ICCEPM 2024 https://dx.doi.org/10.6106/ICCEPM.2024.0775
The 10th International Conference on Construction Engineering and Project Management
Jul. 29-Aug.1, 2024, Sapporo

Worker Accountability in Computer Vision for Construction Productivity Measurement: A Systematic Review

Mik Wanul KHOSIIN[1], Jacob J. LIN[2], Chuin-Shan CHEN[3]*

[1] *Department of Civil Engineering, College of Engineering, National Taiwan University, Taiwan,* E-mail address: d10521024@ntu.edu.tw.
[2] *Department of Civil Engineering, College of Engineering, National Taiwan University, Taiwan,* E-mail address: jacoblin@ntu.edu.tw.
[3*] *Department of Civil Engineering, College of Engineering, National Taiwan University, Taiwan,* E-mail address: dchen@ntu.edu.tw.

Abstract: This systematic review comprehensively analyzes the application of computer vision in construction productivity measurement and emphasizes the importance of worker accountability in construction sites. It identifies a significant gap in the connection level between input (resources) and output data (products or progress) of productivity monitoring, a factor not adequately addressed in prior research. The review highlights three fundamental groups: input, output, and connection groups. Object detection, tracking, pose, and activity recognition, as the input stage, are essential for identifying characteristics and worker movements. The output phase will mostly focus on progress monitoring, and understanding the interaction of workers with other entities will be discussed in the connection groups. This study offers four research future research directions for the worker accountability monitoring process, such as human-object interaction (HOI), generative AI, location-based management systems (LBMS), and robotic technologies. The successful accountability monitoring will secure the accuracy of productivity measurement and elevate the competitiveness of the construction industry.

Keywords: Construction Productivity, Computer Vision, Accountability Monitoring.

1. INTRODUCTION

Productivity monitoring, a continuous observation, involves the obtained progress from the resources used as input in the projects (PMBOK[1], [2], [3]). Traditional productivity monitoring practices have often failed to achieve their primary objective due to a lack of study on workers' accountability. McKinsey & Company[4] reported that the construction sector's performance has constantly been the lowest since 1995 until now. The value added per hour worker for construction was sixty thousand dollars, 1.7 times smaller than the manufacturing industry in 2005. Needless to say, the current situation demands improvement in construction productivity.

Computer vision is a solution for improving construction productivity monitoring and controlling practices. However, since the interaction of workers with other objects has not been addressed yet, productivity value still cannot be properly visualized through this technique. In Figure 1, a construction worker practically has accountability with all existing entities such as other workers, tools, materials, heavy equipment, and workspace. Hence, it generates some prompts, such as how many entities are involved, the relationship of the resources, how good the product is, and their operational systems. The project manager must understand all the complexities and work patterns on the construction site before measuring productivity. Unfortunately, engineers have not optimally transformed this situation into a computer vision model.

In recent studies, experts have extensively used computer vision in construction sites. Table 1 shows that they have reviewed productivity monitoring in several categories, such as digital applications in performance assessment, the influence of weather on productivity, critical factors of performance measurement, activity recognition on workers, and BIM for productivity improvement. Each group offers comprehensive data, issues, scope, and future direction. At the technology level, Pal A. et al.[5], Barbosa A. et al.[6], Alaloul W. S. et al.[7], Sherafat B. et al.[8], and Archchana S. et al.[9] explain methods commonly applied in productivity monitoring which can investigate objects involved in the project, track, and be able to understand the activities as an input instrument (Eq. 1) in productivity measurement. Current techniques can also measure the progress form the workers as an output variable (Eq. 1). Moreover, the reviews of some critical factors (Moohialdin A. et al.[10], Khalid K.H. et al.[11], Rathnayake A. et al.[12]) causing low construction productivity is essential to pay attention to. However, a fundamental understanding of interactions has not been considered as a key aspect of productivity monitoring. Consequently, experts cannot demonstrate an explicit productivity value of workers through computer vision techniques.

To bridge this gap, this study proposes a systematic review of accountability monitoring to support the productivity measurement process. This research scheme will have a structure as follows: the introduction highlights the importance of the connection between input and output in evaluating construction performance. The methodology section discusses paper review techniques, which include literature review and bibliography analysis. Then, in the next section, we will comprehensively discuss related studies in accountability monitoring for productivity measurement. In the future studies section, this study proposes a conceptual framework for productivity monitoring through computer vision techniques. Finally, the conclusion section provides critical statements that can encourage readers to consider accountability monitoring as a future research direction.

Table 1. Current review papers in productivity monitoring

Category	Author	Activities	Limitation
Smart construction management	Pal A., 2021[5]	Reviewing state-of-the-art visual data analytics in the context of construction project management	High-level and general techniques only
Digital technologies application	Barbosa A., 2021[6]; Alaloul W. S., 2021[7]	Investigating recent methods used for construction productivity monitoring	Discussing either the input or the output of productivity monitoring only
Weather effects	Moohialdin A.S.M., 2019[10]	Analyzing the weather effect on construction worker productivity	However, this aspect has less impact on the performance monitoring process.
Critical factors	Khalid K.H., 2023[11]; Rathnayake A., 2023[12]	Listing the factors affecting construction productivity	The connection part is not the critical factors
Activity recognition	Sherafat B., 2020[8]	Discussing automated methods for activity recognition of construction entities	It did not discuss how we link input and output together.
Building information modeling (BIM)	Archchana S., 2023[9]	Identifying the role of BIM in productivity measurement	No explanation of how to integrate BIM into a computer vision system.

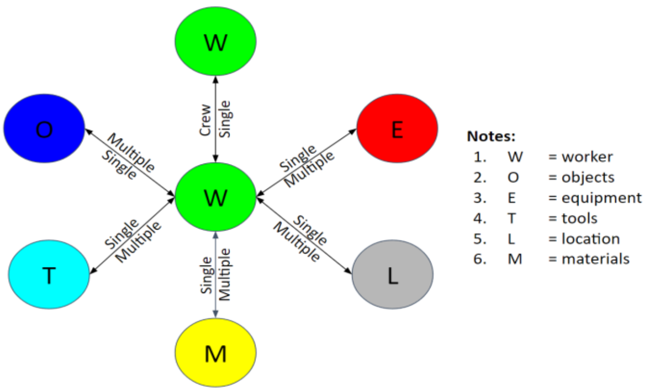

Fig. 1. The accountability among the construction entities

2. RESEARCH METHODOLOGY

Computer vision has been applied in all fields that have visual data as a controlling tool to encourage work productivity, especially in the construction industry. Therefore, the availability of abundant references will be both an advantage and a challenge at the same time. Figure 2 outlines a structured approach for conducting a systematic review of research, specifically in accountability monitoring, productivity measurement, and construction. This approach is organized into three primary phases: identification, screening, and selection, each consisting of multiple steps to refine and select the most relevant literature. This first phase focuses on defining the scope and sources for the literature search in the beginning. The scope is clearly identified as pertaining to accountability monitoring, productivity measurement, and construction. The sources for the literature are divided into two categories: types of references and types of databases. References include textbooks, reports, journal articles, and conference papers, while databases include Web of Science (WoS), Scopus, Institute of Electrical and Electronics Engineers (IEEE), and Google Scholar. The literature search, as per step three, reviews various topics like productivity monitoring, computer vision, and construction management, leading to the identification of a specific number of papers in different categories.

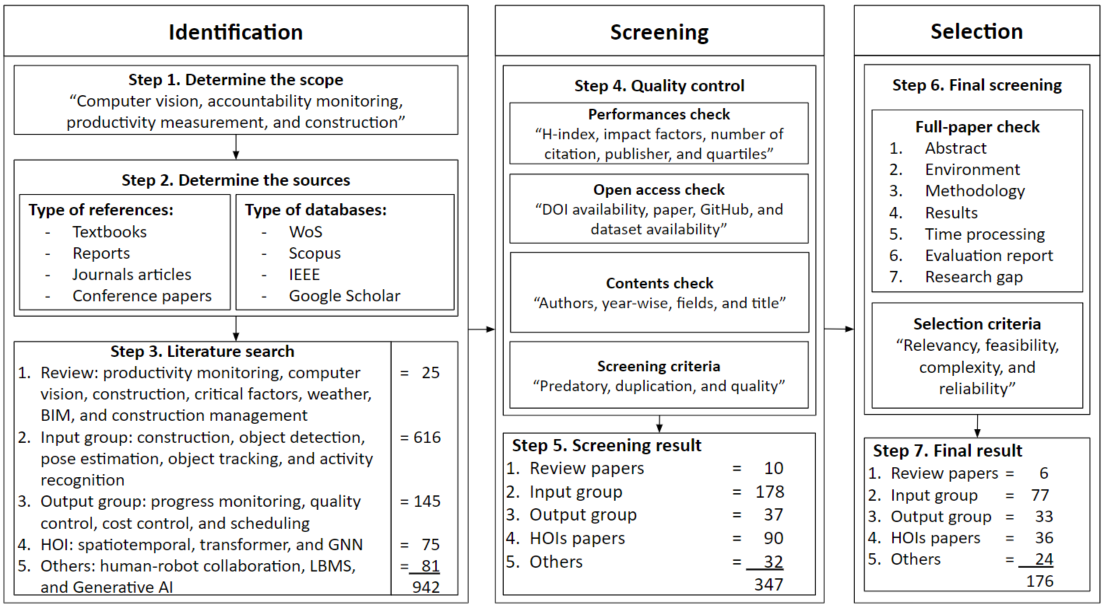

Fig. 2. Research Methodology

The screening process begins with a quality control step that checks the performance of the papers based on metrics like the H-index, impact factors, and citation quartiles. It also includes an open access check for the digital object identifier (DOI) availability, GitHub repositories, and dataset availability, followed by a content check of authors, year-wise, and fields. Screening criteria are applied to filter out predatory, duplicated, and low-quality papers. The screening results are then quantified, listing the number of review papers, input group papers, output group papers, papers on human-object interactions (HOIs), and others that passed the screening. The final phase involves a thorough check of the full papers, assessing sections such as the abstract, methodology, results, and identified research gaps. The selection criteria are based on relevance, feasibility, complexity, and reliability. The final result tabulates the number of papers that make it through this selection process, categorized into review papers, input groups, output groups, HOIs papers, and others, leading to a final count of selected papers for potential inclusion in the research.

3. WORKER ACCOUNTABILITY MONITORING

To understand worker performance and their accountability on construction sites through computer vision techniques, this stage is divided into three discussion categories such as input, connection, and output groups.

3.1. The vision-based method for the input groups

In the concept commonly used to measure productivity (P) [2], [13], there are two essential instruments, namely units of input (I) and output (O) (Eq. 1). At the construction site, these two instruments were obtained from a visual observation process in the field for the productivity monitoring process. Recently, experts have used computer vision techniques to detect[14], [15], classify, track[16], [17], and understand the activities[18] carried out by entities in construction projects. Figure 3 visualizes a systematic workflow as a productivity measurement chain related to project management or operational systems, where the tracking and management of various components are crucial. The workflow is segmented into three interconnected stages: input groups, connections, and output groups, each critical to the process's overall efficiency and effectiveness. At the Input stage, the system gathers crucial data through several advanced methods, including object detection in You Only Look Once (YOLO) [19], Faster R-CNN (Regional Convolutional Neural Network) [20], Mask R-CNN[21]), tracking in Deep SORT (Simple Online and Realtime Tracking) [16], and recognizing objects and activities through You Only Watch Once (YOWO) [22][23]. This encompasses a comprehensive collection of data points ranging from the location and timing of events to more intricate details, such as the specific characteristics of objects and statistical information that can be quantified and analyzed. The methods employed are sophisticated enough to understand not just the presence of objects but also their movements and the context in which they operate, which is vital for accurately assessing the system's functioning.

$$Productivity\ (P) = \frac{Unit\ of\ Output\ (O)}{Unit\ of\ Input\ (I)} \tag{1}$$

3.2. The vision-based method for the connection groups

In the connection stage, the focus shifts to accountability monitoring, ensuring that every element within the process, such as workers, objects, or equipment, is tracked and accounted for. This is where the collected data is contextualized by using the spatio-temporal aspects, as well as the quality of attention and interactions within the system. This stage is pivotal for maintaining control over the process, as it bridges the initial data collection with the final outcomes, ensuring that every action and interaction is purposeful and leads to a measurable outcome. We already have many works in the input and output parts that will be described in the following section. However, there are no studies focusing on how we link the output and the input work together. This scheme is proposed to describe and help experts in determining their future direction in the state-of-the-art productivity measurement process. In addition, the connection part can assist stakeholders in identifying workers' responsibility and ownership to support the quality control process.

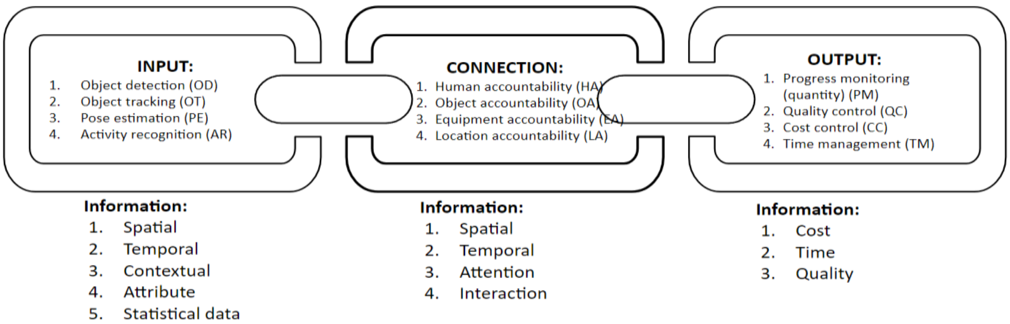

Fig. 3. The role of connection task in productivity monitoring

3.3. The vision-based method for the output groups

Finally, the output stage discussed progress monitoring[24], [25], [26], [27], quality, time, and cost control at the construction level. Output contains the data process through the input and connection stages that translate into tangible outcomes that dictate the project's success. This enables a practical application of the data collection process to support the decision-makers evaluating performance. Figure 3 represents a dynamic and interactive system where each stage is integral to the overall functionality and where the flow of information is meticulously managed to ensure the system's goals are achieved. After these three instruments (input, connection, and output) are completed, accountability, responsibility, and productivity value can be achieved accurately.

4. FUTURE RESEARCH DIRECTION

Worker accountability can be investigated through several potential approaches as future research directions, such as human-object interaction (HOI), generative artificial intelligence, location-based management systems (LBSM), and robotic technologies.

4.1. Human-object interaction

Figures 1 and 3 illustrate the complex interactions at construction sites that require thorough investigation for accountability prior to measuring productivity. Figure 4 presents a workflow for assessing sustainable construction productivity, emphasizing the importance of understanding interactions between various entities for effective worker accountability monitoring. For instance, Worker-1's interactions with colleagues, tools, and materials are analyzed, allowing the project manager to attribute specific progress tasks (Progress-1 and Progress-3) to this individual. Subsequently, Worker-1's productivity is evaluated. If found lacking, the manager must re-examine and adjust the interaction process. Additionally, Figure 4 elucidates various on-site interaction scenarios, such as task allocations among workers, the number of workers involved in each task, and their communication patterns within the workspace. This detailed understanding enhances the clarity and traceability of the accountability monitoring process.

In computer vision, the worker accountability process is called human-object interaction (HOI) detection, which can be implemented after we obtain essential information such as spatiotemporal[18], [28], [29], attention, body posture, interaction, etc. Several potential methods to detect HOI include graph neural networks[30], [31], [32], [33], [34] (GNN), transformers[35], [36], [37], [38], pose estimation[38], [39], etc. Based on Figure 4, worker-1 interacts not only with objects (material, tools, and equipment) but also with other workers (human-human interaction, HHI), which is related to location (human-location interaction, HLI). This shows that the research space in the worker accountability monitoring process is vast and is critical in the productivity measurement process. However, experts do not have focused their studies on discussing this stage, so as a future direction, HOI has excellent potential for further exploration and development.

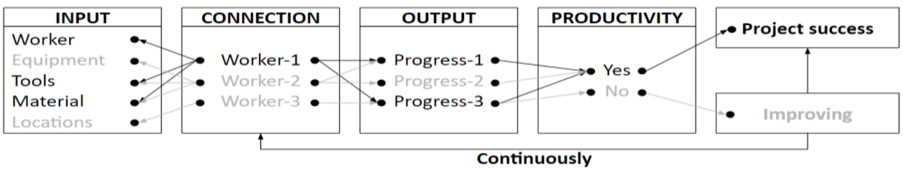

Fig. 4. The contextual workflow of productivity monitoring

4.2. Generative AI for worker accountability

Generative AI[40] is a form of artificial intelligence that leverages generative models to create text, images, or other media. These models, trained on existing data, replicate their patterns and structures to generate new, similar content. The early 2020s witnessed significant advancements in this field with the development of transformer-based deep neural networks, leading to the rise of various generative AI platforms capable of interpreting natural language prompts. This era introduced powerful tools like Generative Pre-trained Transformer (GPT), Microsoft Copilot, Bard, and a state-of-the-art large language model for coding (LLaMA), marking substantial progress in AI. These advancements facilitate the rapid interpretation of visual data into text and vice versa, enhancing processes like annotation, initial contextual analysis, and overall computer vision model development. Integrating large language models (LLMs) with computer vision techniques can significantly improve efficiency in accountability and productivity monitoring.

4.3. Location-based management system (LBMS)

In construction management, Human-Location Interaction (HLI) is vital. If end-of-project productivity evaluations indicate suboptimal worker performance, supervisors must assess the efficacy of workspace utilization and mobilization. Key considerations include strategic worker placement, workforce size, layout optimization, zoning, material and tool positioning, and the planning of mobilization routes and schedules to ensure dynamic movement and avoid productivity-hindering collisions. The Location-Based Management System (LBMS) [41], [42], [43], [44] is essential in this context, emphasizing location as a crucial factor in construction project work sequence management. Its goal is to distribute resources effectively by location and workforce. Computer vision technologies enhance this by offering detection, tracking, and spatiotemporal analytics. Inputs from Human-Object Interaction (HOI) models can refine project scheduling, increasing precision and circumventing scheduling conflicts. Therefore, LBMS merits increased attention for improved location management and enhanced productivity in future construction projects.

4.4. Robotics for worker accountability

Workers play a pivotal role in the realm of construction. However, the future foresees a shift towards integrating robots[45], [46], [47] to assist in manufacturing, transportation, installation, and monitoring tasks at construction sites. Similar to humans, these robots require interaction with surrounding objects during their activities, introducing a new layer of complexity to productivity measurement in construction projects. Nonetheless, robots also offer potential as a tool for accountability monitoring by project managers. These robots can be programmed to operate within specified patterns and workspaces, alerting them to any deviations from established standards. The effectiveness of these robots is contingent on the sophistication of the underlying computer vision models developed for them. Therefore, for successful worker accountability monitoring and to maintain competitiveness within the construction industry, it is essential to consider and integrate advancements in robotics and model development.

5. CONCLUSION

Computer vision technologies, while adept at capturing extensive visual data on construction sites, encounter difficulties in effectively demonstrating tangible productivity recognition. Recent studies highlight a lack of systematic integration between the input and output datasets, adversely affecting the measurement, monitoring, and enhancement of productivity in construction projects. This issue has not been sufficiently prioritized in performance assessments by academic reviewers. A detailed systematic review is necessary to establish a connection between the input and output phases. At the input stage, the focus is on object detection, tracking, pose, and activity recognition, to understand the characteristics and movement of involved entities. Subsequently, in the output phase, the emphasis is on quantifying the volume and quality of outputs via progress monitoring. The application of Human-Object Interaction (HOI) techniques is essential in linking inputs and outputs. Additionally, exploring other technologies like generative AI, LBMS, and robotics is important for future integration possibilities. Lastly, worker accountability monitoring extends beyond measuring productivity to supporting risk mitigation, quality control, and time management, thereby enhancing the construction industry's competitiveness.

ACKNOWLEDGMENTS

This research was supported by the Ministry of Education Taiwan (Grant number: MOE-TSP-110.08.16) and facilitated by the National Center for Research on Earthquake Engineering and the Department of Civil Engineering, National Taiwan University (NCREE-NTUCE) Joint Artificial Intelligence Research Center. This research is also funded by The Ministry of Science and Technology (MOST) through a project (Grant number: 108-WFA-0110-731).

REFERENCES

[1] Project Management Institute, *A guide to the project management body of knowledge (PMBOK® guide)*, vol. 40. 2008.

[2] P. Hee-Sung, T. S. R., and T. R. L., "Benchmarking of Construction Productivity," *J Constr Eng Manag*, vol. 131, no. 7, pp. 772–778, Jul. 2005, doi: 10.1061/(ASCE)0733-9364(2005)131:7(772).

[3] V. Gaspersz, "Manajemen Produktivitas Total Strategi Oeningkatan Produktivitas Bisnis Global," *Gramedia Pustaka Utama, Jakarta*, 1998.

[4] R. Farmer, "McKinsey & company," in *Management Consultancy: What Next?*, 2016. doi: 10.1057/9781403907189_24.

[5] A. Pal and S. H. Hsieh, "Deep-learning-based visual data analytics for smart construction management," *Automation in Construction*, vol. 131. Elsevier, p. 103892, 2021. doi: 10.1016/j.autcon.2021.103892.

[6] A. S. da Barbosa and D. B. Costa, "PRODUCTIVITY MONITORING OF CONSTRUCTION ACTIVITIES USING DIGITAL TECHNOLOGIES: A LITERATURE REVIEW," in *IGLC 2021 - 29th Annual Conference of the International Group for Lean Construction - Lean Construction in Crisis Times: Responding to the Post-Pandemic AEC Industry Challenges*, 2021. doi: 10.24928/2021/0141.

[7] W. S. Alaloul, K. M. Alzubi, A. B. Malkawi, M. Al Salaheen, and M. A. Musarat, "Productivity monitoring in building construction projects: a systematic review," *Engineering, Construction and Architectural Management*, vol. 29, no. 7, pp. 2760–2785, Jan. 2022, doi: 10.1108/ECAM-03-2021-0211.

[8] B. Sherafat *et al.*, "Automated Methods for Activity Recognition of Construction Workers and Equipment: State-of-the-Art Review," *J Constr Eng Manag*, vol. 146, no. 6, 2020, doi: 10.1061/(asce)co.1943-7862.0001843.

[9] S. Archchana and W. Pan, "BUILDING INFORMATION MODELLING FOR CONSTRUCTION PRODUCTIVITY MEASUREMENT," in *World Construction Symposium*, 2023. doi: 10.31705/WCS.2023.25.

[10] A. S. M. Moohialdin, F. Lamari, M. Miska, and B. Trigunarsyah, "Construction worker productivity in hot and humid weather conditions: A review of measurement methods at task, crew and project levels," *Engineering, Construction and Architectural Management*, vol. 27, no. 1. 2020. doi: 10.1108/ECAM-05-2018-0191.

[11] K. Mhmoud Alzubi, W. Salah Alaloul, A. B. Malkawi, M. Al Salaheen, A. Hannan Qureshi, and M. Ali Musarat, "Automated monitoring technologies and construction productivity enhancement: Building projects case," *Ain Shams Engineering Journal*, vol. 14, no. 8, 2023, doi: 10.1016/j.asej.2022.102042.

[12] A. Rathnayake and C. Middleton, "Systematic Review of the Literature on Construction Productivity," *J Constr Eng Manag*, vol. 149, no. 6, 2023, doi: 10.1061/jcemd4.coeng-13045.

[13] T. H. Randolph, "Labor Productivity and Work Sampling: The Bottom Line," *J Constr Eng Manag*, vol. 117, no. 3, pp. 423–444, Sep. 1991, doi: 10.1061/(ASCE)0733-9364(1991)117:3(423).

[14] Z. Qilin, W. Zhichen, Y. Bin, L. Ke, Z. Binghan, and L. Boda, "Reidentification-Based Automated Matching for 3D Localization of Workers in Construction Sites," *Journal of Computing in Civil Engineering*, vol. 35, no. 6, p. 04021019, Nov. 2021, doi: 10.1061/(ASCE)CP.1943-5487.0000975.

[15] M. B. Eddine, A. Mohamad, and K. Hiam, "Vision-Based Framework for Intelligent Monitoring of Hardhat Wearing on Construction Sites," *Journal of Computing in Civil Engineering*, vol. 33, no. 2, p. 4018066, Mar. 2019, doi: 10.1061/(ASCE)CP.1943-5487.0000813.

[16] N. Wojke, A. Bewley, and D. Paulus, "Simple online and realtime tracking with a deep association metric," in *Proceedings - International Conference on Image Processing, ICIP*, 2017. doi: 10.1109/ICIP.2017.8296962.

[17] E. Konstantinou, J. Lasenby, and I. Brilakis, "Adaptive computer vision-based 2D tracking of workers in complex environments," *Autom Constr*, vol. 103, pp. 168–184, 2019, doi: https://doi.org/10.1016/j.autcon.2019.01.018.

[18] T. Ghazaleh, H. Amin, and B. Nizar, "Two-Dimensional and Three-Dimensional CNN-Based Simultaneous Detection and Activity Classification of Construction Workers," *Journal of Computing in Civil Engineering*, vol. 36, no. 4, p. 4022009, Jul. 2022, doi: 10.1061/(ASCE)CP.1943-5487.0001024.

[19] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2016. doi: 10.1109/CVPR.2016.91.

[20] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," *IEEE Trans Pattern Anal Mach Intell*, vol. 39, no. 6, 2017, doi: 10.1109/TPAMI.2016.2577031.

[21] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask R-CNN," *IEEE Trans Pattern Anal Mach Intell*, vol. 42, no. 2, 2020, doi: 10.1109/TPAMI.2018.2844175.

[22] O. Köpüklü, X. Wei, and G. Rigoll, "You Only Watch Once: A Unified CNN Architecture for Real-Time Spatiotemporal Action Localization," *CoRR*, vol. abs/1911.06644, 2019, [Online]. Available: http://arxiv.org/abs/1911.06644

[23] M.-Y. Cheng, A. F. K. Khitam, and H. H. Tanto, "Construction worker productivity evaluation using action recognition for foreign labor training and education: A case study of Taiwan," *Autom Constr*, vol. 150, p. 104809, 2023, doi: https://doi.org/10.1016/j.autcon.2023.104809.

[24] J. J. Lin and M. Golparvar-Fard, “Construction Progress Monitoring Using Cyber-Physical Systems,” in *Cyber-Physical Systems in the Built Environment*, 2020, pp. 63–87. doi: 10.1007/978-3-030-41560-0_5.
[25] G. A.S. and J. B. Edayadiyil, “Automated progress monitoring of construction projects using Machine learning and image processing approach,” *Mater Today Proc*, vol. 65, pp. 554–563, 2022, doi: https://doi.org/10.1016/j.matpr.2022.03.137.
[26] L. J. J., H. K. K., and G.-F. Mani, “A Framework for Model-Driven Acquisition and Analytics of Visual Data Using UAVs for Automated Construction Progress Monitoring,” *Computing in Civil Engineering 2015*. in Proceedings. pp. 156–164, Nov. 14, 2022. doi: doi:10.1061/9780784479247.020.
[27] L. J. J., H. K. K., and G.-F. Mani, “A Framework for Model-Driven Acquisition and Analytics of Visual Data Using UAVs for Automated Construction Progress Monitoring,” *Computing in Civil Engineering 2015*. in Proceedings. pp. 156–164, Nov. 14, 2022. doi: doi:10.1061/9780784479247.020.
[28] N. Wang *et al.*, “Exploring Spatio-Temporal Graph Convolution for Video-based Human-Object Interaction Recognition,” *IEEE Transactions on Circuits and Systems for Video Technology*, p. 1, 2023, doi: 10.1109/TCSVT.2023.3259430.
[29] D. Purwanto, Y. T. Chen, and W. H. Fang, “First-Person Action Recognition with Temporal Pooling and Hilbert-Huang Transform,” *IEEE Trans Multimedia*, vol. 21, no. 12, 2019, doi: 10.1109/TMM.2019.2919434.
[30] F. Scarselli, M. Gori, A. C. Tsoi, M. Hagenbuchner, and G. Monfardini, “The graph neural network model,” *IEEE Trans Neural Netw*, vol. 20, no. 1, 2009, doi: 10.1109/TNN.2008.2005605.
[31] P. Veličković, A. Casanova, P. Liò, G. Cucurull, A. Romero, and Y. Bengio, “Graph attention networks,” in *6th International Conference on Learning Representations, ICLR 2018 - Conference Track Proceedings*, 2018. doi: 10.1007/978-3-031-01587-8_7.
[32] M. Tomei, L. Baraldi, S. Calderara, S. Bronzin, and R. Cucchiara, “Video action detection by learning graph-based spatio-temporal interactions,” *Computer Vision and Image Understanding*, vol. 206, 2021, doi: 10.1016/j.cviu.2021.103187.
[33] Y. Huang, H. Bi, Z. Li, T. Mao, and Z. Wang, “STGAT: Modeling spatial-temporal interactions for human trajectory prediction,” in *Proceedings of the IEEE International Conference on Computer Vision*, 2019. doi: 10.1109/ICCV.2019.00637.
[34] H. Tang, P. Wei, J. Li, and N. Zheng, “EvoSTGAT: Evolving spatiotemporal graph attention networks for pedestrian trajectory prediction,” *Neurocomputing*, vol. 491, 2022, doi: 10.1016/j.neucom.2022.03.051.
[35] A. Vaswani *et al.*, “Attention is all you need,” in *Advances in Neural Information Processing Systems*, 2017.
[36] J. Park, J. W. Park, and J. S. Lee, “ViPLO: Vision Transformer Based Pose-Conditioned Self-Loop Graph for Human-Object Interaction Detection,” in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2023. doi: 10.1109/CVPR52729.2023.01645.
[37] Z. Liang, Y. Guan, and J. Rojas, “Visual-Semantic Graph Attention Network for Human-Object Interaction Detection,” *CoRR*, vol. abs/2001.02302, 2020, [Online]. Available: http://arxiv.org/abs/2001.02302
[38] Z. Liang, J. Liu, Y. Guan, and J. Rojas, “Pose-based Modular Network for Human-Object Interaction Detection,” *CoRR*, vol. abs/2008.02042, 2020, [Online]. Available: https://arxiv.org/abs/2008.02042
[39] R. Dominic, T. C. Wilfredo, T. Shuai, and G.-F. Mani, “Vision-Based Construction Worker Activity Analysis Informed by Body Posture,” *Journal of Computing in Civil Engineering*, vol. 34, no. 4, p. 4020017, Jul. 2020, doi: 10.1061/(ASCE)CP.1943-5487.0000898.
[40] H. Yan, Y. Liu, L. Jin, and X. Bai, “The development，application，and future of LLM similar to ChatGPT,” *Journal of Image and Graphics*, vol. 28, no. 9, 2023, doi: 10.11834/jig.230536.
[41] O. Seppänen, G. Ballard, and S. Pesonen, “The Combination of Last Planner System and Location-Based Management System,” *Lean Construction Journal*, vol. 6, Jan. 2010.
[42] J. Ratajczak, M. Riedl, and D. T. Matt, “BIM-based and AR application combined with location-based management system for the improvement of the construction performance,” *Buildings*, vol. 9, no. 5, 2019, doi: 10.3390/buildings9050118.
[43] R. Kenley and O. Seppänen, *Location-Based Management for Construction: Planning, Scheduling and Control*. 2016. doi: 10.4324/9780203030417.
[44] H. Huang, “Location Based Services,” in *Springer Handbooks*, 2022. doi: 10.1007/978-3-030-53125-6_22.
[45] C.-J. Liang, X. Wang, V. R. Kamat, and C. C. Menassa, “Human–Robot Collaboration in Construction: Classification and Research Trends,” *J Constr Eng Manag*, vol. 147, no. 10, 2021, doi: 10.1061/(asce)co.1943-7862.0002154.
[46] Y. Liu, M. Habibnezhad, and H. Jebelli, “Brainwave-driven human-robot collaboration in construction,” *Autom Constr*, vol. 124, 2021, doi: 10.1016/j.autcon.2021.103556.
[47] M. Zhang, R. Xu, H. Wu, J. Pan, and X. Luo, “Human–robot collaboration for on-site construction,” *Automation in Construction*, vol. 150. 2023. doi: 10.1016/j.autcon.2023.104812.