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Construction Project Monitoring Using Computer Vision Technology – A Literature Review

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Abstract

The construction industry is witnessing a transformative shift with the adoption of computer vision (CV) technologies for productivity monitoring and performance evaluation. This review consolidates the advancements in CV applications, focusing on areas, such as real-time progress tracking, resource management, and safety monitoring. The analysis highlights how automated systems, powered by deep learning models and object detection algorithms, are replacing traditional manual methods, offering enhanced accuracy, efficiency, and decision-making capabilities. Despite these advancements, challenges, such as scalability, variability in construction environments, and limited system integration remain barriers to widespread adoption. Furthermore, critical gaps, including the limited use of advanced CV models for multi-resource tracking and the lack of intuitive interfaces for real-time visualization, are identified. This study underscores the necessity for further innovation and research to address these limitations, enabling the construction industry to harness the full potential of CV technologies. The findings offer valuable insights into how CV can drive a data-centric approach to safer and more efficient construction practices.

Keywords: Construction project monitoring, productivity tracking, performance evaluation, automation, computer vision

INTRODUCTION

The construction industry is characterized by its complexity and reliance on meticulous resource management, coordination, and execution to meet stringent timelines and budgetary constraints. Traditionally, monitoring productivity and evaluating performance on construction sites have been dependent on manual processes, which are often labor-intensive, prone to human error, and lack real-time insights. As construction projects become increasingly complex, there is a growing demand for innovative, automated solutions to enhance operational efficiency, accuracy, and decision-making.

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Computer vision (CV), a branch of artificial intelligence, has emerged as a transformative technology capable of addressing these challenges. CV enables the automated analysis of visual data, such as images and videos, to perform tasks like activity recognition, object detection, and progress tracking with minimal human intervention. By leveraging advanced algorithms and machine learning models, CV applications are redefining how construction activities are monitored and managed.

Recent research highlights the significant role of CV in improving various facets of construction management, including tracking worker productivity, monitoring equipment utilization, evaluating safety measures, and ensuring project progress aligns with schedules. Methods, such as deep learning-based object detection models and machine learning-driven tracking systems have demonstrated potential to streamline workflows and minimize inefficiencies. However, the adoption of CV in the construction sector is still limited by challenges, such as environmental variability, scalability issues, and difficulties in integrating these technologies into existing systems.

This review paper seeks to explore the advancements in CV applications within the construction industry, focusing on their role in productivity monitoring and performance evaluation. It consolidates findings from existing research, identifies challenges and gaps in implementation, and discusses opportunities for future innovation. By providing a comprehensive understanding of CV technologies and their potential, this paper aims to support the construction sector's transition toward more efficient, automated, and data-driven management practices.

LITERATURE REVIEW

Computer Vision in Construction Industry

The construction industry is gradually moving toward integrating technology into various sectors, aiming to enhance project performance by reducing manual processes wherever possible. However, the pace of technology adoption has not met initial expectations.

Teizer (2015) [1] conducted a comprehensive review of research articles, technical reports, and case studies to assess the effectiveness, limitations, and applicability of current methods and technologies. Findings from this review highlighted significant advancements; however, persistent challenges remain. Major issues include scalability limitations, difficulties in achieving real-time processing, and the need for improved robustness and accuracy of vision algorithms under diverse conditions. Additionally, the integration of vision systems with other sensory data continues to pose challenges for the industry.

Yang, Park, et al. (2015) [2] also reviewed vision-based methods for automating construction performance monitoring, aiming to overcome the limitations of traditional manual processes. They categorized methods into project-level monitoring for infrastructure and building elements, and operation-level monitoring for equipment and workers. Techniques, such as 3D reconstruction and machine learning-based tracking were highlighted, with challenges including real-time accuracy and managing complex dynamic environments. They emphasized the need for large datasets and proposed future research integrating vision systems with other sensors and advancing machine learning for better performance monitoring.

Further exploring the role of technology, Moragane, Perera, and Palihakkara (2022) [3] examined current applications of computer vision (CV) in construction project management (CPM). Their study, employing interviews and the Delphi Technique, identified seven essential CPM phases: initial planning, data acquisition, information retrieval, verification, progress estimation and comparison, result visualization, and schedule updating. CV was found to facilitate tasks, such as crane operation, work item tracking, safety monitoring, and earthmoving activities, showcasing its versatility. The research underscored the need for integrating CV with other technologies and highlighted that educating workers on CV applications could advance technological adoption in the sector. They recommended further investigation into the interplay between CV and CPM for enhanced project management.

In a related study by Rehman, Shafiq, and Ullah (2022) [4] noted that while traditional CPM methods are often manual and prone to errors, CV offers the potential for real-time and automated progress tracking. The review outlined four main processes in CV-based CPM: data acquisition, information retrieval, progress estimation, and output visualization. However, existing techniques often rely on human intervention and lack full integration, limiting their practicality. The authors highlighted the need for fully automated and interconnected systems to make CV-based CPM a viable alternative. Future research should focus on achieving seamless integration and real-world applicability to drive industry adoption.

Bozorgzadeh and Umar (2023) [5] extended this discourse by exploring the adoption of AI and CV in the UK's construction sector, where manual data collection is still prevalent, causing inefficiencies and delays. Their research combined a literature review and a survey of industry practitioners, revealing that while there is awareness of CV-based Construction Project Management Systems (CV-CPM), barriers, such as high implementation costs, insufficient expertise, and resistance to change hinder its widespread use. Despite these obstacles, the potential for enhanced decision-making and competitive advantages supports its adoption. The study concluded that CV-CPM could greatly improve progress detection and data accessibility but stressed the importance of addressing financial impacts and fostering a culture of change through training and awareness programs to ensure successful implementation.

Al-Sinan, Bubshait, and Aljaroudi (2024) [6] presented a forward-thinking approach to automating construction scheduling through the integration of machine learning (ML) and building information modeling (BIM). Their proposed system uses BIM's International Foundation Class (IFC) 3D files from past projects to train ML models that generate project schedules, sequence activities, and predict costs and resource requirements. This method addresses the limitations of traditional scheduling processes, which are often time-consuming and prone to errors, and current software tools that still require manual input. The study reviewed various ML techniques and prior AI applications in construction, outlining a theoretical framework for the system. Challenges identified included improving the IFC standard, integrating safety risk identification, and enhancing autonomous progress monitoring. The authors concluded that while their system holds potential to improve scheduling efficiency and accuracy, further research is necessary to implement and evaluate it across diverse construction projects.

In summary, the reviewed literature highlights the significant strides being made toward integrating advanced technologies, such as computer vision, machine learning, and artificial intelligence into construction project management. With continued research and strategic implementation, the construction industry stands on the brink of a technological evolution that promises to elevate project management practices and outcomes.

Incorporating Technology for Construction Project Monitoring

The recent advancements in visual based technology have caught the attention of the construction industry and many researchers have highlighted ways to integrate it into the existing system for optimized results.

One significant development in this domain is the Integrated Building Information System (IBIS), created by Zhang, Bakis, Lukins, et al. (2009) [7], to semi-automate the measurement of construction progress and provide early warnings of potential delays by leveraging computer vision technology. IBIS utilizes digital images captured on-site to monitor construction progress and assist in various project management tasks. The system is structured into four main modules: computer vision, work breakdown structure (WBS), scheduling and budgeting, and progress measurement with early alert capabilities. By analyzing on-site images, IBIS can detect building components and link the identified progress to project schedules, facilitating semi-automated work measurement and interim payment calculations. Its effectiveness was demonstrated during the construction of the School of Informatics buildings at the University of Edinburgh, where it successfully identified building components approximately 70% of the time. Despite challenges, such as image clutter, lighting variations, and limited camera coverage, IBIS offers valuable support by enhancing progress measurement and issuing early warnings of potential delays. The study suggests that the system's applications could extend beyond traditional building construction to other types of projects, indicating its broader potential in construction project monitoring.

Further advancing technology in construction monitoring, Gong and Caldas (2010) [8] presented a computer vision-based video interpretation model to address the limitations of traditional, labor-intensive data collection methods. Conventional approaches, such as manual observations and survey-based data collection are costly, slow, and require significant manual effort. The proposed model automates real-time extraction and analysis of productivity data from construction operation videos, demonstrated through a concrete column pour case study. This system effectively detects production cycles and identifies abnormalities, enhancing productivity analysis. Despite the initial setup complexity, the model offers long-term benefits in reducing workload and improving data accuracy, showcasing the potential for streamlined, automated productivity monitoring in the construction industry.

Dimitrov and Golparvar-Fard (2013) [9] developed an automated material classification system for construction progress monitoring, focusing on unordered image collections taken under varying site conditions. The method used a combination of Leung-Malik filter banks and HSV color values, classified through a χ^2 kernel Support Vector Machine (SVM) classifier. The system was tested across different datasets, achieving a peak classification accuracy of 97.1% and demonstrating robust performance even with reduced image sizes. While challenges remained, such as confusion among similar material types and sensitivity to image quality, the research highlighted the system's potential for integration into automated as-built 3D modeling systems. Future work suggested refining segmentation techniques and incorporating 3D geometrical data to further enhance material classification accuracy.

Aiming to enhance the monitoring of indoor construction projects, Hamledari, McCabe, and Davari (2016) [10] developed an algorithm for detecting and evaluating indoor partition components through 2D images. The algorithm was segmented into four modules targeting specific construction elements: studs, insulation, drywall at various stages, and electrical outlets. Extensive tests using image datasets from smartphones and UAVs demonstrated the algorithm's effectiveness, with strong performance even under lower-resolution conditions. The study indicated that this approach could provide real-time situational awareness and improve decision-making, safety, and productivity in construction, thereby refining project oversight and site management.

Luo, Xiong, et al. (2018) [11] provided a significant contribution by introducing an advanced convolutional neural network (CNN) designed to improve construction site management. This CNN uniquely integrates RGB, optical flow, and gray image streams to monitor and classify worker activities, achieving an average accuracy rate of 85%. The framework was validated on a new real-world dataset focusing on activities, such as steel bending, transporting, and walking among steel reinforcement fixers. The application of such image processing techniques showed potential for real-time productivity monitoring, enabling immediate feedback for both workers and managers. While the model demonstrated promising outcomes, the study noted limitations, including challenges with real-time tracking, defining action sequences over time, and the small dataset size. Future research aims to expand the activity database and enhance recognition capabilities for further improving on-site productivity monitoring.

Arabi, Haghighat, and Sharma (2020) [12] presented a comprehensive solution for detecting construction vehicles using deep learning. Their approach included the development and deployment phases, using an optimized MobileNet single shot detector suited for embedded devices. The system maintained a high mean average precision above 90% during field tests, validating its real-time effectiveness. The study covered aspects like model training, hardware optimization, and economic analysis, demonstrating its value in supporting safety monitoring and productivity assessments in construction settings.

Rahimian, Seyedzadeh, et al. (2019) [13] introduced an innovative framework combining image processing, machine learning, BIM, and virtual reality (VR) for automated construction project simulation. The proposed system links BIM models to a Unity engine to create VR environments and generate synthetic RGB-D images for training neural networks. Site images are processed daily through CNNs to detect & identify objects, which then are compared with as-planned BIM models to monitor progress. The research demonstrated that this system effectively supports remote construction monitoring and enhances visualization through VR technology. The study emphasized that this approach allows construction firms to track project progress and spot discrepancies without disrupting on-site operations, resulting in significant time saving and increased accuracy.

Arabi, Haghighat, and Sharma (2020) [12] provided a comprehensive solution in their study which outlines the use of deep learning for detecting construction vehicles. The research detailed the entire development-to-deployment process, starting with data preparation, model selection, training, and validation using an optimized version of the single shot detector MobileNet, ideal for embedded devices. The second phase focused on model optimization, hardware selection, economic analysis, and practical field implementation. The system demonstrated consistent performance, achieving over 90% mean average precision, validating its real-time application in construction environments. This solution has shown to enhance safety monitoring, improve productivity assessments, and support managerial decision-making, highlighting its practicality and effectiveness for real-world construction scenarios.

Real-time construction object detection using YOLO deep learning models was the focus of research conducted by Nath and Behzadan (2020) [14]. The study aimed to automate the identification of buildings, equipment, and workers under varied visual conditions. A dataset, Pictor-v2, comprising 3,500 images and 11,500 object instances, was created, and transfer learning was employed to train YOLO-v2 and YOLO-v3 models. Among the tested models, YOLO-v3 demonstrated superior performance with a mean average precision (mAP) of 78.2%, excelling in detecting larger objects in well-lit, less crowded environments. The authors suggested that while YOLO-v3 is effective, further work are to be directed towards enhancing detection capabilities in more challenging conditions, such as poor lighting and congested scenes.

An automated framework for monitoring the progress of precast wall installations using surveillance videos was developed by Zhichen Wang, Qilin Zhang, Bin Yang, et al. (2020) [15]. Their methodology combined object detection, instance segmentation, and multi-object tracking to detect and track precast walls in real time. Mask R-CNN was utilized for object detection and segmentation, while DeepSORT facilitated tracking across video frames. The captured temporal and spatial data were stored in JSON format and linked to a Building Information Model (BIM) for visual progress tracking and status updates. Real-world tests validated the framework, achieving over 90% precision for detecting and segmenting precast walls under various conditions. This study highlighted the significant improvement in monitoring efficiency and accuracy offered by advanced computer vision techniques over traditional manual or sensor-based approaches, confirming the feasibility of real-time, automated construction management.

Bhokare, Goyal, et al. (2022) [16] took a different approach by developing a smart scheduling system that incorporates computer vision for real-time tracking of construction progress. This system detects activities like excavation, screeding, bricklaying, and carpentry to automatically update the project schedule. The model, trained on an annotated dataset derived from 20 short YouTube video clips, used YOLO v3 as the classifier and trained on Google Colab. Integrated into a smart scheduling tool, the system generated Gantt charts that reflected detected activities, updating timelines accordingly. While the average training accuracy was 78%, challenges included the limited size of the training dataset and difficulties with detecting simultaneous activities. Despite these constraints, the project demonstrated versatility and potential for enhancements in future applications.

Chen, Lian, et al. (2022) [17] advanced the field of construction resource detection by integrating computer vision (CV) with edge computing to address limitations associated with traditional CV approaches. Conventional methods often require substantial computational power and can incur significant latency and high data transmission costs. To overcome these challenges, the researchers embedded a YOLO-v5 model for hardhat detection directly onto edge devices, such as a Raspberry Pi (R. Pi) microcomputer, enabling local video data processing. This approach achieved high detection accuracy for identifying hardhat presence and color while reducing the need for data transmission to central servers. Performance comparisons between the R. Pi and a local computer validated the practicality and efficiency of edge computing for real-time construction monitoring. This solution demonstrated potential for enhancing safety and productivity on construction sites by providing an effective, decentralized resource detection method.

By leveraging YOLO v8 for its real-time capability and high accuracy, Yang, Wilde, Menzel, et al. (2023) [18] focused on monitoring window installation processes. The project incorporated data collected from construction site images and videos, with a conservative approach using QR codes to detect installations from the exterior. High-definition images were annotated and segregated into training, validation, and testing sets, supported by various augmentations to enrich training quality. The YOLO v8 model achieved optimal performance at epoch 82, achieving an impressive mAP50 of 0.953 and mAP50-95 of 0.678. Although the results were promising, the authors noted the limitation of training on a single dataset and advocated for more diverse data to improve model generalization. The study concluded that the YOLO-based model holds significant potential for practical application in monitoring construction progress, particularly in window installations.

Lung and Wang (2023) [19] investigated the application of deep learning, specifically using the Single Shot Multibox Detector (SSD), to automate image recognition for construction site management. Their study targeted the detection of key site elements, such as workers, machinery, and materials to enhance supervision, safety, and project management. The researchers compiled a dataset of 461 images from both online sources and actual construction sites, followed by data preprocessing and training a CNN-based SSD model. The model achieved a 64% F1 score and 66% overall accuracy, reflecting moderate success in object recognition. Limitations were noted in precision and recall, particularly in cluttered construction settings. The authors concluded that while AI has considerable potential for minimizing manual oversight and supporting decision-making in construction, refining models, using larger datasets, and incorporating continuous learning are essential to improve accuracy and applicability in real-world scenarios.

To conclude, these studies collectively highlight the substantial progress being made in incorporating advanced technologies, such as deep learning, computer vision, and edge computing in construction project monitoring. While notable successes have been achieved in enhancing safety, efficiency, and real-time supervision, challenges related to data diversity, precision in complex environment and model generalization persist. Continued research and development in these areas will be crucial to overcoming these limitations and unlocking the full potential of automated construction management systems, fostering safer, more productive, and data-driven construction practices.

MAJOR FINDINGS FROM THE REVIEWED PAPER

The reviewed studies illustrate the transformative potential of computer vision (CV) technologies in enhancing productivity monitoring within the construction industry. Key findings from these papers are summarized as follows:

- Computer vision systems have demonstrated significant capability in automating real-time monitoring of construction activities. For example, Gong and Caldas (2010) [8] showcased how video interpretation models can track production cycles and detect anomalies in construction operations, reducing the dependency on time-consuming manual observations. Similarly, Zhichen Wang et al. (2020) [15] employed CV-based object detection and tracking frameworks to monitor precast wall installations, achieving over 90% precision, which underscores the reliability of CV for high-stakes monitoring tasks.

- The use of state-of-the-art deep learning models, such as YOLO (Chen et al., 2022 [17] Yang et al., 2023 [18]), has significantly improved the accuracy and reliability of on-site activity recognition. For instance, Chen et al. (2022) [17] demonstrated how edge-computing-enabled YOLO models could ensure high accuracy in detecting hardhats while minimizing latency. Luo et al. (2018) [20] validated the application of convolutional neural networks (CNNs) in recognizing complex worker activities, achieving an 85% classification accuracy, thereby proving their robustness in dynamic site environments.
- Beyond productivity monitoring, CV technologies are contributing to improved safety and resource management. Arabi et al. (2020) [12] utilized MobileNet SSD to detect and track construction vehicles, enabling safer operations and better equipment utilization. By integrating safety monitoring into productivity frameworks, such applications address multiple operational challenges simultaneously, ensuring that construction sites are both efficient and compliant with safety standards.
- Integrating CV with Building Information Modeling (BIM) has emerged as a promising approach to tracking project progress. Rahimian et al. (2019) [13] demonstrated the use of synthetic RGB-D image datasets for linking as-planned BIM models with as-built site conditions, providing real-time progress updates and discrepancy analysis. Similarly, Zhichen Wang et al. (2020) [15] combined CV-based tracking with BIM for seamless visualization of progress, which allowed stakeholders to evaluate construction activities without requiring on-site presence.
- Despite these advancements, significant challenges persist. Environmental variability, such as lighting and clutter, continues to affect the reliability of CV systems, as noted by Hamledari et al. (2016) [10] and Dimitrov and Golparvar-Fard (2013) [9]. Limited datasets for training machine learning models, as highlighted by Yang et al. (2023) [18], pose barriers to generalizing these systems for diverse construction scenarios. Additionally, computational constraints, especially in real-time deployment on resource-limited devices, as observed by Arabi et al. (2020) [12], remain a technical bottleneck.
- The integration of CV with complementary technologies, such as edge computing and virtual reality has opened new possibilities for enhancing decision-making and operational efficiency. Chen et al. (2022) [17] proposed edge-computing frameworks to reduce latency and ensure real-time processing, while Rahimian et al. (2019) [13] explored virtual reality as a tool for immersive progress visualization. These innovations indicate that future research should focus on leveraging such integrations to address existing limitations and unlock the full potential of CV in construction management.

LIMITATIONS OF THE STUDY

Despite the significant advancements in computer vision (CV) technologies for construction productivity monitoring and performance evaluation, several limitations have been identified that hinder their widespread adoption and full potential.

- Construction sites present highly dynamic and variable environments, including changes in lighting, weather, and cluttered backgrounds. These factors can significantly affect the accuracy and reliability of CV systems, as noted in studies, such as Hamledari et al. (2016) [10] and Dimitrov and Golparvar-Fard (2013) [9]. The robustness of detection and tracking algorithms under these challenging conditions remains a critical limitation.
- Many CV models, including those employing advanced architectures like YOLO (Yang et al., 2023), [18] often rely on specific datasets for training and testing. The lack of diverse and extensive datasets limits the ability of these systems to generalize across different construction scenarios. This creates challenges in adapting these models for varied site conditions and project requirements.
- Real-time processing is a key requirement for effective on-site monitoring, but many CV applications face computational bottlenecks, especially when deployed on resource-constrained devices. For example, Arabi et al. (2020) [12] highlighted the limitations of deploying deep

learning models on embedded devices, which may struggle to handle the computational demands of complex CV algorithms.

- Combining CV with other technologies, such as Building Information Modeling (BIM) and Internet of Things (IoT), poses significant integration challenges. Rahimian et al. (2019) [13] and Zhichen Wang et al. (2020) [15] noted that ensuring compatibility and seamless data exchange between CV systems and project management tools remains a technical hurdle.
- Scaling CV applications to large construction projects is another limitation. The current systems often work well in controlled environments or small-scale implementations but may encounter difficulties in maintaining performance and efficiency when applied to complex, multi-site projects.
- The deployment of CV systems involves significant initial investment in hardware, software, and training. Arabi et al. (2020) [12] and Chen et al. (2022) [17] highlighted that cost-related barriers, including expenses for acquiring and maintaining advanced CV tools, deter small and medium-sized enterprises from adopting these technologies.
- The use of video and image data in CV systems raises concerns about privacy and security, particularly in sensitive construction projects. Ensuring compliance with data protection regulations while maintaining the operational effectiveness of these systems remains a challenge.
- The effective use of CV technologies requires trained personnel who can operate, interpret, and maintain these systems. A lack of expertise in advanced CV tools and techniques, as highlighted by several studies, poses a significant barrier to adoption in the construction industry.
- While many CV systems excel in detecting and tracking activities, there is a notable gap in translating this data into actionable productivity metrics. Few studies, such as Dimitrov and Golparvar-Fard (2013) [9], focus on linking activity detection with performance benchmarks or overall project efficiency.
- CV systems are heavily reliant on the quality of input data, such as high-resolution images and videos. Low-quality or incomplete data, as observed in studies like Hamledari et al. (2016) [10], can reduce the accuracy of analysis and impair system performance.

CONCLUSIONS

The application of computer vision (CV) in the construction industry has demonstrated significant potential to transform productivity monitoring and performance evaluation. By automating tasks, such as activity detection, resource utilization tracking, and progress analysis, CV systems have proven effective in enhancing accuracy, operational efficiency, and project timelines. The reviewed studies highlight the success of advanced technologies, including deep learning-based object detection models, real-time monitoring frameworks, and integrations with tools like Building Information Modeling (BIM) and edge computing, in addressing longstanding challenges in construction project management.

However, the adoption of CV technologies is still hindered by several limitations. Challenges, such as site variability, computational inefficiencies, high costs of implementation, and scalability issues remain prevalent. Additionally, the reliance on limited datasets for training and a shortage of skilled personnel restrict the ability to generalize and deploy CV systems across diverse construction environments. These barriers need to be addressed to fully unlock the potential of CV in the construction sector.

Future research should focus on enhancing the robustness of CV models, integrating these systems with complementary technologies, and developing scalable and cost-efficient solutions. Efforts should also aim to improve accessibility for smaller organizations by reducing implementation costs and developing user-friendly interfaces. Expanding the application of CV to provide actionable productivity metrics and facilitate intuitive visualization tools will further enhance its utility.

In summary, computer vision offers a powerful tool for advancing construction management practices. By overcoming existing challenges and leveraging ongoing technological advancements, CV systems can pave the way for a safer, more efficient, and technologically driven construction industry, contributing to its long-term sustainability and innovation.

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