Ekanayaka, E.M.K.K. and Eranga, B.A.I., 2025. Enhancing labour productivity in the Sri Lankan construction industry through computer vision. In: Waidyasekara, K.G.A.S., Jayasena, H.S., Wimalaratne, P.L.I. and Tennakoon, G.A. (eds). *Proceedings of the 13th World Construction Symposium*, 15-16 August 2025, Sri Lanka. pp. 635-648. DOI: https://doi.org/10.31705/WCS.2025.48. Available from: https://ciobwcs.com/papers/

ENHANCING LABOUR PRODUCTIVITY IN THE SRI LANKAN CONSTRUCTION INDUSTRY THROUGH COMPUTER VISION

E.M.K.K. Ekanayaka[1] and B.A.I. Eranga[2]

ABSTRACT

Labour productivity is a crucial factor in the success of construction projects. However, Sri Lankan construction industry has been struggling to enhance labour productivity due to inadequate labour management, poor monitoring systems and safety-related problems. These various challenges have led to problems such as project delays and cost overruns, and poor site performance. Computer vision (CV) has been found to overcome these issues and enhance labour management in the construction industry. Additionally, CV can monitor the activities of labours, track activities, control behaviour, detect the location and identify objects continuously, which ultimately enhances the labour productivity. By automating data collection through cameras and AI models, site managers gain accurate insights into performance without disrupting workflows. It ensures transparency, accountability, and quick response to inefficiencies. This research study focuses on deploying CV to improve labour productivity in the Sri Lankan construction industry. This study was based on information gathered from 16 expert interviews involving construction professionals and IT specialists. The findings highlight CV applications in labour management and further present substantial possibilities to transform the construction industry through CV. Moreover, the study highlights real-time monitoring together with task optimization, safety improvement and workforce efficiency enhancement. Finally, this research provides CV applications and key stages as follows with a view to indicating appropriate decisions to make. Application of CV can assist in avoiding problems and identifying the best practices in the application of CV technologies in the Sri Lankan construction industry.

Keywords: *Computer Vision (CV); Labour Productivity; Smart Construction; Sri Lanka, Sustainability.*

1. INTRODUCTION

Construction industry is one of the largest industries which deals with gross domestic product (GDP) in both developing and developed countries (Yu et al., 2022). It plays a critical role in the economic landscape of nations, serving as a key driver of growth and development (Norouzi et al., 2021). According to Lawal and Rafsanjani (2021), the construction sector consists of residential buildings along with commercial structures and infrastructure projects including roads, bridges, and airports. Zhang et al. (2021) added that the construction industry is a highly labour-intensive sector with numerous

[1] Undergraduate, Department of Building Economics, University of Moratuwa, Sri Lanka, ekanayakaemkk.20@uom.lk

[2] Lecturer, Department of Building Economics, University of Moratuwa, Sri Lanka, isurue@uom.lk

construction activities. Despite its crucial role, the construction industry faces persistent challenges in terms of labour productivity, which hinder its efficiency and growth (Abdel-Hamid & Abdelhalim, 2020).

Labour productivity plays a critical role in ensuring the timely and cost-effective completion of construction projects (Gondia et al., 2019). However, traditional labour management practices such as manual monitoring and paper-based reporting have proven to be insufficient. Because these methods fail to provide the real-time performance data needed for effective decision-making (Abdelalim & Said, 2021). This has contributed to recurring project delays, cost overruns, and inefficient resource allocation within the sector (Almamlook et al., 2020; Tokarsky et al., 2020). In the Sri Lankan construction industry, ineffective monitoring and lack of real-time tracking systems have been identified as significant barriers to improving productivity (Manoharan et al., 2023a). In addition, the lack of automated safety monitoring systems further exacerbates operational inefficiencies and increases the risk of on-site accidents (Manoharan et al., 2023b).

In order to address these challenges, the modern construction industry applies automated data collection (ADC) techniques that enhance the real-time measurement of labour productivity (Fang et al., 2020). Presently, several intelligent technologies are being applied such as building information modelling (BIM) (Olugboyega et al., 2021), sensor technologies (Rao et al., 2022), CV (Ekanayake et al., 2021), and data analytics tools for construction labour productivity monitoring. Among these technologies, CV is considered the most applicable in the construction industry (Li et al., 2024). Evidently, Rao et al. (2022) stated that CV allows machines to interpret visual data, so that serves as an effective method for real-time monitoring and labour tracking and safety management on construction sites. Moreover, Fang et al. (2020) highlighted that CV systems have revolutionized construction labour management systems by enabling tasks including motion tracking, behaviour analysis, location estimation and object recognition. According to Lim et al. (2022), the integration of sensors and cameras with CV systems has enabled enhanced site monitoring which ensures operational labour optimization and safe compliance standards.

CV has benefited many countries to continuously monitor workforce activities, helping track movement to boost productivity, control behaviour, and recognize objects (Fang et al., 2020). Lim et al. (2022) stated that in South Korea, CV systems have been used to promote construction automation to speed up processes, increase productivity, and reduce safety risks by monitoring personal protective equipment, labour productivity and safety on construction projects. In China CV has assisted in ensuring safety regulations compliance by monitoring the behaviour and site conditions of the workers (Fang et al., 2020). Even though studies have shown its advantages in different global contexts for enhancing construction efficiency and safety (Fang et al., 2020), there has been limited research on the feasibility of applying CV in the Sri Lankan context (Dilaksha et al., 2024; Liyanage et al., 2023; Herath et al., 2022).

Therefore, this research aims to bridge the existing gap by exploring the potential of CV to enhance labour productivity in Sri Lanka's construction industry. It focuses on improving labour supervision, real-time performance tracking, and enforcing safety measures on construction sites. By examining how CV technologies have been used globally, CV can be adapted to the local context. The study seeks to provide valuable insights into integrating CV for more efficient and safer construction practices in Sri Lanka.

2. LITERATURE REVIEW

2.1 LABOUR PRODUCTIVITY IN CONSTRUCTION INDUSTRY

Labour productivity stands as a critical performance factor for construction projects to reach their successful completion (Kim et al., 2019). However, the construction industry face persistent inefficiencies due to delays, cost overruns, and poor resource management (Mahamid, 2018; Abdel-Hamid & Abdelhalim, 2020). These challenges arise from a heavy reliance on manual labour, limited automation, and insufficient real-time monitoring, as described by Naoum (2016). Moreover, Perera et al. (2023) stated that traditional labour management methods such as manual reporting and human observation fail to deliver precise evaluations of labour performance and site conditions which results in coordination issues and productivity losses. Additionally, inefficient labour management systems further contribute to operational delays, inefficient task distribution, and deviations from project schedules and budgets (Erdogan et al., 2019; Zhang et al., 2021). The current approaches to labour management systems do not solve problems regarding unproductive works, inefficient task distribution and insufficient labour performance feedback (Dev & Mishra, 2020; Guo et al., 2017). Therefore, growing complexity of projects is creating the need for improved labour monitoring solutions, as current methods are becoming less effective (Rao et al., 2022).

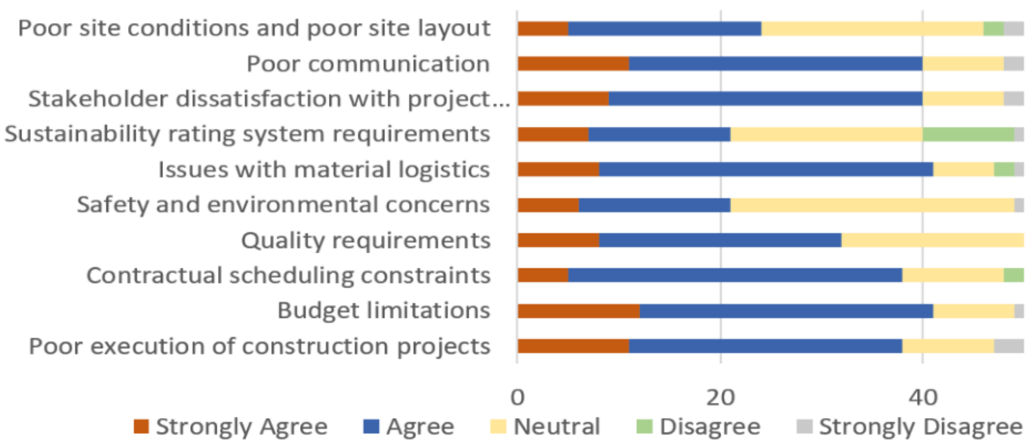

Figure 1: Issues in the current construction industry (Source: Developed by authors)

Figure 1 presents the most critical issues influencing labour productivity in the construction projects. According to figure 1, the scale includes project execution challenges starting from budget restrictions progressing to safety risks with participants mostly disagreeing about proficient management.

2.2 TECHNOLOGICAL INNOVATIONS TO ADDRESS LABOUR PRODUCTIVITY ISSUES IN CONSTRUCTION

The construction industry needs modern technological solutions to resolve its existing productivity problems (Abdelalim & Said, 2021). Several organizations place digital technologies and artificial intelligence (AI) among key elements capable of transforming labour productivity (Gondia et al., 2019). In recent years, there has been a growing emphasis on adopting technologies such as BIM, use of drones, internet of things (IoT), and robotic systems to streamline construction processes and enhance efficiency (Rao et al., 2022). Furthermore, Heidari et al. (2023) mentioned that several intelligent technologies such as BIM (Olugboyega et al., 2021), AI, sensors (Rao et al., 2022), CV (Ekanayake et al., 2021) and data analytics tools have been applied for construction labour productivity monitoring (Elghaish et al., 2020). These technologies automate manual execution of tasks to create improved resource utilization and better project oversight which results in safer workplace conditions (Rao et al., 2022). This shift has brought the industry toward automated approaches which leads to improved project control and management (Wang et al., 2020). Through automating processes and improving resource utilization, these technologies have the potential to significantly enhance labour productivity, project management, and overall efficiency (Rao et al., 2022; Chen et al., 2022), subsequently, transforming the construction sector into a more streamlined and safer industry.

2.3 COMPUTER VISION EVOLUTION AND BENEFITS IN CONSTRUCTION

CV stands out as one of the most effective tools among various technological solutions to address labour productivity challenges in the construction sector (Li et al., 2024). According to Liu et al. (2021), CV helps machines interpret visual elements and perform processing operations that perform better than other technologies. Although BIM and IoT are mainly focused on the maintenance of structural elements and resource management systems, CV provides dynamic, real-time, on-site monitoring of employee performance and behaviour (Li et al., 2024). The combination of cameras, sensors, and image processing algorithms enables CV to monitor labour activities and performance with safe compliance without constant human supervision (Paneru & Jeelani, 2021). Key applications of CV include tracking worker activities, verifying compliance with safety protocols such as the use of personal protective equipment (PPE), and detecting unsafe or non-standard practices (Fang et al., 2020; Li et al., 2024). Furthermore, CV facilitates location tracking to enhance safety in hazardous areas and optimize the distribution of labour across the site (Son et al., 2019). As a result, these functionalities contribute to improved safety, reduced human error, and more efficient site monitoring, thereby enhancing overall labour productivity in construction environments (Fang et al., 2020; Li et al., 2024).

Table 1 presents the widely used applications of CV in labour management within the construction industry, many of which are currently being implemented in various countries around the world.

Table 1: Main applications of CV in labour management

Application	Description	References
Safety Assurance	Automatic detection of PPE compliance and safety hazard areas	Fang et al. (2020); Lim et al. (2022)
Labour Behaviour Recognition	Identify and monitor labour activities.	Li et al. (2024); Paneru & Jeelani (2021)
Location and Tracking	Labour location tracking in real-time in the site, where proactive safety measures and efficient site navigation can be done.	Fang et al. (2020); Li et al. (2024)

Application	Description	References
Labour Activity Recognition	Tracks specific labour activities for safety and operational standards.	Fang et al. (2020); Liu et al. (2021)
Blindspot Monitoring	Monitor and determine the dynamic range of equipment blind spots to prevent accidents caused by limited visibility.	Guo et al. (2017); Akinsemoyin et al. (2023)

CV delivers substantial promise for improving labour productivity levels throughout Sri Lanka. CV implementation at Sri Lankan construction sites will lead to improved tracking of real-time labour activities and enhanced performance analytics (Dilaksha et al., 2024; Liyanage et al., 2023). Moreover, Madugu (2023) stated that project managers can detect underperforming team members and inefficient processes using this system thus enabling them to take prompt corrective actions which stop project delays and prolongation costs. Implementation of CV systems enables both safety standard compliance tracking and lower work-related accident rates which lead to increased employee satisfaction (Ji et al., 2023; Liu et al., 2021). The construction industry of Sri Lanka benefits from CV as it represents a cost-effective approach to increase productivity while protecting workers from harm and optimizing project delivery.

3. METHODOLOGY

The study adhered a qualitative research approach. It is a process that focuses on interpreting the deeper meanings of textual data collected from interviews, focus groups, and open-ended surveys (Rampin & Rampin, 2021). Researchers use this method to investigate experiences as well as behaviours and social processes (Bingham, 2023). A purposive expert sampling method was used to select participants with both construction and IT expertise to ensure the relevance and depth of data. Semi-structured interviews served as the data collection method to allow open discussions while ensuring participant consistency. For analysis, content analysis was conducted using NVivo 12 software, allowing to identify key themes and insights that aligned with the objectives of the study. Interview transcripts were systematically coded and grouped into relevant categories, allowing for the recognition of expert opinions and practical considerations related to the integration of computer vision in construction practices.

Research data was obtained from in-depth interviews with industry professionals who held positions as project managers, and quantity surveyors, as well as IT specialists with expertise in CV. The research design included semi-structured interviews that provided both in-depth conversational opportunities as well as standardized interview protocols. Through this methodology, the research gathered extensive insights in a standardized format. Interview sessions lasting 30 to 45 minutes were conducted physical meetings and online meetings via Zoom and Microsoft Teams, depending on the availability of participants. Sixteen interviews were conducted, leading to data saturation was achieved at 13 interviews and it confirmed from 3 more interviews. The data collected was categorized into specific sections to represent all aspects of CV integration in the practices of the construction sector in Sri Lanka.

Although the selected respondents did not have direct experience in applying CV in construction projects. But they have significant knowledge of both the construction industry and related CV applications. Their insights were considered valuable due to their expertise, as they were able to provide informed perspectives on the potential CV applications for labour productivity. Accordingly, their contributions were used to explore the practical implications, feasibility and future integration of CV in the Sri Lankan construction context. Table 2 presents the summary of each expert with relevant experience in the construction industry and IT field.

Table 2: Profile of the experts

Respondent	Discipline	Designation	Experience (in Years)
R1	Civil Engineer	Project Manager	31
R2	Quantity Surveyor	Academic cum Quantity Surveyor	14
R3	Quantity Surveyor	Chartered Quantity Surveyor	09
R4	Quantity Surveyor	Academic cum Quantity Surveyor	10
R5	Quantity Surveyor	Academic cum Quantity Surveyor	08
R6	Quantity Surveyor	Academic cum Quantity Surveyor	12
R7	Quantity Surveyor	Quantity Surveyor	09
R8	Quantity Surveyor	Chartered Quantity Surveyor	28
R9	Quantity Surveyor	5D BIM Quantity Surveyor	08
R10	Quantity Surveyor	Senior Quantity Surveyor	15
R11	Quantity Surveyor	Chartered Quantity Surveyor	28
R12	Quantity Surveyor	Academic cum Quantity Surveyor	08
R13	Quantity Surveyor	Senior Quantity Surveyor	10
R14	Software Engineer	Senior Software Engineer	12
R15	Software Engineer	Senior Software Engineer	09
R16	Software Engineer	Senior Software Engineer	08

4. FINDINGS AND ANALYSIS

4.1 THE ROLE AND IMPACT OF COMPUTER VISION IN LABOUR MANAGEMENT

The practical application of CV in Sri Lanka's construction industry remains limited, but experts are highly optimistic about its potential to improve labour productivity and safety. R4 emphasized that "*CV has enormous potential, especially in areas such as safety, quality control and labour management*," while R6 noted that it improves efficiency and reduces accidents. Respondents highlighted CV's capabilities in real-time labour monitoring, PPE compliance, and hazard detection near heavy machinery. R14 added that CV can automate workforce tracking and reduce manual errors, while R15 emphasized its role in real-time project analysis for improved productivity. Despite these benefits, R4, R9, and R12 observed that the industry still depends heavily on manual processes due to slow technology adoption and low awareness. As R13 concluded, CV presents a powerful opportunity for real-time workforce monitoring, with the potential to transform labour management practices across the Sri Lankan construction sector.

4.2 APPLICATIONS OF COMPUTER VISION IN CONSTRUCTION

The wide range of possible applications of CV on Sri Lankan construction sites offers both enhanced safety performance and higher productivity levels. Most respondents highlighted that few applications such as real-time monitoring, automated attendance tracking, safety compliance monitoring, work progress tracking, strategic workforce planning and resource optimization. Moreover, they stated that real-time worker identification through this technology removes the need for manual attendance sheets while simultaneously decreasing time fraud incidents on the site.

Figure 2 illustrates the various benefits and applications of CV in the construction industry, highlighting its role in improving labour productivity.

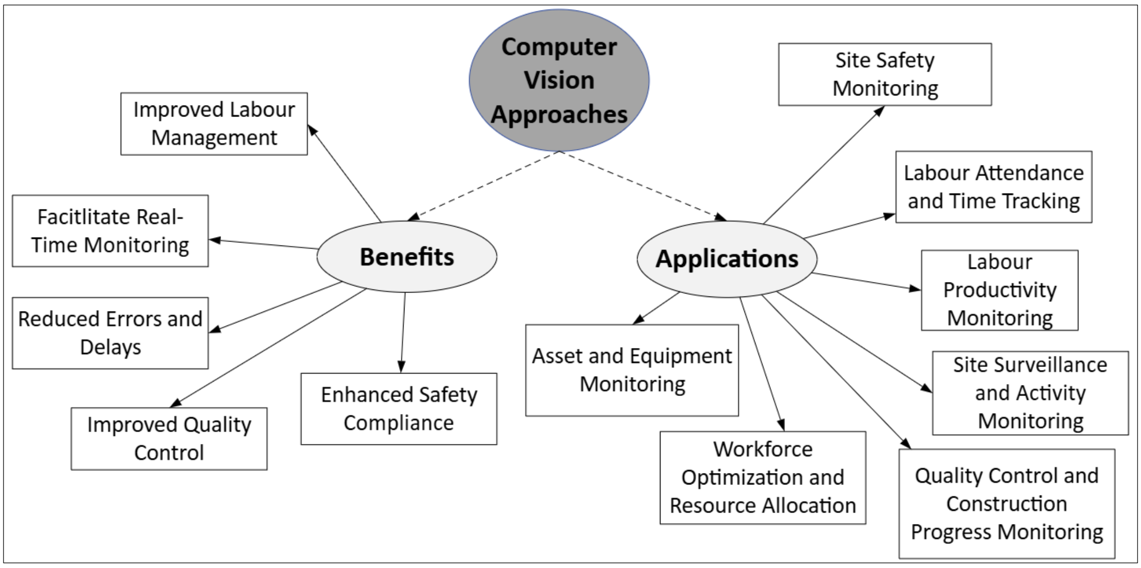

Figure 2: CV benefits and applications (Source: Developed by authors)

4.2.1 Automated Attendance Tracking

R1 along with other experts suggested that automated attendance tracking systems using facial recognition can simplify employee check-in procedures by eliminating human errors from manual attendance systems. This system would reduce tracking time and enhance staff recording precision in a field where errors frequently occur. Similarly, R12 and R15 explained that automated attendance tracking through facial recognition technology speeds up attendance procedures with more accuracy. Moreover, R3 explained that facial recognition systems used for employee attendance tracking provide detailed attendance documentation that minimizes both false reports and unauthorized personnel.

4.2.2 Real-Time Activity Monitoring & Productivity Tracking

Beyond attendance tracking, real-time monitoring of labour activities is another crucial application. According to R6 "real-time employee location tracking allows better workforce management through the identification of unnecessary site movements to prevent downtime occurrences". R2 and R10 stated that this monitoring system provides immediate productivity benefits to managers because they can swiftly detect operational inefficiencies and resolve them. Moreover, AI systems enable the distribution of tasks into smaller divisions according to employee daily work activities according to R5.

Supervisors gain enhanced performance metric tracking abilities through this approach to optimize resource distribution.

4.2.3 Safety Compliance and Hazard Detection

Most respondents highlighted that CV assists with safety monitoring tasks by detecting unsafe worker behaviours and hazardous materials and improper equipment handling to minimize accidents. Moreover, R3 and R12 explained that CV serves as a monitoring system to check if workers wear appropriate PPE because it helps maintain safety standards and protect workers from site accidents. Similarly, R4 pointed out "*CV can monitor worker safety by detecting whether they are wearing the proper PPE and alerting supervisors to any non-compliance*". Additionally, the various capabilities of CV position it as an excellent option for both safety improvement on construction sites and worker adherence to essential safety requirements.

4.2.4 Work Progress Analysis and Task Completion Tracking

CV functions as a tool to track work progress as well as to analyse task completion. R1, R5, R11 and R12 respondents explained how AI systems use project timelines to analyse site images for work progress evaluation. Furthermore, these respondents noted that this information gained enables accurate reporting and prevents delays because it detects slow progress at an early stage. R6 indicated "*automated workflow optimization through AI-based systems delivers predictive information to optimize staffing assignments and reduce operations expenses*". As mentioned by R14, verification of project progress is effectively emerging through time-lapse imagery combined with object recognition and BIM model integration.

4.2.5 Strategic Workforce Planning and Resource Optimization

The respondents R2 and R13 explained that CV helps organizations with strategic workforce planning as well as resource optimization. Similarly, R8 stated that the analysis of worker movement patterns through CV systems produces predictive information which helps organizations properly distribute their workforce into low-productivity areas that risk delays. Moreover, R8 highlighted that this form of data-driven decision-making supports better scheduling, reduces downtime, and enhances overall operational efficiency.

Table 3 summarizes the basic applications of CV in construction labour management. It outlines the primary functionality of each application and explains how it is implemented using CV on construction sites.

Table 3: Functional applications and execution of CV on construction sites

Application	Functionality	CV-based Implementation Approach
Automated Attendance Tracking	Records worker attendance accurately and prevents time fraud	Facial recognition systems at entry points automatically identify and log workers in real time
Real-Time Activity Monitoring	Tracks worker movements, identifies idle time, and classifies daily tasks	AI analyses CCTV/video feeds to detect and categorize worker actions across the site

Application	Functionality	CV-based Implementation Approach
Safety Compliance Monitoring	Ensures workers wear PPE and follow safety guidelines	Object detection identifies missing helmets or vests, behaviour recognition flags unsafe practices
Work Progress and Task Completion Tracking	Monitors task progress and verify if scheduled work is completed	Time-lapse videos and object recognition compare actual site visuals with planned models or drawings
Workforce Optimization and Planning	Enhances labour allocation and reduces inefficiencies	AI-based movement analysis highlights resource gaps; predictive models suggest adjustments

4.3 KEY STAGES IN IMPLEMENTING A COMPUTER VISION SYSTEM FOR LABOUR MANAGEMENT

All respondents highlighted that the implementation of a CV system comprises several critical stages designed to improve labour productivity. As suggested by many experts, the first phase is data collection, where tools such as CCTV cameras, drones, and IoT sensors capture images or videos of workers and on-site activities. After data is collected, it goes through pre-processing, where irrelevant information such as blurry images is removed and quality is improved for better accuracy. R4, R7, and R11 described this as "data pre-processing," which ensures that the data is ready for analysis. After pre-processing, the system enters the model training phase, where it learns to recognize patterns such as PPE compliance and inactive workers, as noted by R5.

Once trained, the system is optimized to operate effectively in real time, and R7 emphasizes that this includes system adjustments and the use of high-performance hardware to "optimize performance". R12 further added that "real-time alerts and reports" support rapid management responses. The final stage is deployment, which involves integrating the CV system into daily operations for continuous monitoring and updates. As R4 explained, this includes tracking task progress and PPE compliance, and R16 noted that it is essential to link CV outputs with existing project management tools to make informed decisions.

Figure 3 illustrates the workflow of applying CV for labour productivity analysis in construction industry. It begins with data preparation, where raw images and videos are cleaned, labelled, and normalized. The processed data is then used in the training phase, where learning algorithms such as machine learning, deep learning, and image processing are applied and optimized. Finally, in the inference stage, the trained model is deployed to analyse new images and draw meaningful insights related to site activities and labour productivity.

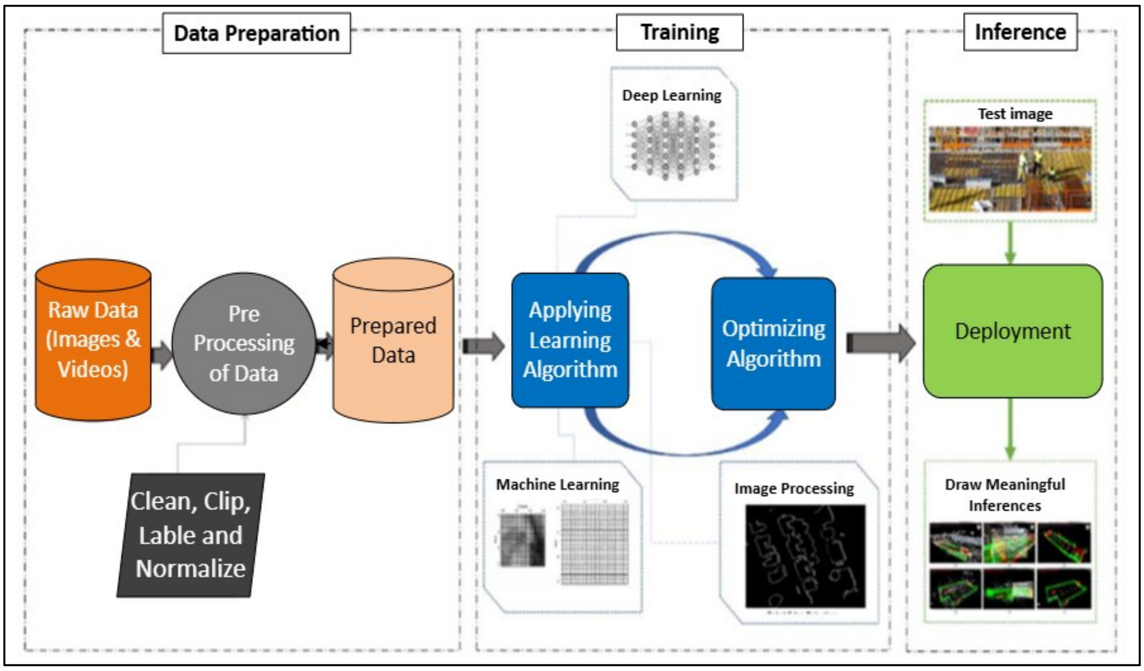

Figure 3: CV process (Source: Developed by authors)

4.4 INTEGRATION OF CV-BASED LABOUR MONITORING SYSTEMS INTO CONSTRUCTION OPERATIONS

The integration of CV into real-time labour monitoring systems presents a significant advancement in construction workforce management. As highlighted by R1, "*CV-based real-time tracking systems serve to both verify compliance with safety requirements and work completion progress*," thereby enabling remote supervision and reducing the reliance on constant physical oversight. R5 further noted that CV can identify idle workers, detect inefficiencies, and provide feedback for process optimization, contributing to enhanced productivity and more efficient use of labour resources. In terms of safety, R7 stated "*CV systems can detect workers without PPE and instantly alert site supervisors for corrective actions, ensuring immediate compliance with safety standards*". Similarly, R13 emphasized that "*CV-based systems notify managers of inefficiencies or safety risks in real time, helping prevent accidents before they occur*". Moreover, CV technologies offer predictive capabilities through real-time dashboards that monitor labour productivity and attendance. R9 stated that integration with enterprise resource planning (ERP) systems allows for optimized workforce scheduling and resource allocation. Additionally, R5 and R15 noted that such integration enables managers to anticipate workforce limitations and make timely adjustments, ultimately improving project efficiency and delivery outcomes.

Figure 4: Recognize the worker pose
Source: Developed by authors

Figure 4 illustrates the process of tracking workers using CV on construction sites. The system starts with an RGB image before applying depth data to determine worker positioning. Next, the software tracks the highlighted worker through its monitoring system. The system generates an outline of the worker's movements to evaluate their physical location for both safety and productivity assessment. This data is analysed to assess whether workers are actively engaged in tasks or idle. By identifying inactive periods or inefficiencies, the system provides valuable insights that can be used to enhance labour allocation, reduce idle time, and ultimately improve overall productivity on construction sites.

5. CONCLUSION

The research examined the role of CV in improving construction labour productivity across Sri Lanka by addressing workforce management issues. Sri Lankan construction sites rely heavily on supervisors for labour management, but this system creates multiple inefficiencies and tracking errors in workforce monitoring. Furthermore, Existing systems lack real-time data with detailed insights that hinder timely decision-making processes, leading to project delays or increased costs. Therefore, some companies implement the modern technologies to address labour productivity issues. Among these technologies, CV is the most suitable technology.

CV provides an innovation through automated labour monitoring technology that improves real-time productivity tracking and safety compliance systems. Implementing key systems that identify and track labour activities, track attendance, monitor progress, and identify risks delivers significant operational benefits and increased site accountability. Furthermore, this technology generates useful data that enables better workforce performance evaluation and improved workforce management programs. In this context, the successful implementation of CV requires close collaboration between technology providers and construction companies and employees to achieve smooth integration and maximize its potential.

Finally, this study confirms that integrating CV can significantly improve labour productivity by reducing downtime, optimizing task allocation, and minimizing human errors in reporting. In addition, it improves safety by identifying unsafe practices in real-time, thereby preventing potential accidents and ensuring compliance with safety regulations. Future development efforts in this area should be continued, and these technologies should be refined for widespread construction use, making them accessible, affordable, and scalable to the Sri Lankan construction industry. Furthermore, it is recommended that future research continues to examine the limitations to CV adoption in Sri Lankan construction industry, explore practical strategies for CV implementation and develop customized CV technologies tailored to the specific needs of small and medium-sized contractors.

6. REFERENCES

Abdelalim, A. M., & Said, S. O. M. (2021). Dynamic labour tracking system in construction project using BIM technology. *International Journal of Civil and Structural Engineering Research*, *9*(1), 10-20. https://www.researchgate.net/publication/361402008

Abdel-Hamid, M., & Abdelhaleem, H. M. (2020). Impact of poor labour productivity on construction project cost. *International Journal of Construction Management*, *22*(12), 2356–2363. https://doi.org/10.1080/15623599.2020.1788757

Akinsemoyin, A., Awolusi, I., Chakraborty, D., Al-Bayati, A. J., & Akanmu, A. (2023). Unmanned aerial systems and deep learning for safety and health activity monitoring on construction sites. *Sensors*, *23*(15), 6690. https://doi.org/10.3390/s23156690

Almamlook, R., Bzizi, M., Al-Kbisbeh, M., Ali, T., & Almajiri, E. (2020). Factors affecting labour productivity in the construction industry. *American Journal of Environmental Science and Engineering*, *4*(2), 24-30. https://doi.org/10.11648/j.ajese.20200402.13

Bingham, A. J. (2023). From data management to actionable findings: A five-phase process of qualitative data analysis. *International Journal of Qualitative Methods*, *22*. https://doi.org/10.1177/16094069231183620

Chen, C., Gu, H., Lian, S., Zhao, Y., & Xiao, B. (2022). Investigation of edge computing in computer vision-based construction resource detection. *Buildings*, *12*(12), 2167. https://doi.org/10.3390/buildings12122167

Dev, E. R., & Mishra, A. K. (2020). Assessment of casual labour management practices in construction projects. *Saudi Journal of Business and Management Studies*, *5*(9), 482–489. https://doi.org/10.36348/sjbms.2020.v05i09.001

Dilaksha, S., Ranadewa, K., Weerasooriya, D., Parameswaran, A., & Weerakoon, P. (2024). Comparative analysis of challenges in manual and automated construction progress monitoring in Sri Lanka. In Y. G. Sandanayake, K. G. A. S. Waidyasekara, K. A. T. O. Ranadewa, & H. Chandanie (Eds.), *Proceedings of the World Construction Symposium 2024* (pp. 379–394). Department of Building Economics. https://doi.org/10.31705/wcs.2024.30

Ekanayake, B., Wong, J. K., Fini, A. A. F., & Smith, P. (2021). Computer vision-based interior construction progress monitoring: A literature review and future research directions. *Automation in Construction*, *127*, 103705. https://doi.org/10.1016/j.autcon.2021.103705

Elghaish, F., Matarneh, S., Talebi, S., Kagioglou, M., Hosseini, M. R., & Abrishami, S. (2020). Toward digitalization in the construction industry with immersive and drones technologies: A critical literature review. *Smart and Sustainable Built Environment*, *10*(3), 345–363. https://doi.org/10.1108/sasbe-06-2020-0077

Erdogan, S. A., Šaparauskas, J., & Turskis, Z. (2019). A multi-criteria decision-making model to choose the best option for sustainable construction management. *Sustainability*, *11*(8), 2239. https://doi.org/10.3390/su11082239

Fang, W., Ding, L., Love, P. E., Luo, H., Li, H., Peña-Mora, F., Zhong, B., & Zhou, C. (2020). Computer vision applications in construction safety assurance. *Automation in Construction*, *110*, 103013. https://doi.org/10.1016/j.autcon.2019.103013

Gondia, A., Siam, A., El-Dakhakhni, W., & Nassar, A. H. (2019). Machine learning algorithms for construction projects delay risk prediction. *Journal of Construction Engineering and Management*, *146*(1). https://doi.org/10.1061/(asce)co.1943-7862.0001736

Guo, H., Yu, Y., & Skitmore, M. (2017). Visualization technology-based construction safety management: A review. *Automation in Construction*, *73*, 135–144. https://doi.org/10.1016/j.autcon.2016.10.004

Heidari, A., Peyvastehgar, Y., & Amanzadegan, M. (2023). A systematic review of the BIM in construction: From smart building management to interoperability of BIM & AI. *Architectural Science Review*, *67*(3), 237–254. https://doi.org/10.1080/00038628.2023.2243247

Herath, H. M. K. K. M. B., Karunasena, G. M. K. B., & Prematilake, R. D. D. (2022). Computer vision for agro-foods: Investigating a method for grading rice grain quality in Sri Lanka. In N. Kumar, C. Shahnaz, K. Kumar, M. Abed Mohammed, & R. S. Raw (Eds.), *Transactions on Computer Systems and Networks* (pp. 21–34). Springer. https://doi.org/10.1007/978-981-16-9324-3_2

Ji, J., Pannakkong, W., & Buddhakulsomsiri, J. (2023). A computer vision-based system for metal sheet pick counting. *Computers, Materials & Continua/Computers, Materials & Continua (Print)*, *75*(2), 3643–3656. https://doi.org/10.32604/cmc.2023.037507

Kim, S., Chang, S., & Castro-Lacouture, D. (2019). Dynamic modeling for analyzing impacts of skilled labour shortage on construction project management. *Journal of Management in Engineering*, *36*(1), 04019035. https://doi.org/10.1061/(asce)me.1943-5479.0000720

Lawal, K., & Rafsanjani, H. N. (2021). Trends, benefits, risks, and challenges of IoT implementation in residential and commercial buildings. *Energy and Built Environment*, *3*(3), 251–266. https://doi.org/10.1016/j.enbenv.2021.01.009

Li, J., Miao, Q., Zou, Z., Gao, H., Zhang, L., Li, Z., & Wang, N. (2024). A review of computer vision-based monitoring approaches for construction workers' work-related behaviors. *IEEE Access*, *12*, 7134–7155. https://doi.org/10.1109/access.2024.3350773

Lim, J., Jung, D. G., Park, C., & Kim, D. Y. (2022). Computer vision process development regarding worker's safety harness and hook to prevent fall accidents: Focused on system scaffolds in South Korea. *Advances in Civil Engineering*, *2022*(1), 4678479. https://doi.org/10.1155/2022/4678479

Liu, W., Meng, Q., Li, Z., & Hu, X. (2021). Applications of computer vision in monitoring the unsafe behavior of construction workers: Current status and challenges. *Buildings*, *11*(9), 409. https://doi.org/10.3390/buildings11090409

Liyanage, S., Basnayake, N., Gamage, M., Prabhashi, P., Kasthuriarachchi, S., & Abeywardhana, L. (2023). Sustainable growth through automation: Machine learning and computer vision advancements in Sri Lankan floriculture. In *2023 5th International Conference on Advancements in Computing (ICAC)* (pp.107–112). IEEE. https://doi.org/10.1109/icac60630.2023.10417228

Madugu, A. A., Fikri, M. S., Shuaib, A. R., & Abdullahi, M. A. (2023). Towards a conceptual framework for application of computer vision in construction cost control. In *IOP Conference Series Earth and Environmental Science* (Vol. 1274, p. 012027). IOP Publishing. https://doi.org/10.1088/1755-1315/1274/1/012027

Mahamid, I. (2018). Study of relationship between cost overrun and labour productivity in road construction projects. *International Journal of Productivity and Quality Management*, *24*(2), 143-164. https://doi.org/10.1504/ijpqm.2018.091791

Manoharan, K., Dissanayake, P. B., Pathirana, C., Deegahawature, D., & Silva, K. R. R. (2023a). A labour performance score and grading system to the next normal practices in construction. *Built Environment Project and Asset Management*, *13*(1), 36–55. https://doi.org/10.1108/bepam-10-2021-0125

Manoharan, K., Dissanayake, P., Pathirana, C., Deegahawature, D., & Silva, R. (2023b). Assessment of critical factors influencing the performance of labour in Sri Lankan construction industry. *International Journal of Construction Management*, *23*(1), 144–155. https://doi.org/10.1080/15623599.2020.1854042

Naoum, S. G. (2016). Factors influencing labour productivity on construction sites. *International Journal of Productivity and Performance Management*, *65*(3), 401–421. https://doi.org/10.1108/ijppm-03-2015-0045

Norouzi, M., Chàfer, M., Cabeza, L. F., Jiménez, L., & Boer, D. (2021). Circular economy in the building and construction sector: A scientific evolution analysis. *Journal of Building Engineering*, *44*, 102704. https://doi.org/10.1016/j.jobe.2021.102704

Olugboyega, O., Edwards, D. J., Windapo, A. O., Omopariola, E. D., & Martek, I. (2021). Development of a conceptual model for evaluating the success of BIM-based construction projects. *Smart and Sustainable Built Environment*, *10*(4), 681–701. https://doi.org/10.1108/sasbe-02-2020-0013

Paneru, S., & Jeelani, I. (2021). Computer vision applications in construction: Current state, opportunities & challenges. *Automation in Construction*, *132*, 103940. https://doi.org/10.1016/j.autcon.2021.103940

Perera, W. S. D., Ranadewa, K. A. T. O., Parameswaran, A., & Weerasooriya, D. (2023). Status quo of digitalisation in the Sri Lankan construction industry. In Y. G. Sandanayake, K. G. A. S. Waidyasekara, T. Ramachandra, & K. A. T. O. Ranadewa (Eds.), *Proceedings The 11th World Construction Symposium* (p. 945). Department of Building Economics. https://doi.org/10.31705/wcs.2023.76

Rampin, R., & Rampin, V. (2021). Taguette: Open-source qualitative data analysis. *The Journal of Open-Source Software*, *6*(68), 3522. https://doi.org/10.21105/joss.03522

Rao, A. S., Radanovic, M., Liu, Y., Hu, S., Fang, Y., Khoshelham, K., Palaniswami, M., & Ngo, T. (2022). Real-time monitoring of construction sites: Sensors, methods, and applications. *Automation in Construction*, *136*, 104099. https://doi.org/10.1016/j.autcon.2021.104099

Son, H., Choi, H., Seong, H., & Kim, C. (2019). Detection of construction workers under varying poses and changing background in image sequences via very deep residual networks. *Automation in Construction*, *99*, 27–38. https://doi.org/10.1016/j.autcon.2018.11.033

Tokarsky, A., Topchiy, D., Ekba, S., Bolgov, V., & Gorochov, A. (2020). Methodological foundations of assessment of the impact of State construction supervision during reprofiling big urban areas. In *E3S Web of Conferences* (Vol. 164, p. 04037). EDP Sciences. https://doi.org/10.1051/e3sconf/202016404037

Wang, M., Wang, C. C., Sepasgozar, S., & Zlatanova, S. (2020). A systematic review of digital technology adoption in off-site construction: Current status and future direction towards industry 4.0. *Buildings*, *10*(11), 204. https://doi.org/10.3390/buildings10110204

Yu, Y., Junjan, V., Yazan, D. M., & Iacob, M. (2022). A systematic literature review on circular economy implementation in the construction industry: A policy-making perspective. *Resources Conservation and Recycling*, *183*, 106359. https://doi.org/10.1016/j.resconrec.2022.106359

Zhang, Y., Wang, T., & Yuen, K. (2021). Construction site information decentralized management using blockchain and smart contracts. *Computer-Aided Civil and Infrastructure Engineering*, *37*(11), 1450–1467. https://doi.org/10.1111/mice.12804