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INTEGRATING COMPUTER VISION INTO QUALITY ASSURANCE OF STRUCTURAL CONCRETE IN SRI LANKAN CONSTRUCTION INDUSTRY

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ABSTRACT

The Sri Lankan construction industry struggles with persistent quality issues in structural concrete works, including cracks, honeycombing, spalling, and misaligned reinforcement, resulted in cost overruns, delays, and safety risks due to inefficient manual inspections. This study investigates the integration of computer vision (CV) technologies leveraging convolutional neural networks (CNNs) and deep learning algorithms into quality management processes to enable proactive, automated defect detection during construction. A literature review identifies CV's efficacy for real-time monitoring and its superiority over traditional methods, while highlighting adoption barriers including data scarcity, high initial costs, skill shortages, and infrastructure limitations specific to Sri Lanka. Semi-structured interviews with ten industry experts reveal strong consensus on CV's potential for accuracy, standardisation, and productivity gains, but they also confirm the sector's incompetence, particularly among small contractors facing a shortage of human and financial resources. Key recommendations include government-incentivised pilot projects, localised datasets, workforce training, awareness programs, and hybrid LLM-mobile applications as scalable entry points. Findings highlight the need for a tailored framework to transition from reactive to predictive quality assurance. By addressing contextual challenges through phased implementation and policy support, CV integration promises enhanced structural integrity, reduced rework, and sustainable development in Sri Lanka's construction landscape. This research provides a roadmap for digital transformation, with implications for similar developing economies.

Keywords: *Computer Vision; Concrete Defects Construction Industry; Quality Management; Sri Lanka.*

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1. INTRODUCTION

The construction industry is a major contributor to the economic and physical development of a developing country, especially Sri Lanka (Madushika & Thayaparan, 2024). However, the Sri Lankan construction sector faces numerous complications, including cost overruns and delays in the project, which are rooted in the quality issues during the construction, as it requires numerous rework and repairs (Madushika & Thayaparan, 2024; Nawade et al., 2022). The common types of quality issues include structural defects including cracks, honeycomb, surface delamination, poor workmanship, water leakage and misalignment of reinforcement (Nawade et al., 2022). Therefore, maintaining the structural quality is the top priority, as the undetected defects cause potential defects on the appearance, durability, functionality, financial returns and safety of structures (Abdelalim et al., 2024; Madushika & Thayaparan, 2024). Madushika & Thayaparan (2024) stated that using the traditional quality management system in Sri Lanka is inefficient, since it fails to achieve early and precise defect detection. Rather than depending on the conventional approaches, it is vital to switch to innovative quality management techniques to improve construction efficiency, ensure sustainability and reduce the cost of reworks through facilitating early defect detection through automated real time monitoring (Wendabona, 2024). The development and adoption of industry-specific Artificial Intelligence (AI) solutions tailored to the unique needs and constraints of the construction industry can help to improve the quality of construction structures (Wijesinghe et al., 2024). Computer Vision (CV), especially those based on convolutional neural networks, has proven to be well-suited for automated early defect detection in concrete structures as it addresses most of the limitations of conventional inspection methods and offers innovative solutions for real-time structural quality monitoring throughout the construction process (Wang et al., 2022). The global construction industry has shown significant attention towards employing CV tools since it enables real-time tracking, improve the efficacy of defect detection, lower long-term maintenance costs and facilitate prompt remedial actions (Abdelalim et al., 2024).While the global literature has extensively investigated CV algorithms and technical architectures for structural defect detection (Jiang & Messner, 2023; Pan et al., 2025), the application of CV within the socio-economic and infrastructural constraints of developing economies, particularly Sri Lanka, remains unexplored. This study addresses that gap by investigating the feasibility, barriers, and adoption strategies for CV integration within Sri Lanka's construction quality management system. Accordingly, this study aims to explore the feasibility of introducing CV technologies into the quality management system for structural concrete in Sri Lanka's construction industry. To achieve this, the study pursues objectives including identifying limitations and challenges in integrating CV applications into construction quality management, assessing Sri Lanka-specific barriers and enablers to CV adoption, and proposing context-specific strategies to facilitate the effective integration of CV technologies into Sri Lankan construction quality management practice.

2. LITERATURE REVIEW

2.1 COMMON STRUCTURAL DEFECTS IN CONSTRUCTION

Structural defects in construction represent failures to meet functional, performance, statutory, or user requirements of buildings or civil structures, compromising their integrity and durability (Ekanayake, 2022; Kang et al., 2025). These defects commonly manifest in concrete elements as cracks, segregation, spalling, disintegration, honeycombing, and delamination, while reinforcement misalignment, corrosion of embedded metals, and reinforcing steel further accelerate structural deterioration (Bahreini & Hammad, 2024; Obiora et al., 2022). Similarly, misalignment and bulging in columns, beams, and slabs are often due to inadequate formwork and supervision. Misalignments of doors, window frames, and lintel-frame gaps commonly undermine structural functionality and aesthetics (Dahanayake & Ramachandra, 2015; Olanrewaju & Lee, 2022).

Unaddressed defects escalate from minor issues to major failures, causing structural instability, collapse risks, safety threats, costly rework, time overruns, and reduced project productivity and efficiency (Hussamadin et al., 2023; Karunasena et al., 2025; Obiora et al., 2022). Dahanayake & Ramachandra (2015) emphasise the "doing things right the first time" principle to ensure efficiency, safety, and quality standards in construction. Implementing this requires identifying and preventing defect causes, including incompatible materials, poor workmanship, insufficient supervision, improper installation, mix design flaws, weak management, and maintenance neglect (Dahanayake & Ramachandra, 2015).

Sri Lanka's current quality management system relies on reactive defect detection, addressing issues only when obvious defects necessitate repairs (Dubas & Pasławski, 2018). Traditional quality management relies on manual visual inspections for structural stability assessment, which are inconsistent, subjective, and error-prone while failing to detect early-stage defects (Abdelalim et al., 2024; Hui et al., 2025; Mirbod & Shoar, 2023). Even though traditional quality management techniques help to maintain the quality of structures through rework or repair, it results in a cost overrun (Dahanayake & Ramachandra, 2015). This necessitates a shift to innovative digital solutions in the Sri Lankan construction industry.

2.2 COMPUTER VISION AS A TOOL FOR DEFECT DETECTION

CV is a key AI domain that enables autonomous recognition, analysis, and evaluation of visual content in images and videos using extensive training datasets, thereby improving defect detection accuracy and efficiency (Ekanayake, 2022; Ettalibi et al., 2024; Jiang & Messner, 2023). CV tools are widely applied for structural defect assessment due to their efficiency, economy, and precision (Hui et al., 2025; Pan et al., 2025). Structural cracking, honeycombing and surface porosity detection are emerging defects, where the recent hybrid deep learning models exhibited acceptable real-time detection performance (Das et al., 2025).Reinforcement misalignment detection, formwork quality inspection and multi-defect simultaneous classification are still in its infancy and have limited validated models used in the construction site (Pan et al., 2025).Moreover, CV extracts high-dimensional real world data to advise decision making (Zhong et al., 2019). Integration with deep learning (DL) techniques, including advanced CNN architectures, two-stage models, back-propagation networks, and YOLO, enhances concrete defect recognition, enabling image processing, categorisation, detection, and segmentation for precise diagnosis and quality improvement (Ekanayake, 2022; Hui et al., 2025; Wijesinghe et al., 2024). Automated real time monitoring thus advances construction quality control (Wijesinghe et al., 2024).

Image acquisition and dataset preparation constitute the initial step in CV-based defect detection, ensuring sufficient data quantity and quality for effective DL model training (Kang et al., 2025; Zhong et al., 2019). Automated tools, including high-definition or handheld cameras, CCTV, drones, and UAVs capture visual data from construction sites (Gang, 2024; Mirbod & Shoar, 2023; Kang et al., 2025). Kang et al. (2025) and Gang (2024) recommend using smartphone photography with zoom lenses for cost effective, standards compliant imaging without additional equipment. Public datasets provide an alternative for image acquisition to train CV models (Gang, 2024; Munawar et al., 2021). Data augmentation techniques, including rescaling, rotation, shifting, and preprocessing, address high quality image scarcity by expanding datasets, enhancing diversity, noise resistance, and generalisation (Kang et al., 2025; Munawar et al., 2021). Collected images enable CV tasks including retrieval, object detection, semantic segmentation, and categorisation into predefined groups (Nath & Behzadan, 2020). Datasets are then pre-processed and divided into training and testing sets (Gang, 2024; Munawar et al., 2021).

Image processing is an important step to transform images from unprocessed visual input into information that an ML model can interpret (Jiang & Messner, 2023; Gang, 2024). After preprocessing, feature extraction is done to derive vectors for defect classification (Jiang & Messner, 2023). Techniques like Histogram of Oriented Gradients (HOG) or Local Binary Patterns (LBP) analyse structural properties and textures for defect identification (Hui et al., 2025; Mirbod & Shoar, 2023). Gang (2024) recommends replacing these noise-sensitive, feature-based ML methods with deep learning for superior accuracy in real-world construction defect detection. Gang (2024) specifies DL's revolutionary impact on CV applications, particularly defect detection. Convolutional neural networks (CNNs) excel at automatically extracting complex features from raw images, eliminating manual detection needs (Jiang & Messner, 2023; Gang, 2024). CNNs comprise three core layers: convolutional layers for feature extraction, pooling layers to reduce spatial dimensions and computational costs, and fully connected layers that flatten features for optimisation and classification (Pan et al., 2025).

Ekanayake (2022) and Lee et al. (2020) classify the object detection algorithms into two major groups: one-stage and two-stage models, based on their functional output. Two-stage detectors, such as Faster R-CNN, prioritise detection accuracy by first proposing regions of interest before categorising them (Lee et al., 2020; Pan et al., 2025). Conversely, one-stage models, such as YOLO and Single Shot MultiBox Detector (SSD), provide quick, real-time prediction speeds by treating the entire detection task as a regression issue in a single pass (Ekanayake, 2022; Hui et al., 2025). CNN-based models perform with high accuracy and reliability in detecting and classifying concrete defects. Moreover, integrating CNN into frameworks such as R-CNN or U-Net to offer accurate defect detection, localisation, and quantification (Gaur et al., 2023; Madushika & Thayaparan, 2024; Wijesinghe et al., 2024). Pan et al. (2025) identify reporting as the final stage that converts computational output into useful engineering insights.

Utilisation of complex DL algorithms, such as CNN, helps to achieve robust and improved quality assurance through addressing the limitations of traditional quality management across both pre-concreting and post-concreting phases (Ettalibi et al., 2024; Gaur et al., 2023). During the pre-concreting stage, CV-integrated systems based on CNN architectures can provide real-time monitoring of reinforcement alignment, work positioning of the formwork and mix design compliance before concrete is placed (Ekanayake, 2022; Pan et al., 2025). In the post-concreting phase, CV tools can be used to efficiently detect defects, such as cracks, honeycombing, spalling, and delamination (Abdelalim et al., 2024; Hui et al., 2025). The automated imaging and classification at the documentation and traceability phase provide a documented record of defects with dates and geolocations, enhancing accountability and dispute resolution (Hussamadin et al., 2023). Moreover, it is recommended to integrate CV-based QM systems with BIM or Digital Twins (DT) to enhance system efficiency (Madushika & Thayaparan, 2024). The construction industry can move from a "reactive" quality management approach to a "proactive" and "predictive" approach by incorporating CV into pre- and post-concreting processes, significantly reducing the rework costs and improving structural integrity (Wijesinghe et al., 2024).

2.3 CHALLENGES IN ADOPTING CV IN SRI LANKA

Several challenges that hinder the integration of -CV-based defect detection for construction quality management are identified (Ettalibi et al., 2024). The lack of training data and computational resources for creating, training, and implementing sophisticated CV models is the biggest obstacle to the adoption of CV-based systems (Ekanayake, 2022; Jiang & Messner, 2023; Pan et al., 2025). It is essential to expand and maintain the defect database to improve model accuracy, as insufficient annotated data can reduce model accuracy and reliability (Costa et al., 2024; Lee et al., 2020). High DL complexity drives substantial hardware, software, training, consulting, and operational costs (Ekanayake, 2022; Islam et al., 2024; Wijesinghe et al., 2024). Small and medium-sized contractors, who are dominating the Sri Lankan construction industry, have low levels of financial resources needed for making large, up-front investments in technology (Wijesinghe et al., 2024).Furthermore, the period required to achieve a measurable return on investment (ROI) from CV integration is notably prolonged, particularly in developing countries. This extended timeframe often leads organisations to hesitate in adopting CV technologies for quality management purposes (Wijesinghe et al., 2024).

Emuze et al. (2023) highlighted professionals' inadequate technological expertise as a key barrier to adopting CV. Construction professionals are expected to acquire new technological competencies due to the complexity of integrating CV with technologies like BIM (Costa et al., 2024). In addition, the scarcity of skilled AI engineers in the construction sector is a significant challenge in developing customised solutions (Abioye et al., 2021). Moreover, poor digital infrastructure is identified as a major hindrance to the real-time deployment of CV- based tools, since digital infrastructure is still at a primary stage in most Sri Lankan construction sites, with poor connectivity and limited hardware and infrastructure needs (Wendabona, 2024). Finally, the absence of any regulatory standard or government policy framework which encourages the use of digital quality management technologies in construction delays the digitalisation of QM in Sri Lankan construction. Emuze et al. (2023) highlight that, in developing nations, construction firms adopt innovations only when authorities enforce supportive policies (Emuze et al., 2023). Therefore, the authorities need to handle non-technical challenges, particularly costs and establish frameworks for CV integration.

This study mainly focuses on concrete structural defects prevalent in Sri Lankan construction projects, which compromise structural integrity, escalate rework costs and contribute to frequent delays and safety risks (Dahanayake & Ramachandra, 2015). Traditional manual inspections practised in Sri Lanka, which rely on subjective visual assessments, fail to detect early-stage issues efficiently, leading to reactive quality management (Das et al., 2025). , This study tries to address the drawbacks of the current QM systems and to provide suggestions and recommendations to facilitate CV implementation, mitigating potential risks involved in digitalisation within the unique economic and operational environment of the Sri Lankan construction industry (Abioye et al., 2021; Costa et al., 2024).

3. RESEARCH METHODOLOGY

Research methodology is a systematic approach to scientifically solving research problems by defining a comprehensive strategy for conducting investigations (Mendis, 2023). This study aims to evaluate the feasibility of CV technologies and facilitate their integration into quality management practices for concrete structures within the Sri Lankan construction industry. It's important to analyse the practical applicability of CV-integrated tools along with their adaptability, feasibility, and industry capability for CV adoption. A literature review was conducted as the first phase of this study to understand the integration of CV into the QM of concrete structural works and its implications for the construction industry by exploring existing research on CV applications in construction, the challenges faced in defect detection, and current QM practices. Then, 10 semi-structured interviews are conducted to collect insights from construction professionals to identify prevailing trends, challenges, and levels of awareness related to CV technologies and their applications. The interview facilitates assessing both the technological applicability and the practical capability of the Sri Lankan construction industry for the adaptation of CV. The respondent's profile is provided in the Table 1.

Table 1: Profile of the respondents

Code	Organisation type	Designation	Experience
R1	QS Consultancy Firm	Director	33
R2	Contractor Organisation	QMS Engineer	15
R3	Consultant Organisation	Structural Engineer	30
R4	Education Institute	Researcher and Educator	7
R5	Statutory board	Research Material Engineer	12
R6	IT System Custom Software Developer	Chief Executive Officer	3
R7	Contractor Organisation	Structural Engineer	20
R8	Education Institute	PhD Scholar and Lecturer	8
R9	Contractor Organisation	Material Engineer	10
R10	Education Institute	PhD Scholar and Lecturer	10

As shown in the table, semi-structured interviews were conducted by employing purposive sampling to select 10 expert interviewees currently practising in the construction industry, covering Directors, CEOs, Quantity Surveyors, Structural Engineers, QMS Engineers, Material Engineers and PHD scholars who have done research related to CV and AI tools. Interviewees were selected based on their expertise, experience and sound knowledge of the construction industry and the AI technologies. Contractors (R2, R7 and R9) shared their experience and challenges in the workplace related to on-site QM practice. The consultant respondents (R1, R3 and R5) provided input on technical standards and regulatory compliance. Academic researchers (R4, R8, R10) were included specifically due to their active research engagement with CV, AI and digital construction technologies, which help to establish technical validation of the feasibility of adoption based on evidence (Ekanayake, 2022). The technology developer, respondent (R6), provided information regarding the cost and approach to be followed to develop an application for CV-based quality management. . The purposive sampling facilitates exploration of complex industry dynamics and ensures representation of the key groups involved in any future CV implementation pathway. (Ekanayake, 2022). Instead of statistical representativeness, sample size in qualitative inquiry is validated by the extent of data saturation, which is when more interviews do not yield new thematic content (Malterud et al., 2016).Data saturation point was found in this sample after interviewing the eight respondents, where the themes of the main dimensions of CV potential, barriers and adoption strategies showed consistent convergence of perspectives across respondents. Therefore, the sample size of 10 respondents is considered to be appropriate to achieve the goal of the study. Moreover, this study adopted a qualitative research approach to analyse the integration of CV in QM for Sri Lankan construction. The NVivo software was used to analyse the collected data using code-based thematic coding, enabling systematic identification of patterns.

4. RESEARCH FINDINGS AND DISCUSSION

This section presents and discusses the principal research findings derived from the expert interviews conducted as part of this study. The insights gathered from these interviews provide valuable qualitative evidence, reflecting the perspectives, experiences, and professional judgments of industry practitioners regarding the Importance of integrating computer vision into the quality management of the Sri Lankan construction industry. These findings highlight the benefits of applying CV in construction quality management, identify the challenges associated with its adoption in Sri Lanka, and propose strategies to facilitate its effective integration into construction quality management practices.

4.1 POTENTIAL OF CV IN CONSTRUCTION QUALITY MANAGEMENT

The experts were invited to share their perspectives on the potential benefits of integrating CV into construction quality management practices and summarised in Figure 1.

Name	Files	References
Potential of CV in construction quality management	8	22
Better than the manual process	1	1
Can facilitate consistent quality monitoring	1	2
Cost of paper is reduced	1	1
CV and 3D models can be used with machine learning	1	1
CV can detect visual defects	1	1
Early defect detection	2	3
Facilitate automated reporting	1	2
Good at verifying materails and workmanship quality	1	1
Improve efficiency and reduce rework	1	1
Reduce Subjectivity	2	3
Strength and design adequacy cannot be verified	1	1

Figure 1: Potential of CV in construction quality management

The experts identified several potential capabilities of Computer Vision (CV) that could effectively address the limitations of existing quality management practices in the Sri Lankan construction industry. In addition to the general findings, Respondent R2 highlighted that CV can enhance efficiency, particularly when integrated with mobile or drone-based imaging systems. Furthermore, Respondent R6 emphasised that CV has the potential to reduce subjectivity in quality inspections, thereby minimising disputes in decision-making processes. Respondent R4 highlighted that the integration of CV technologies has the potential to create new employment opportunities, driven by the increasing demand for AI specialists. In addition to these features, Table 2 presents a list of key benefits that can be achieved through the integration of CV technologies and the number of respondents agreed.

Table 2: Key benefits of CV technologies

Benefits of CV technologies	The number of Respondents
Accuracy in Defect Detection	10
Consistency and Standardisation of Quality Control Procedures	9
Enhanced Documentation and Traceability	9
Productivity Improvements	10
Improved Efficiency and Reduced Inspection Time	10
Improved Worker Safety	10
Integration with Digital Platforms	10
Lower Project Costs and Reduced Rework	7
Real-Time Monitoring	10
Reduction in Human Error	7
Supports Proactive and Predictive Quality Management	10

According to the findings presented in the Table 2, all respondents emphasised that maintaining high accuracy in defect detection is mandatory for CV systems. However, R1 noted that human verification is essential, as CV tools cannot independently handle complex problem-solving tasks, and emphasised the need for workforce discipline to enhance efficiency and reduce inspection time. Similarly, R1, R9, and R10 acknowledged that human intervention is crucial in quality inspection processes. R8 reinforced this perspective, stating that *"CV technologies should be seen as a support tool rather than a replacement for engineers, and their successful use in Sri Lanka will depend on gradual adoption, strong leadership commitment, localised datasets, and integration with existing quality management practices to build trust and demonstrate long-term value." Further, R1 emphasised the necessity to train these systems to* replicate the thoughtful analysis of an experienced QA engineer. Further, R1 also highlighted that training data should be cautiously selected and entered into CV models to ensure that CV models can "imagine and visualise" structural conditions similar to an expert. This approach enables the models to examine complex situations, spot defect patterns, and produce clear, insightful results rather than simple mechanical outputs. R1 also noted that CV models will gradually minimize the need for manual checks on routine tasks, while maintaining human decision for complex scenarios. This automation perspective is reinforced by R6, who recommended integrating CV with robotics to enable greater automation and promoted using analytical algorithms instead of statistical machine learning approaches.

4.2 CHALLENGES IN ADOPTING CV

Despite the abundant benefits, certain challenges remain inevitable. The identified challenges are summarised Table 3.

Table 3: Common barriers to the adoption of CV

Common Barriers to the Adoption of CV	Number of Participants
Unavailability of Datasets	10
Challenges in data management and privacy	8
Insufficient digital infrastructure on construction sites	9
Adverse environmental conditions	7
High Initial Cost	8
Difficulties in integration with existing workflows	7
Scarcity of skilled AI professionals	9
Lack of standards and regulatory support	8

Experts also provided practical recommendations to address the primary cost barriers hindering the adoption of CV technologies. To mitigate data insufficiency, R2, R6, and R8 suggested developing and maintaining localised datasets tailored for CV model training, enabling context-specific defect recognition in concrete structures while reducing reliance on foreign datasets ill-suited to local materials and environmental conditions. For data security concerns raised by 8 respondents, experts encouraged secure cloud storage solutions backed by robust contractual agreements and data management protocols, ensuring compliance with Sri Lankan data protection regulations while enabling access across project teams. Furthermore, R8 identified organisational resistance to change as a key factor delaying technology integration, which also contributes to workflow integration challenges, as noted by seven respondents. To address this, R2 encouraged programming CV tools for seamless alignment with existing quality assurance procedures, thereby minimising operational disruptions during adoption. Complementing this approach, R6 proposed that initiating implementation with simple mobile applications as a low-risk entry point.

In addition to the barriers, the substantial cost associated with CV integration is a major obstacle to its implementation. Figure 2 illustrates the important cost barriers impeding CV adoption.

Name	Files	References
Cost barriers that hinders the implementation of CV	4	4
Graphics Processing Unit (GPU) cost is high	1	1
High purchasing cost	1	1
High upfront investment in hardware, software, training and system integration	2	2

Figure 2: Cost barriers for the implementation of CV

The barriers depicted in Figure 2 mainly concern initial implementation costs, as experts emphasised that ongoing integration expenses exert minimal influence. R6 offered a detailed breakdown of CV model development and maintenance costs, supported by specific figures. According to R6, "*deploying CV models capable of detecting defects across a 8-storey building in a single scan incurs a monthly recurring charge of approximately $10,000. Data collection costs approximately $9,000, while model development costs $6,000, yielding a total initial development cost of $15,000. Monthly maintenance thereafter is estimated at $10,000.*" Professionals were also invited to offer recommendations for overcoming these cost barriers. Accordingly, respondents R2 and R8 proposed conducting pilot projects and implementing them in phases, supported by government incentives.

4.3 SUGGESTIONS TO FACILITATE THE ADOPTION OF CV

The experts were requested to provide suitable recommendations to overcome these barriers and to improve the CV for construction quality management. Accordingly, R1 highlights that the "CV *cannot stand alone, should be integrated with other systems*" Further, R2 defended his answer by stating "*early defect detection can be achieved, especially when integrated with mobile or drone-based imaging systems*"

Finally, industry experts were requested to evaluate the preparedness of the Sri Lankan construction industry for adopting CV technologies in quality management. The majority declare that the industry remains unprepared for CV tool implementation, with R10 particularly emphasising the numerous restrictions prevalent in Sri Lanka. Conversely, R3 contended that the industry is prepared to adopt CV technologies, a view that contradicts the dominant expert perspective. Respondents R2 and R4 took a balanced position, describing the industry as partially ready and R2 substantiated this by observing that larger contractors are increasingly embracing digital tools, while smaller contractors struggle with cost and skill limitations. R6 similarly asserted that the industry is not equipped for large-scale CV models. Furthermore, participants were invited to offer recommendations for integrating CV technologies into the Sri Lankan construction industry, particularly within quality management processes. Figure 3 summarises the key suggestions provided by the experts.

Name	Files	References
Suggestions to adopt CV tools in Sri Lankan Construction QM	1	1
Conduct awareness and training programmes	4	5
Implement specification, requirements and standards for digital implemtations	2	3
Improve site-level digital facilities	1	1
Increase the number of construction projects	1	1
Initiatives should be taken by government authorities or third party testing organisations	1	1
Phased adoption and collaboration with tech providers or universities to create loacal data sets	2	2
Start with small technologies tailored for Sri Lankan context	2	2

Figure 3: Suggestions to adopt CV technologies in the Sri Lankan construction

The suggestions outlined in Figure 3 reveal a strong expert expectation on conducting awareness programs and workforce training to facilitate CV adoption, as R1, R2, and R3 emphasised their critical role. R8 provided comprehensive strategies by mentioning that "*To support adoption, the industry should start with small pilot projects, invest in training* *and upskilling, encourage collaboration between industry and universities, improve site-level digital readiness, and develop national guidelines or standards (even roadmaps) to support the use of AI-based tools in construction quality management."* Complementing this, R3 suggested collaboration with international contractors to enable pilot projects that expose local professionals to AI tools, while R9 preferred government initiative, stating, "*The first step should be taken by the research authorities to make it a standard*." Further, R2 emphasised that "*Phased adoption and collaborations with tech providers, create local datasets for CV models*" to address dataset scarcity. Similarly, R6 recommended to commence with accessible mobile applications tailored to the Sri Lankan context, proposing LLM-based solutions that minimise CV dependency. Further, mentioned that "*such applications would particularly benefit small-scale contractors, given their relatively low development cost of approximately $4,000 and a monthly maintenance fee of $100*."

The results of this study revealed that, according to expert respondents, the CV-based tools have potential for improving quality management processes in the construction industry in Sri Lanka. However, the implementation of efficient CV-based QM tools is dependent on the specific features of the Sri Lankan construction industry, such as data availability, the cost of data, the skills of the working population and infrastructure. The results indicate that the transition to CV in Sri Lanka is likely to be a gradual process, rather than one of overnight, blanket deployment.

5. CONCLUSIONS AND RECOMMENDATIONS

The findings from this study affirm the transformative potential of CV technologies in elevating quality management practices for concrete structural works within the Sri Lankan construction industry. CV addresses critical limitations of traditional manual inspections, including subjectivity, inefficiency, and high rework costs, by enabling accurate, real-time defect detection. However, persistent barriers, including data scarcity, high initial implementation expenses, skill shortages, and infrastructural constraints, render the industry largely unprepared for widespread adoption, as highlighted by most expert respondents. While larger contractors show partial readiness through digital tool adoption, smaller firms face disproportionate challenges, underscoring the need for context-specific adoption. A multi-phased framework is recommended to facilitate CV integration. In order to adopt this framework, awareness programs should be established on CV in construction by the government and professional organisations. In addition, it's recommended to collaborate with universities and the industry to introduce AI/CV-related modules into construction engineering curricula. Furthermore, government-funded pilot projects should be launched to build confidence among private contractors regarding the ROI, since uncertain ROI is a significant hindrance to the adoption of CV. Developing localised datasets and LLM-hybrid mobile applications is proposed as a practical solution that facilitates small-scale contractors, gradually scaling to full CV systems aligned with existing workflows. Moreover, regulatory standards should be established, public-private partnerships for secure cloud infrastructure should be promoted, and BIM-CV integration should be encouraged to ensure sustainability.

This study contributes to the academic field by providing a detailed analysis of the feasibility of the CV adoption for quality management in the Sri Lankan construction industry. Moreover, it discusses the state of readiness in Sri Lanka and a framework to implement a phased approach. The study was conducted with 10 expert interviewees using purposive sampling, which provides valuable insights but might not represent the broader spectrum of views and experiences in the Sri Lankan construction industry, which becomes a limitation of this study. Further research should be conducted to investigate the technical performance of CV models trained with the locally developed Sri Lankan concrete defect datasets. Studies quantifying the cost-benefit ratio of the usage of CV in Sri Lankan construction projects would add weight to the business case for the industry to take up CV. The Proposed strategies and future research have the potential to change Sri Lanka's quality management paradigms from reactive to proactive, promoting structural safety and economic efficiency.

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