

5.6 Chapter Summary

This chapter develops a blockchain-based conceptual framework for construction process traceability, which contains two essential modules: (1) the computer vision module for extracting worker activity information from far-filed surveillance videos; and (2) the blockchain module for guaranteeing data security, transparency, and traceability demands. A consortium blockchain system was developed to validate our approach based on the general BaaS platform-"PolyChain," while a high-rising building project was used as the case. We reveal that our proposed framework can improve the quality traceability of construction processes by automatically extracting activity information and recording such information in a trustable manner. We also suggest that the BaaS-based framework can be practically used by project managers to improve the visibility of the construction process and then reduce disputes.

CHAPTER 6 Barrier Identification, Analysis, and Solutions of Blockchain Adoption in Construction[4]

6.1 Introduction

Scott et al. (2021) reported that blockchain-related publications in construction have increased by an average of 184% per year from 2017 to 2021. However, we have seen very few practical blockchain implementations in the construction industry, and most previous blockchain systems have been created and verified in a laboratory setting (Hunhevicz and Hall, 2020). This indicates that construction organizations are hesitant to adopt blockchain technology. Hence, a comprehensive understanding on blockchain adoption barriers is required for promoting its implementation in construction.

Although existing studies have provided insights into understanding blockchain adoption barriers, there is a lack of theoretical foundations during the barrier identification process in previous studies. Notably, theoretical frameworks such as the technology-organization-environment (TOE) and technology acceptance model (TAM) can assist in formulating adoption decisions among firms.

[4] This chapter is based on a published study and being reproduced with the permission of Emerald Publishing.
Wu, H., Zhong, B., Zhong, W., Li, H., Guo, J., and Mehmood, I. (2023). Barrier Identification, Analysis, and Solutions of Blockchain Adoption in Construction: A Fuzzy DEMATEL and TOE integrated Method. *Engineering, Construction, and Architectural Management*. https://doi.org/10.1108/ECAM-02-2023-0168.

Additionally, existing studies have not thoroughly uncovered the interrelationships among blockchain adoption barriers. There have been very few successful blockchain projects in the construction industry. Given the nascent stage of blockchain technology, finding experts with sufficient knowledge and experience related to blockchain adoption decisions is challenging. Purposeful sampling in panel selection is essential, as blindly expanding sample sizes can affect confidence in the results. In this context, addressing the uncertainty and subjectivity in expert-based evaluations is critical. Previous studies used crisp values that cannot accurately express the vagueness and uncertainty of real-world decision problems.

To address the gaps above, we have conducted a study to determine the critical barriers to the adoption of blockchain in the construction industry and propose potential solutions. Specifically, the objectives of this study are to (1) review barriers to blockchain adoption, (2) identify the key barriers and explore their interrelationships, and (3) propose relevant solutions to promote blockchain adoption in the industry. To achieve these objectives, we have adopted the TOE framework to identify relevant barriers and subsequently applied the fuzzy Decision-Making Trial and Evaluation of Laboratory (DEMATEL) method to analyze their prominence and causality. TOE is the most comprehensive model for explaining technology adoption at the organizational level and can accommodate different technological, sectoral, and national situations (Nilashi et al., 2016). The TOE framework has been widely used in exploring innovation adoption among construction organizations, such as BIM (Qin et al., 2020) and construction robots (Pan and Pan, 2019). The fuzzy DEMATEL method suits complex decision problems characterized by vagueness and uncertainty since it can handle the imprecision from ill-defined information and investigate the interrelationships among identified barriers (Qi et al., 2020).

The structure of this chapter is as follows: in Section 6.2, we provide a detailed description of our research methodology. The main findings of our study are presented in Section 6.3, which includes the identification of key barriers and their interrelationships. Section 6.4 discusses the theoretical and practical implications of our findings, as well as the limitations. Section 6.5 finally summarizes conclusions.

6.2 Research Method

The overall methodology is presented in Figure 6.1, which contains three stages: Barrier identification with the technology-organization-environment (TOE) framework (Stage 1); data collection (Stage 2); and barrier analysis using the fuzzy Decision-Making Trial and Evaluation of Laboratory (DEMATEL) method (Stage 3). Details of each stage were introduced in the following sections.

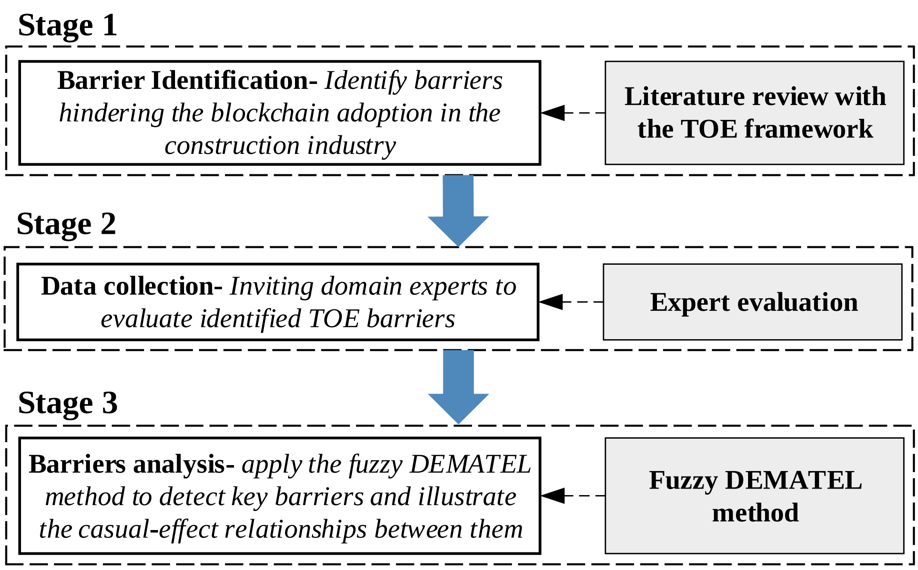


Figure 6.1. Research methodology of blockchain adoption barrier analysis.

6.2.1 Barriers Identification

Blockchain adoption barriers proposed by previous studies were summarized with the technology-organization-environment (TOE) framework based on the literature review. In this research, we adopt the TOE framework for barrier identification. In our previous work (Wu et al., 2022e), we conducted a systematic review and identified 141 journal. A manual review of these articles was conducted to identify initial TOE barriers. Moreover, aiming to ensure the completeness of the results, these initial barriers were compared with those identified in more recent works. Finally, the resulting set of TOE barriers, along with their explanations, are presented in Table 6.1.

Table 6.1 TOE-based blockchain adoption barriers

TOE view	Barriers	Descriptions	Reference
Technological context	T1- Scalability	The blockchain system may face scalability concerns in practical applications, such as low throughput rate and high latency.	Yang et al. (2020a), Perera et al. (2020), Li et al. (2019), and Wang et al. (2020c).
	T2- Smart contracts' security	A smart contract normally involves high-valued assets or transactions, which is possibly to be attacked, causing unacceptable losses.	Saygili et al. (2022), Wu et al. (2021b), and Li and Kassem (2021).
	T3- Immutability challenge of smart contracts	Smart contracts are suitable to explicit transactions and may not be suitable for high-dynamic-complexity construction projects in which there are many unexpected scenarios.	Das et al., (2020), Sheng et al. (2020), and Lumineau et al., (2021).
	T4- Interoperability	The information exchange between different blockchains is challenging. Additionally, how to integrate blockchain with traditional information systems should be further discussed.	Li et al. (2019), Tao et al., (2022), and Xu et al. (2022).

Organizational context	O1- Lack of awareness and understanding of blockchains	Blockchain is still a relatively new concept. Construction participants may be unaware of it potentials.	Olawumi et al. (2020), Li et al. (2022), and Zhang et al. (2023).
	O2- Resistance in changing original management process	Blockchain may fundamentally change existing collaboration and management processes, leading to resistances to change.	Wu et al. (2022a) and Walsh et al., (2021)
	O3- Financial constraints	Construction firms need to undertake initial development costs, deployment costs, and maintenance costs.	Zhong et al. (2020) and Ding et al. (2023)
	O4- Lack of sufficiently skilled people	People with related knowledge and experience are still scarce in the construction industry.	Sheng et al. (2020), Sharma and Kumar (2020), and Wu et al. (2021b)
	O5-Negative attitudes towards data privacy issues and data disclosure	Organizations may view information as a competitive advantage, making it difficult for them to share valuable and critical information.	Perera et al. (2020) and Li et al. (2019)

Environmental context	E1- Lack of collaborative culture	Current contractual relationships are mainly based on confrontational situations, revealing the lack of collaborative culture.	Sadeghi et al. (2021) and Xu et al. (2023)
	E2- Lack of mature policy environments	Regulatory uncertainty may increase construction stakeholders' hesitation on adopting blockchain.	Li and Kassem (2021), Wu et al. (2021b).
	E3-Industry concerns about technological maturity	Blockchain is a fast-evolving technology and construction stakeholders may concern about the risks related to the technological uncertainty	Sharma and Kumar (2020), Xu et al. (2023)

6.2.2 Data collection

The selection of experts is an essential part in the proposed framework for obtaining reliable results. Rather than distributing questionnaires indiscriminately, we adopted a purposeful sampling strategy. Specifically, we invited experts from academia who have published research related to blockchain in the construction industry, and professionals from the industry who have practical experience with blockchain projects. In total, 20 experts were invited to participate in the survey, and their details, including educational background and years of experience in construction management, are presented in Table 6.2. The questionnaire (Online link: https://forms.office.com/r/TtimXqUmtU) was administered in either Chinese or English via email and consisted of two parts: (1) demographic information, and (2) an evaluation matrix in which the influence of one barrier on the others was measured using a Likert scale ranging from 0 to 4. The experts were informed that their data would be kept confidential and used solely for academic purposes. The original data obtained from the experts will be processed for barrier analysis.

Table 6.2. Demographics of invited experts

Demographics	**Category**	**Count**
Education	Bachelor	6
	Master	1
	PhD	8
	Other	5
Years of experience	1-5	5

	6-10	5
	11-20	2
	21-25	5
	Above 26	3
Organizational background	University Or Research Institute	8
	Construction Company	1
	Real Estate Company	3
	Government	3
	Consulting Company	2
	Other units	3
Country	China	17
	Italy	1
	Switzerland	1
	Australia	1

6.2.3. Fuzzy DEMATEL-based Barrier Analysis

Based on graph theory and matrix tools, Decision-Making Trial and Evaluation of Laboratory (DEMATEL) can develop a visual structure to examine the causal relationship between various barriers using the knowledge and experience of invited experts (Jassbi et al., 2011). It can discover key barriers by calculating each barrier's center degree and cause degree, creating the causal diagram, and establishing the category to which variables belong (cause group or result group) (Feng and Ma, 2020). Hence, DEMATEL was suitable for this study. Additionally, to address ambiguities in language estimation, the fuzzy set theory was employed in the DEMATEL (Farooque et al., 2020). The fuzzy DEMATEL allows for the necessary flexibility to handle uncertainty and imprecision resulting from ill-defined information. By utilizing the fuzzy DEMATEL method, key barriers were identified and the causal relationships between them were examined using the knowledge of the invited experts, which can handle the bias and uncertainty of human-made judgments. The steps of the fuzzy DEMATEL approach are shown in Figure 6.2 and are explained in detail as follows.

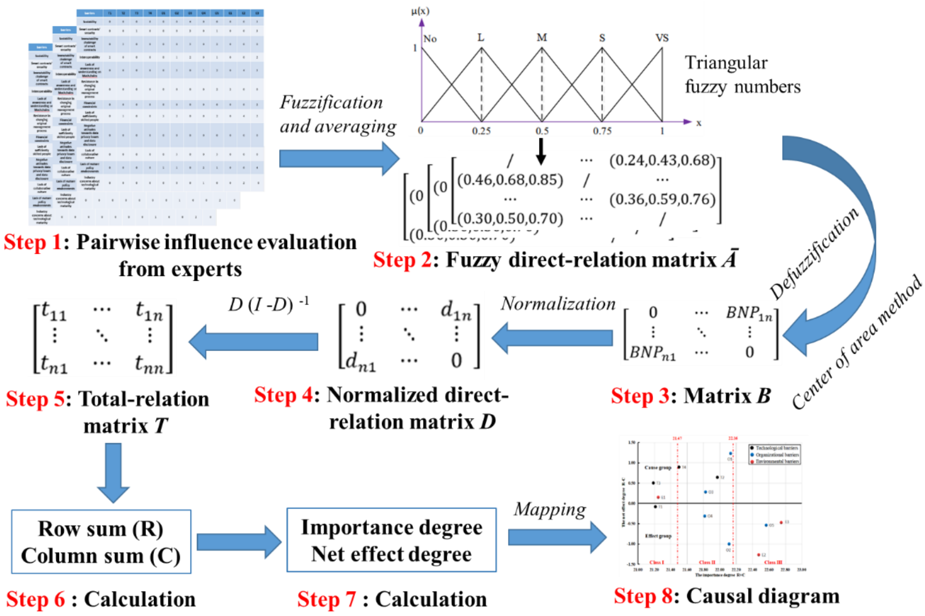


Figure 6.2. Process steps of the fuzzy DEMATEL method.

- **Step 1**: Establishing an initial direct-relation matrix based on the identified TOE barriers. Each participant was asked to evaluate the influence of barrier i on barrier j using a linguistic scale from 0 to 4 (0 means no influence; 1-4 means the degree of influence from small to large). The results would be transformed into a pairwise comparison matrix $A_{n\times n}$, in which n is the total number of identified TOE barriers.

- **Step 2**: Transferring the evaluation data into positive triangular fuzzy numbers. Triangular fuzzy numbers are widely used to deal with the ambiguities of experts' assessments due to its conceptual simplicity and ease of computation (Kouhizadeh et al., 2021; Yadav et al., 2023). Each triangular fuzzy number can be expressed as a triplet (*l*, *m*, *r*), where the parameters *l*, *m*, and *r* indicate the smallest possible value, the most promising value, and the largest possible value, respectively. Table 3 presents the used triangular fuzzy numbers. Hence, the matrix $A_{n\times n}$ would be transformed into the fuzzy initial direct-relation matrix Ã. The opinion of each expert is captured in a separate fuzzy matrix presented in Eq. (6.1), where s is the number of experts with $1 \le s \le S$ and $\tilde{a}_{ij}^{s} = (l_{ij}^{s}, m_{ij}^{s}, r_{ij}^{s})$ ($1 \le i, j \le n$) indicates the judgement of the influence of barrier i on barrier j. Then, the fuzzy direct-relation matrix $\bar{A}$ that aggregates the opinions from all invited experts can be obtained, with the element $\bar{a}_{ij}$ calculated by Eq. (6.2). The diagonal element (*i* = *j*) of the matrix $\bar{A}$ is (0, 0, 0).

Table 6.3. Triangular fuzzy numbers

Linguistic term	**Influence score**	**Triangular fuzzy number**
No influence	0	(0, 0, 0.25)
low influence	1	(0, 0.25, 0.50)
Medium influence	2	(0.25, 0.50, 0.75)
Strong influence	3	(0.50, 0.75, 1)
Very strong influence	4	(0.75, 1, 1)

$$\tilde{A}^s = \begin{bmatrix} \tilde{a}_{11}^s & \cdots & \tilde{a}_{1n}^s \\ \vdots & \ddots & \vdots \\ \tilde{a}_{n1}^s & \cdots & \tilde{a}_{nn}^s \end{bmatrix} \tag{6. 1}$$

$$\bar{a}_{ij} = \frac{1}{S} \sum_{s=1}^{S} \tilde{a}_{ij}^s \tag{6. 2}$$

- **Step 3**: Defuzzifying fuzzy numbers to crisp values. There is a need for defuzzification since the form of fuzzy numbers is not compatible with various matrix operations (Yadav et al., 2023). The defuzzification converts the fuzzy numbers to crisp values. The fuzzy numbers are defuzzied using the method adopted by Madhavan et al. (2021), i.e., best non-fuzzy performance (BNP). The crisp value of the fuzzy numbers can be computed with Eq.(6.3):

$$BNP_{ij} = \frac{\left(m_{ij} - l_{ij}\right) + \left(r_{ij} - l_{ij}\right)}{3} + l_{ij} \tag{6.3}$$

where BNP_{ij} represents the achieved crisp value. After the defuzzification process, the new matrix B is obtained as $B = \left[BNP_{ij}\right]_{n \times n}$.

- **Step 4**: Constructing the normalized direct-relation matrix *D*. The matrix *B* can be normalized through Eq.(6.4) and Eq.(6.5) to acquire the normalized direct-relation matrix *D*. A commonly utilized method for normalization is employing the normalization factor *k* calculated by Eq.(6.4). The normalized direct-relation matrix *D* is developed by multiplying the normalization factor k by the matrix *B*:

$$k = \frac{1}{\max\limits_{1 \le i \le n} \left(\sum_{j=1}^{n} BNP_{ij}\right)} \tag{6.4}$$

$$D = k \cdot B \tag{6.5}$$

- **Step 5**: Obtaining the total-relation matrix *T*. Once the normalized direct-relation matrix *D* is constructed, the total-relation matrix *T* that reflects the overall impact relationship between barriers can be computed via Eq.(6.6).

$$T = D\left(I - D\right)^{-1} \tag{6.6}$$

where *I* is the identity matrix.

- **Step 6**: Calculating the row sums and column sums from the total-relation matrix T. Suppose t_{ij} is the (i, j) element of matrix T, then the sum of i^{th} row R_i and sum of j^{th} column C_j can be calculated by Eqs. (6.7)-(6.8).

$$R_i = \sum_{j=1}^{n} t_{ij} \tag{6.7}$$

$$C_j = \sum_{i=1}^{n} t_{ij} \tag{6.8}$$

- **Step 7**: Determining the importance and net effect degree of barriers. The importance degree *R*+*C* measures the prominence of a barrier. The net effect degree *R*-*C* represents the cause-effect relationship between the barriers, which categorizes barriers into “cause” and “effect” groups. It can be explained that if the value of *R*-*C* is positive, the barrier belongs to the “cause” group. In contrast, if the value of *R*-*C* is negative, the barrier belongs to the “effect” group.
- **Step 8**: Developing the causal diagram. The causal diagram is created by mapping the data set of (*R*+*C*, *R*-*C*), with *R*+*C* being the horizontal axis and *R*-*C* being the

vertical axis.

6.3 Results

The reliability of the questionnaires was assessed by the indices of Cronbach's α (Pan et al., 2020). The value of Cronbach's α from data on all the 132 assessed cells was 0.975 and it revealed that the obtained results are highly reliable ($\alpha > 0.7$). The results of the method were presented from two aspects: Importance analysis and causality analysis. The importance degree ($R+C$) and the net effect degree (R-C) of identified barriers are presented in Table 6.4. Furthermore, as shown in Figure 6.3, the causal diagram can be obtained via mapping the dataset of ($R+C$, R-C). Based on Table 6.4 and Figure 6.3, key barriers can be identified with consideration of the importance degree, net effect degree, R and C values. Details of these two types of analysis are presented in the following section.

6.3.1 Results of the Importance Analysis

The results of blockchain adoption barriers in construction were presented from two aspects: Importance analysis and causality analysis. The R+C value refers to how important a barrier is to the whole system, thus facilitating the identification of key factors. As shown in Table 6-.4, environmental barriers have the highest average value of 22.16, followed by organizational barriers at 22.09, while technological barriers have the lowest average of 21.47.

Table 6.4. Degree of blockchain adoption barriers

TOE Barriers	*R*	*C*	*R*+*C*	***R*+*C* Rank**	*R*-*C*	***R*-*C* Rank**	**Class**
Technological barriers			**21.47**		**0.33**		
T1: Scalability	10.56	10.65	21.21	11	-0.09	7	Effect
T2: Smart contracts' security	11.31	10.67	21.97	6	0.64	3	Cause
T3: Immutability challenge of smart contracts	10.84	10.35	21.19	12	0.50	4	Cause
T4: Interoperability	11.20	10.31	21.50	9	0.89	2	Cause
Organizational barriers			**22.09**		**-0.34**		
O1: Lack of awareness and understanding of blockchains	11.68	10.45	22.13	4	1.23	1	Cause
O2: Resistance in changing original management process	10.56	11.56	22.11	5	-1.00	11	Effect
O3: Financial constraints	11.05	10.77	21.83	7	0.28	5	Cause
O4: Lack of sufficiently skilled people	10.75	11.07	21.82	8	-0.31	8	Effect
O5: Negative attitudes towards data	11.	11.5	22.5	2	-	10	Effect

privacy issues and data disclosure	01	5	7		0.54		
Environmental barriers			**22.16**		**-0.53**		
E1: Lack of collaborative culture	10.70	10.55	21.25	10	0.15	6	Cause
E2: Lack of mature policy environments	10.60	11.87	22.48	3	-1.27	12	Effect
E3: Industry concerns about technological maturity	11.14	11.61	22.75	1	-0.47	9	Effect

As shown in Figure 6.3, these average values (22,16, 22.09, and 21.47) were used as thresholds for categorizing identified barriers into three classes (Pan et al.,2020). The right part (R+C ≥ 22.16), referred to as Class III, contains the most critical barriers E3, O5, and E2. The left part (R+C ≤ 21.47), termed as Class I, includes E1, T1, and T3. The remaining is Class II (21.47<R+C<22.16), containing T2, T4, O1, O2, O3, and O4. Thus, E3, O5, and E2 are critical barriers according to the importance analysis.

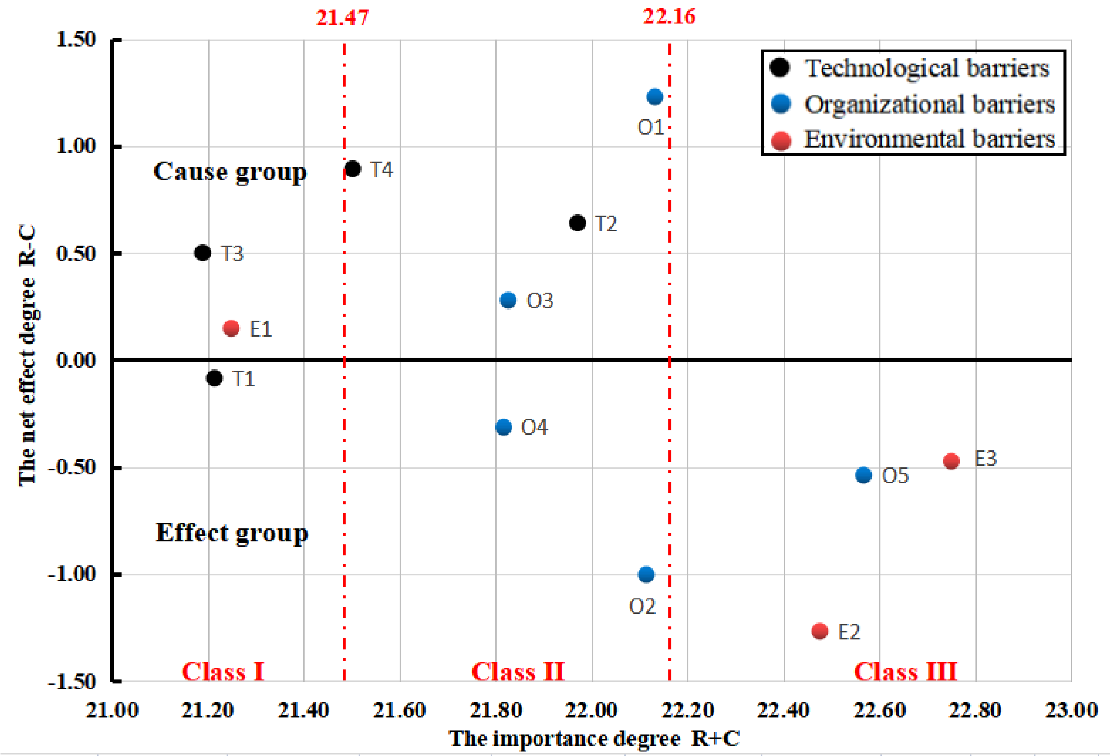


Figure 6.3. The causal diagram of blockchain adoption barriers.

6.3.2 Results of the Causality Analysis

The *R-C* value reveals the influential power of each barrier. More specifically, barriers (*R-C* > 0) that may drive change and have a lasting impact on the system, while barriers (*R-C* < 0) that are reactive and tend to be influenced by other factors were placed in the effect group. Thus, barriers in the cause group should be prioritized when making the policy. According to R-C values, O1, T4, and T2 are the top three casual barriers. That is, these barriers have high influential impacts upon others. O3 is also the cause barrier in Class II. Although T3 and E1 are in the cause group, they are not considered key barriers due to the low importance value. In summary, seven key barriers were identified based on the importance and causality analysis results: T2, T4, O1, O3, O5, E2, and E3.

6.4 Discussion and Implications

6.4.1 Discussion

The gap between increased academic interest and actual implementation necessitates a comprehensive grasp of the barriers to blockchain adoption. This study employed the technology-organization-environment (TOE) framework to identify thirteen barriers, among which the fuzzy Decision-Making Trial and Evaluation of Laboratory (DEMATEL) method identified seven key ones: T2, T4, O1, O3, O5, E2, and E3. Notably, except for T1, most of the technological barriers belong to the cause group, indicating that blockchain adoption is predominantly driven by technology. The identification of T4 and T2 as key barriers is consistent with previous studies (Li and Kassem, 2021; Wang et al., 2022b). For instance, Wang et al. (2022b) noted that blockchain compatibility and technological maturity affected stakeholders' perceived ease of use. Moreover, smart contracts' security is crucial given that they involve high-value assets, and their vulnerabilities, including confidentiality, integrity, non-repudiation, authentication, and authorization, should be considered during deployment (Hasan and Salah, 2018). Notably, the decentralized autonomous organization (DAO) incident in 2016 demonstrated the potential risks of insufficient smart contract security. T2 underscores the importance of interoperability, which can refer to interactions between blockchain and traditional information systems, such as building information modeling (BIM), or among different blockchain networks. Currently, blockchain is not ideally suited for storing large amounts of data, such as BIM models and on-site videos. However, recent studies have proposed solutions to address this issue, such as Tao et al. (2022)'s work on the first problem, while supranational standardization at different levels could facilitate cross-blockchain data sharing (Ølnes et al., 2017).

The study also finds that most organizational barriers (O1, O3, and O5) and environmental barriers (E2 and E3) have high $R+C$ values, indicating their significance in promoting blockchain adoption. In particular, O1 and O3 are causal barriers with high R+C values. Such findings are consistent with Xu et al. (2023), in which the author claimed that construction firms do not understand blockchain potentials and do not know how to implement blockchains. For example, project managers may have misconceptions about blockchain's relationship with Bitcoin. As highlighted by Li et al. (2022c) and Zhang et al. (2023), financial costs may also discourage construction companies from adopting blockchain technology.

Additionally, E2 and E3 are identified as critical barriers due to their high R+C values, supported by recent reports and the study of Wang et al. (2020a). Wang et al. (2020a) found that policy support could be an essential reason for China's success in the blockchain domain. The policy supports, such as the "*Guidance on accelerating the application and industrial development of blockchain technology*" in China and "*The national blockchain roadmap: Progressing towards a blockchain-empowered future*" in Australia, could play a vital role in promoting blockchain adoption in the construction industry.

6.4.2 Theoretical Contributions and Practical Implications

This paper has made several theoretical contributions:

- First, the study identified and examined the blockchain adoption barriers based on previous literature within the technology-organization-environment (TOE) framework. The proposed TOE adoption barriers can serve as a valuable resource for future research in this area.

- Second, the fuzzy Decision-Making Trial and Evaluation of Laboratory (DEMATEL) method was employed to investigate the causal interrelationships among the identified barriers and to identify key barriers. The use of this method improved the reliability of the analysis by handling biases and fuzziness in expert-made evaluations. The study identified seven key barriers, namely T2, T4, O1, O3, O5, E2, and E3, through importance and causality analysis, which can help policymakers prioritize their efforts in decision-making.

Regarding practical contributions, the study suggested that policymakers should prioritize the identified key barriers since tackling all barriers simultaneously is not feasible. The findings of this research can support the policymaking process and accelerate the implementation of blockchains in the construction industry. The study recommended the following practical implications for policymakers:

- First, the government should issue relevant regulations for blockchain projects to alleviate concerns regarding policy uncertainties. Legal issues should be addressed, such as the admissibility of on-chain data as evidence, the right to be forgotten, and the legally binding status of smart contracts (Cermeño, 2016; Li and Kassem, 2021). Additionally, subsidies should be provided to facilitate the diffusion of blockchains in the construction industry (Ding et al., 2023), and relevant training and education programs should be established to enhance project actors' understanding of blockchain.

- Second, relevant governance frameworks and technological standards based on the characteristics of construction projects at the industry level should be introduced. Governance frameworks should take into consideration participant liability, correction methods, and dispute resolution methods(Janssen et al., 2020). Technical standards should be developed to reduce technical uncertainties related to implementing blockchains in construction projects. Modular protocols, for instance, can ensure that different blockchains do not become closed or unable to connect with each other.
- Thirdly, construction organizations should help project managers acquire blockchain knowledge to reduce their bias or preference toward blockchain technology. According to the status quo bias theory (Samuelson and Zeckhauser, 1988), individuals are resistant to adopting new technology when their bias remains with their current technology. Figure 6.4 summarizes the implications of this study.

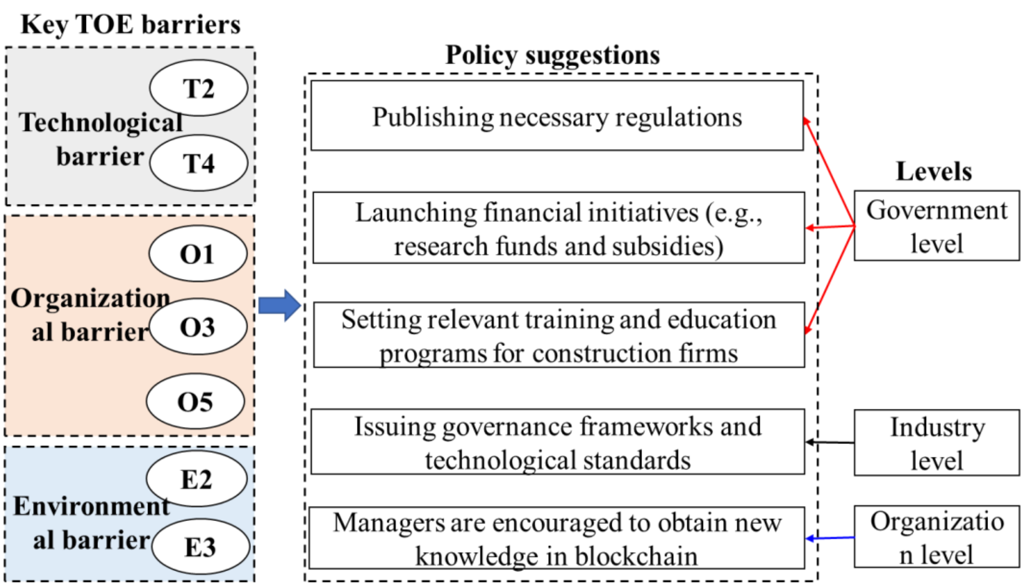


Figure 6.4. Implications from the government, industry, and organization level.

6.4.3 Limitations

This study has several limitations:

- First, the results of this study are based on the expert group's subjective judgments. Such a limitation is frequently associated with exploratory research. Given the infancy of blockchain technology interventions in construction research and practices, a broad-based study is difficult. Few experts, especially from the industry, have enough knowledge of blockchains. Aiming to guarantee the reliability of the result, participants should be knowledgeable in construction project management and blockchain. In this study, we used purposeful sampling (e.g., searching scholars who have published blockchain articles and project managers involved in related projects) to ensure the quality of responses, which also limits the sampling size. Only 20 experts with relevant experiences were invited to this research, and the fuzzy set was used to reduce the influence of bias of a small expert group. With the development of blockchain, future studies can consider a large scale in terms of the number of respondents, especially industrial experts. Moreover, academics and practitioners (e.g., owners, contractors, supervisors, and so on) may hold different viewpoints on adopting this emerging technology. Future studies should seek feedback from a diverse range of stakeholders and analyze similarities and differences in their perspectives.
- Second, most of the invited experts come from China due to the data accessibility and China's leadership position in the blockchain. The author acknowledges that this attribute of our respondents may have an impact on the findings' generalizability. For the sake of generality, a comparative analysis is required for multicounty comparison to assess the effect of variables on blockchain adoption

from different countries.

6.5 Chapter Summary

This chapter conducts a fuzzy Decision-Making Trial and Evaluation of Laboratory (DEMATEL) based analysis to identify key barriers hindering blockchain adoption in construction. Blockchain adoption barriers are firstly determined with the technology-organization-environment (TOE) framework that considers technological, organizational, and environmental contexts. Based on the data collected from 20 qualified experts, seven key barriers were identified through the importance analysis and causality analysis, termly, T2, T4, O1, O3, O5, E2, and E3. Policy suggestions were proposed from the governmental, industrial, and organizational levels. Overall, this study makes contributions to the existing body of knowledge by reviewing blockchain adoption barriers within the TOE framework, identifying key barriers, and proposing corresponding solutions to facilitate blockchain diffusion.

CHAPTER 7 Conclusion

7.1 Introduction

This chapter firstly reviews the research objectives of this thesis. Then, key findings are highlighted, followed by their significance and contributions. Finally, the recommendations for future studies are discussed.

7.2 Review of Research Objectives

Construction quality significantly affects the structural integrity, functionality, and safety of occupants. Unfortunately, quality failures seem to be an ever-present reality in the construction industry. Three issues hindering the improvement of construction quality performance are highlighted in terms of the whole construction process. Firstly, traditional construction conventions are labor-intensive, and the quality performance of final products is inseparable from on-site productive workers, especially for several types of construction products that cannot be directly measured, like concrete grouting for connecting precast components. However, construction workers often endure physical fatigue since they need to complete highly physically demanding tasks, and fatigued workers easily make mistakes, degrading workmanship. Secondly, postconstruction quality inspection is usually conducted by quality inspectors. Manual quality defection inspection (QDI) has limitations in efficiency, accuracy, and reliability. Thirdly, the construction project is a temporary organization involving various stakeholders. These project actors with different objectives, expectations, and interests must interact over long time horizons. Conflicts and opportunistic behaviors are usually observed due to the lack of credible information for quality traceability. The development of worker-robot collaboration (WRC) and blockchain technology could address these quality issues.

However, several research problems should be tackled when utilizing the WRC and blockchain-based construction quality management in future. First, safety concerns, e.g., collision risks, hinder the implementation of WRC teams. Collaboration cannot be real until workers' safety can be guaranteed. The worker may need a reliable and easy-to-use interaction method to control the robotic assistant. Second, data privacy concerns limit the application of multi-robot-based quality defect inspections since collecting sufficient data for training a powerful deep learning model is usually time-consuming and costly in practices. Construction practitioners may encounter the data availability problem. Third, there is a lack of discussions related blockchain-based on-site construction activity information recording. Finally, considering that blockchain is an institutional technology and its adoption will meet more resistances than other digital technologies, it is necessary to investigate possible blockchain adoption barriers and identify key ones.

In light of these questions, research objectives (RO) and chapter structures discussed previously are presented as follows:

- **RO1**: To demonstrate the feasibility of thermal image-based hand gesture recognition for on-site WRC and design a lightweight network to help resource-constrained construction robots recognize hand gestures. This RO is answered in Chapter 3.

- **RO2**: To develop a hierarchical federated learning (FL) framework to help multiple construction robots collaboratively train the defect detection model without sharing their local data. This RO is illustrated in Chapter 4.
- **RO3**: To design a decentralized blockchain framework for recording construction process information and to develop a prototype for supporting quality traceability and accountability. This RO is tackled in Chapter 5.
- **RO4**: To investigate blockchain adoption barriers, identify key ones, and propose policy suggestions for promoting blockchain implementation in the construction industry. This RO is introduced in Chapter 6.

7.3 Summary of Main Findings

The key findings of this research are presented below. Firstly, current construction robots are technically incapable of autonomously performing much useful construction work. Worker-robot collaboration (WRC) is a promising method in which the human worker carries out the planning task and supervises the robot assistant to execute tasks that require physical exertion. A thermal image-based hand gesture recognition method was proposed for safe and efficient interactions in WRC. A thermal dataset containing seven gestures was established, and a lightweight model, termly, ThermalNet, was developed. Experimental results demonstrated the superiority of the ThermalNet compared to other advanced lightweight models, such as MobileNetV2, MobileNetV3, and ShuffleNetV2. Specifically, ThermalNet has fewer parameters (1.8 million), higher accuracy (97.54%), and minimum latency (7.98ms in GPU and 72.31ms in Raspberry Pi).

Secondly, existing DL works concentrated on improving accuracy, and limited attempts have been made to investigate the data availability and privacy issues in quality defect inspection (QDI) tasks. A three-fold hierarchical federated learning (FL) framework was proposed to help different construction robots collaboratively train the defect detection model without averaging data. Given the crack segmentation as the case, the CrackNet was developed. Experimental results indicated that CrackNet with fewer parameters achieves comparable performance with other segmentation algorithms. The proposed FL training strategy has better performance than the traditional centralized training strategy in terms of intersection over union (IoU) and F1. Moreover, the three-fold FL method can reduce communication costs when compared to traditional client-device FL methods.

Thirdly, blockchain is an ideal solution for quality information management, while previous studies mainly concentrated on supply chain information or quality inspection texts. Little is known about blockchain-based construction process information recording. A conceptual framework integrating computer vision and blockchain technology was proposed to bridge this gap. This framework contains two layers: (1) the information collection and processing layer; (2) the blockchain layer. Worker activities during the construction process are recorded by far-field surveillance videos and then extracted by DL models. The extracted information, as well as the raw data, would be recorded in the blockchain system for process quality traceability. Hyperledger Fabric was regarded as the proper architecture for construction quality management. Additionally, a consortium blockchain prototype was developed based on the Blockchain as a Service (BaaS) platform. Experimental results demonstrated the feasibility of the prototype. Specifically, it can reach an acceptable throughput of around 750 with a blockchain size of 2500. The maximum latency was still controlled in 3s with ten nodes.

Fourthly, there is a paucity of blockchain implementations from real-world construction projects. Blockchain adoption may confront various barriers from technology-organization-environment (TOE) contexts. Based on a systematic literature review, 13 barriers were determined within the TOE framework. The fuzzy Decision-Making Trial and Evaluation of Laboratory (DEMATEL) method was used to identify key factors through the importance and causality analysis. The results revealed that the construction industry is more concerned with environmental barriers, such as policy uncertainties (E2) and technology maturity (E3), while most technical barriers are causal factors, such as "interoperability (T4)" and "smart contracts' security (T2)". Policy suggestions from the government, industry, and organization levels were proposed to promote blockchain adoption in the construction industry.

7.4 Significance and Contributions

This research has several practical implications and meanings. It can facilitate the improvement of construction quality performance by proposing numerous digital solutions to tackle current construction quality management issues. More specifically, the proposed method in Chapter 3 enables the transition from labor-intensive construction conventions to worker-robot collaboration (WRC) teams, which can in turn reduce quality errors in construction. The proposed method in Chapter 4 provides construction organizations with a feasible way to conduct quality inspection tasks with robots, which can enhance inspection efficiency and result reliability. The developed method allows robots from different projects to form a system and collaboratively train the defect detection model without data privacy and leakage risks. Moreover, the proposed method in Chapter 5 enables worker activity information during the construction process to be immutably recorded. The recorded data can support quality traceability and accountability, reduce disputes, and mitigate opportunistic behaviors in inter-organizational collaborations. However, blockchain is more than an information innovation for a single organization and represents a wider revolution in institutions, organizations, and governance. Hence, its adoption will definitely meet numerous resistances. Thus, Chapter 6 provides policymakers, researchers, and practitioners with a comprehensive understanding of blockchain adoption barriers and supports policy-making processes by identifying key barriers from the government, industry, and organization levels.

Additionally, the theoretical contributions of each research topic are listed as follows:

- This study provided a feasible method to support safe and efficient WRC. This is one of the first studies investigating thermal image-based hand gesture recognition (HGR) in WRC applications. Existing methods relying on 3-channel RGB images are prone to be affected by on-site environmental disturbances (e.g., poor illumination at night). Moreover, the developed lightweight model allows resource-constrained robots to accurately recognize gestures from thermal images. This model inspires more attention to the practical feasibility of deep learning (DL) models.
- This research first noticed data availability and privacy issues when applying construction robot systems in quality defect inspection (QDI) tasks. Existing defect

detection studies mainly concentrated on improving the performance of DL models. A hierarchical federated learning (FL) framework was proposed to tackle these issues. This is one of the first studies that explored FL potential in QDI tasks. Additionally, a lightweight segmentation algorithm was proposed to reduce communication costs in FL training processes.

- This research provided a blockchain-enabled framework to record activity information of on-site workers for quality traceability. Previous studies in the construction industry mainly focused on the recording of supply chain information or quality inspection texts. Little is known about construction process traceability. The proposed conceptual framework bridge this knowledge gap. Moreover, a prototype was developed based on a general Blockchain as a Service (BaaS) platform.
- This research identified blockchain adoption barriers within the technology-organization-environment (TOE) framework, which can serve as a valuable resource for future research. Causal interrelationships among these barriers were examined through the fuzzy Decision-Making Trial and Evaluation of Laboratory (DEMATEL) method that can handle biases and fuzziness in expert-made evaluations and enhance the reliability of the results.

7.5 Recommendations for Future Research

This section discusses future research directions in worker-robot collaboration (WRC) and decentralized blockchains for enhancing the quality performance of construction projects.

Firstly, how to achieve safe and efficient WRC should be further explored. For example, future works will focus on thermal and RGB data fusion-based hand signal recognition. RGB images typically have high spatial resolution and considerable detail (e.g., color feature, texture information, etc.), while thermal data is robust to lighting conditions. The fusion is more informative than that of single-modality signals. However, how to leverage the useful modality information while avoiding redundant features is still a challenge. Moreover, worker intention prediction could be discussed. Current WRC methods highly rely on human-dominated communications. One-way communications are far away from natural, efficient, and safe WRCs because they bring additional cognitive overload to human workers. Giving two workers' corporations as an example, both of them can know the interaction intention of the other and can give assistance in real time. Hence, a promising solution is to consider a new paradigm of proactive WRC, in which robots have the ability to understand worker intentions and then proactively offer physical assistance instead of just receiving instructions from human workers. That is, a robot can give proactive assistances that is timely, task-appropriate, and wanted by the worker. However, seldom has investigated the feasibility of worker intention recognition in construction.

Secondly, future studies could investigate the feasibility of blockchain-based federated learning (FL) in construction quality inspection. Blockchain can ensure data privacy, model security, and computation auditability. Future studies can focus on blockchain-empowered FL, especially the issues of designing high-efficiency consensus and incentive mechanisms.

Thirdly, blockchain could be a new type of governance mechanism for construction projects since it provides accurate and trustworthy information records for quality accountability and automates some transactions with smart contracts. Future studies can focus on (1) combining different sensing technologies to systematically extract different types of quality information for traceability; (2) designing smart contracts for the compliance checking of construction procedures during a specific period; and (3) automating the generation of smart contracts for quality compliance checking.

Finally, in terms of blockchain adoption, future studies can collect data from different participants to find any differences between different groups. For example, the multistakeholder approach could be used to compare opinions from stakeholders (e.g., owners, contractors, supplies, etc.) with varying backgrounds and expectations. Moreover, longitudinal studies could be adopted to explore the evolution of these barriers and illustrate how much they may shift in specific projects. Game theories can also be used to test the role of specific factors in blockchain implementation.

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