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THE IMPACTS OF COMPUTER VISION TECHNOLOGY IN CONSTRUCTION: INVESTIGATING APPLICATIONS AND CHALLENGES

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ABSTRACT

The application of Computer Vision (CV) is transforming many industrial sectors by improving the interactions of technology with the physical environment. According to the research, CV technology heavily impacts construction by offering enhanced solutions to issues such as safety, quality, and progress. This research employed a Systematic Literature Review (SLR) method to find the applications of CV and the related challenges within the construction sector, ensuing the PRISMA 2020 guidelines and PICO framework for the investigation. Out of the 38 studies that were retrieved through Scopus and Web of Science, the review aimed at comparing the application of CV in the following areas: automated progress monitoring, intelligent tracking, real-time quality assessment, improvement of safety, 3D modeling, and object detection. Nevertheless, certain challenges and threats limit the progress of CV such as the high processing times, technologies still in their infancy, and the complexity of integration with other models. Such challenges are grouped and associated with the application they belong to, and it is seen that automated construction progress monitoring faces the most difficulties. Last of all, this research provides construction stakeholders with a framework that links CV applications and challenges as follows with the view of indicating appropriate decisions to make. It is hoped that this framework will assist in avoiding problems and identifying the best practices in the application of CV technologies in construction.

Keywords: *Applications and Challenges; Computer Vision (CV); Construction Industry; Systematic Literature Review.*

1. INTRODUCTION

Computer vision has become a game-changer across industries, transforming our interactions with technology and our understanding of the world (Paneru & Jeelani, 2021). Its applications range from face detection in smartphones, which secures our devices and facilitates transactions, to driving advancements including self-driving cars through techniques such as Simultaneous Localisation and Mapping (SLAM) and object recognition. In healthcare, it aids in early detection and diagnosis, potentially saving lives

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by identifying cancer cells or classifying skin lesions (Martinez et al., 2019). In transportation, computer vision predicts traffic speeds and manages congestion, leading to smarter city planning and smoother commutes. It is crucial in quality inspection, ensuring products meet standards by detecting defects imperceptible to the human eye, thus preserving brand reputation (Fang, Ding, et al., 2020). Its versatility extends to remote inspections in manufacturing, improving safety and efficiency in monitoring and maintenance (Zhang et al., 2021). Moreover, in construction, computer vision enhances safety management by identifying potential hazards, conducting quality checks, and monitoring productivity, ensuring projects stay on track and within budget (Chen et al., 2022).

The construction industry is on the verge of a technological revolution, with automation enhancing efficiency and precision. Computer vision is playing a pivotal role by automating tasks such as safety monitoring and quality inspections and setting new standards for operational excellence (Fang, Love, et al., 2020). It enables real-time tracking of construction progress by comparing actual and planned models, facilitating immediate corrective actions (Moragane et al., 2022). Moreover, computer vision enhances the navigation of construction vehicles, reducing accidents and improving site logistics through precise manoeuvring. The integration of computer vision with automated and robotic processes allows robots to perform tasks such as bricklaying and welding with unmatched consistency and endurance (Ibrahim et al., 2022). Current applications include remote inspections and 3D modelling, offering detailed insights and time savings. Despite these advancements, there is significant untapped potential in computer vision for construction, promising further transformative developments as the technology continues to mature (Liu et al., 2021).

There is a scarcity of literature that presents the current applications and issues of CV in construction. This paper focuses on the analysis of the uses and difficulties of CV technology in the construction industry by employing a SLR that captures contemporary trends. This study offers a thorough analysis of CV in the construction industry, identifying applications and challenges for future research. The research aims to identify the application and challenges of implementing CV technologies in construction projects and offers a framework as a guiding tool for stakeholders in their decision-making stages.

2. RESEARCH METHODOLOGY

2.1 SYSTEMATIC LITERATURE REVIEW

The SLR was employed to identify the applications and challenges of computer vision in the construction industry. As a structured approach, the SLR acts as a foundation to recognise trends and inconsistencies in existing literature material. To ensure the rigorousness of the research methodology "Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020" guidelines were used.

The PICO framework was selected as the most suitable one among the various SLR tools available. The letters: PICO stands for; Population (P), Intervention (I), Comparison (C), and Outcome (O). The structured elements of PICO fit well into the context of identifying the applications and challenges of computer vision in the construction industry. The research question was formulated as, "What are the applications and challenges of computer vision in the construction industry?".

An initial manual keyword search was initiated to develop the research question. The research findings about applications and challenges related to implementing computer vision in the construction industry were aligned with the PICO elements. The keywords used for PICO elements are presented in Table 1.

Table 1: PICO elements

Population (P)	Intervention (I)	Comparison (C)	Outcome (O)
Construction industry	Computer vision*		Application* Challenge* Barrier* Benefit*

This study utilised three databases. These sources include Scopus and Web of Science which are well-known and credible sources for academic research pertinent to the study's background. A "titles only" approach was used to fine-tune and accurately select studies and a "title-abstract-keyword" approach was utilised to gather detailed results. The Boolean operators (AND, OR) were implemented resulting in more flexibility when seizing the searching outcome. The search filters used were restricted to the last five years starting from the year 2019 to ensure the relevancy and accuracy of the results. The choice was limited only to the articles which were published in English. The search string used to identify relevant records is given below:

> "construction Industry" AND "computer vision*" AND (application* OR challenge* OR barrier* OR benefit*)

2.2 THE SLR PROCESS

The flow diagram for "systematic reviews which included searches of databases and registers only" in the PRISMA (2020) guidelines for systematic reviews was used for this study. The overall summarised process which is followed through the main stages of SLR in this study is presented in Figure 1.

As represented in Figure 1 the identification stage of the SLR began with a total of 112 papers identified through two databases respectively: Scopus (72 records) and Web of Science (40 records). After removing 32 duplicate records, 80 unique records remained for screening. During the screening stage, these 80 records were evaluated for relevance, and 33 were excluded as they were not pertinent to the topic. This left 47 reports, which were sought for full-text retrieval. However, five reports could not be retrieved, resulting in 42 reports for further assessment. These reports were then assessed for eligibility based on specific inclusion and exclusion criteria.

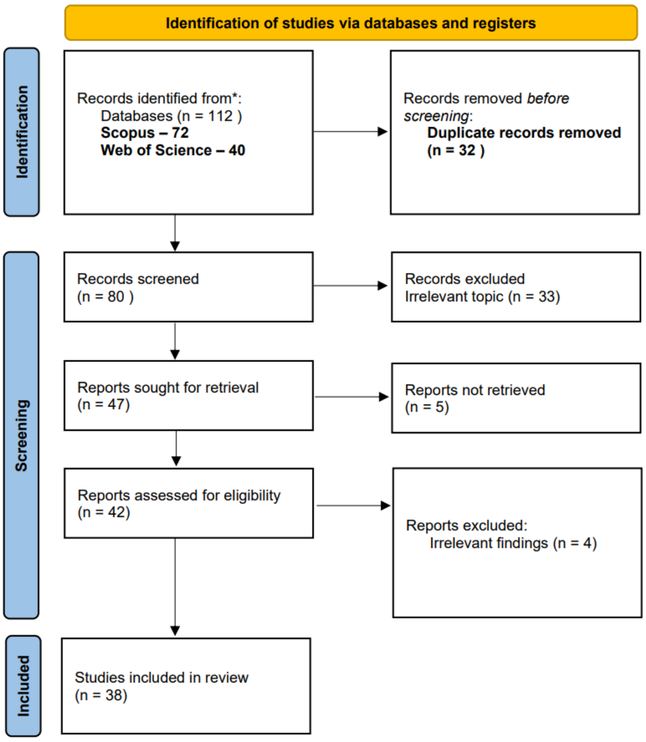

Figure 1: SLR process

Consequently, four reports were excluded due to irrelevant findings. Ultimately, 38 studies were included in the final review as presented in Figure 2 and Figure 3.

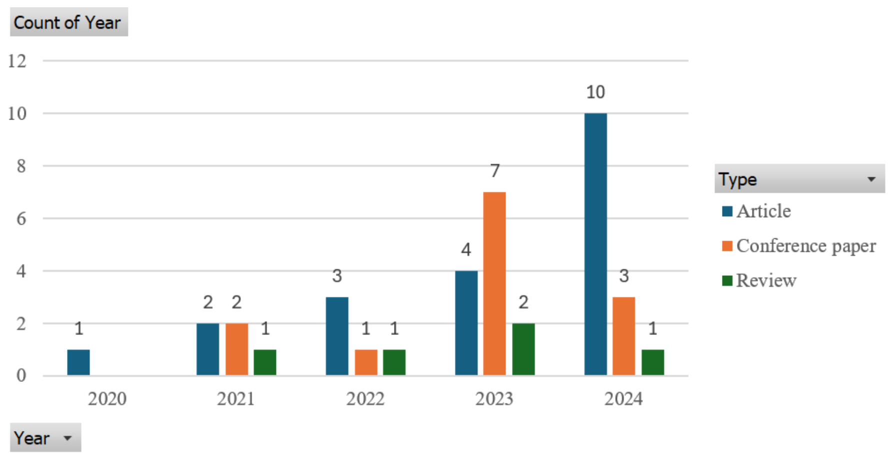

Figure 2: Literature selected

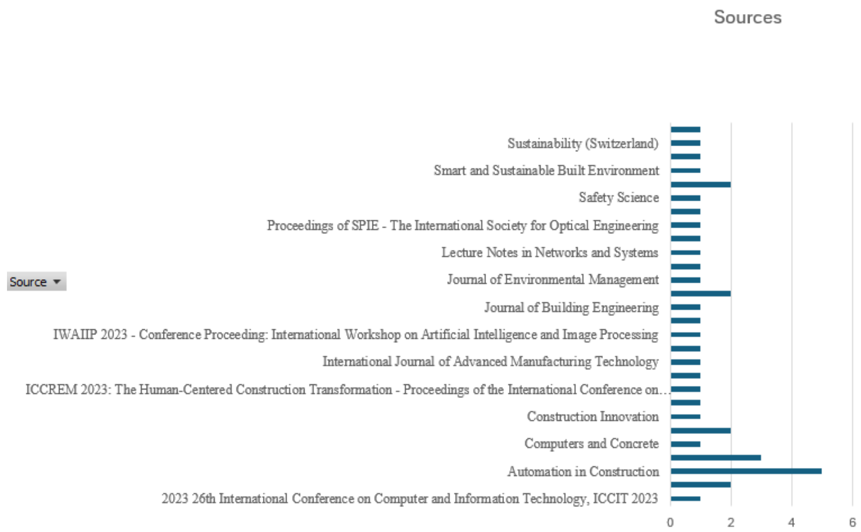

Figure 3: Selected Literature sources

3. RESEARCH FINDINGS AND DISCUSSION

A detailed analysis of the 38 articles selected from the SLR was conducted. The analysis aimed to identify the applications and challenges of computer vision in the construction industry. The next section presents the findings of the analysis.

3.1 APPLICATIONS OF CV TECHNOLOGY IN CONSTRUCTION

According to SLR, the applications of CV technology in construction are analysed and presented in Table 2. All the applications mentioned in Table 2 from SLR have been considered while preparing the framework for this study.

3.2 CHALLENGES FOR CV TECHNOLOGY IN CONSTRUCTION INDUSTRY

The challenges for CV technology in construction are analysed and presented in Table 3. All the challenges for CV in the construction industry which were identified through SLR were included in the framework.

3.3 FRAMEWORK DEVELOPMENT

Framework has been developed to showcase the linkage between applications and challenges for CV in the construction industry. The challenges that arise from each CV application are linked to respective challenges according to the SLR results and it is showcased in Figure 4.

Table 2: Applications of CV in the construction industry

Category	Application	Description	Sources
Automated Monitoring and Progress Tracking	Automated Construction Progress Monitoring	Uses computer vision to track and analyse construction progress automatically, comparing real-time data with plans.	(Feng et al., 2024; Guo et al., 2021; Jiang et al., 2023; Moragane et al., 2024; Pal et al., 2021)
	Intelligent Progress Tracking	Enhances progress monitoring with AI, offering detailed insights into construction stages and potential delays.	(Moragane et al., 2024; Princz et al., 2023)
	Real-Time Activity Intensity Identification	Analyses site activity in real-time to determine intensity levels and workflow efficiency.	(Moohialdin et al., 2023)
	Progress Prediction for Deep Foundation Pit Projects	Predicts construction progress and potential issues for deep foundation pit projects using computer vision techniques.	(Kang et al., 2023)
Quality Control and Assessment	Automated Quality Control	Utilises computer vision to detect and analyse defects or quality issues in construction materials or work.	(Abioye et al., 2021; Martinez et al., 2020; Xie et al., 2024)
	Quality Assessment of Concrete 3D Printing	Evaluates the quality of 3D printed concrete structures, ensuring they meet specified standards.	(Senthilnathan & Raphael, 2022)
	Real-Time Quality Assessment	Provides instant feedback on the quality of construction work during or immediately after execution.	(Martinez et al., 2020)
Safety Monitoring	Safety Monitoring and Enhancement	Monitors construction sites for safety hazards and compliance, enhancing overall safety management.	(Akinsemoyin et al., 2023; Arfan et al., 2023; Hassan et al., 2024; Kim & Yi, 2024)
	PPE Detection and Compliance	Detects whether workers are wearing appropriate PPE and ensure compliance.	(Arfan et al., 2023; Mahmud et al., 2023)
	Fall Prevention and Smart Safety Hook Monitoring	Uses computer vision to prevent falls and monitor the use of safety hooks, enhancing worker safety.	(Khan et al., 2022)
	Automated Risk Assessment for WMSDs	Identifies and assesses risks related to Work-related Musculoskeletal Disorders (WMSDs) using computer vision.	(Sivakumar et al., 2024)
	Hurricane Preparedness and Debris Localization	Assesses hurricane damage and locates debris for efficient cleanup and recovery efforts.	(Kamari & Ham, 2021)
3D Reconstruction and Visualisation	3D Reconstruction and Model Creation	Creates detailed 3D models of construction sites or projects using computer vision technologies.	(Huang et al., 2021; Katsatos et al., 2023; Koulalis et al., 2022)
	Integration with Digital Twins and BIM	Integrates 3D models with digital twins and Building Information Modeling (BIM) for enhanced project visualisation.	(Koulalis et al., 2022; Nguyen et al., 2024)
	Virtual Sensing of Buried Utilities	Uses computer vision to detect and map utilities buried underground, improving planning and safety.	(Oguntoye et al., 2023)
Object Detection and Tracking	Object Detection, Tracking, and Classification	Detects, tracks, and classifies various objects on construction sites to manage inventory and activities.	(Akinsemoyin et al., 2023; Duan et al., 2022; Shrigandhi & Gengaje, 2023)
	Building Automation and Robotics	Employs computer vision for automation and robotics in construction tasks, increasing efficiency and precision.	(Sun et al., 2023)
	Activity Monitoring and Recognition	Monitors and recognises different construction activities to improve workflow and productivity.	(Kikuta & Chun, 2024; Li et al., 2024)
Resource and Waste Management	Waste Identification, Classification, and Forecasting	Identifies, classifies, and forecasts construction waste to optimise waste management and recycling efforts.	(Park et al., 2024; Prasad & Arashpour, 2024; Rodrigo et al., 2024)
	Resource and Waste Optimisation	Utilises computer vision to optimise the use of resources and manage waste more effectively.	(Abioye et al., 2021)

Category	Application	Description	Sources
Data Integration and Analysis	Integration of Various Data Types for Safety and Progress Analysis	Combines data from different sources for comprehensive safety and progress analysis on construction sites.	(J. Liu et al., 2022; Nguyen et al., 2024; Schüle et al., 2024)
	Multi-Modal Data Integration	Integrates multiple types of data (e.g., images, sensor data) for enhanced site analysis and decision-making.	(J. Liu et al., 2022)
	Real-Time Data Retrieval and Interaction	Facilitates real-time access and interaction with data for improved site management and decision-making.	(Nguyen et al., 2024)
Robotic Applications	Automated Rebar Tying	Uses robotics and computer vision for automated rebar tying, improving efficiency and accuracy.	(Feng et al., 2024)
	Robotics for Construction Tasks and Site Monitoring	Implements robotics equipped with computer vision for various construction tasks and site monitoring.	(Kikuta & Chun, 2024; Sun et al., 2023)
Performance Evaluation	Performance Benchmarking of Detection Models	Evaluates and benchmarks the performance of computer vision models used in construction applications.	(Duan et al., 2022)
	Evaluation of Reconstruction Methods	Assesses the effectiveness of different reconstruction methods using computer vision techniques.	(Katsatos et al., 2023)
Others	Underground Construction and Lifecycle Management	Applies computer vision to manage underground construction projects and their lifecycle stages.	(Huang et al., 2021; Mahmud et al., 2023)
	Intelligent Building Management	Uses computer vision for managing and controlling building systems and operations intelligently.	(Ma, 2023)
	Safety Activity Metrics Collection	Collects metrics related to safety activities on construction sites for analysis and improvement.	(Akinsemoyin et al., 2023)
	Data Mining for Safety Management	Applies data mining techniques to safety data to uncover insights and enhance management practices.	(J. Liu et al., 2022)

Table 3: Challenges for CV in the construction industry

Challenge	Description	References
Insufficient Daily Monitoring	Current methods do not effectively capture daily progress due to gaps between as-built 3D point cloud captures, leading to incomplete progress records.	(Patel et al., 2021)
Processing Time	The processing of as-built 3D point clouds requires significant time, which can delay progress monitoring.	(Martinez et al., 2020; Moohialdin et al., 2023; Patel et al., 2021)
Unmodeled Schedule Activities	Some construction activities are not represented in BIM models, making automated progress monitoring of these activities challenging.	(Kang et al., 2023; Patel et al., 2021)
Technological Immaturity	Robotics and computer vision applications in construction are still in the early stages, requiring further development to address specific industry needs.	(Arfan et al., 2023; Xie et al., 2024)
Material Variability	Variability in construction materials, such as lumber misalignments, poses challenges for robotics-based manufacturing, leading to potential reworks and quality control issues.	(Senthilnathan & Raphael, 2022; Xie et al., 2024)
The Complexity of Construction Projects	The intricate nature of construction projects complicates the integration of robotic systems and quality control mechanisms.	(Kang et al., 2023; Patel et al., 2021; Sivakumar et al., 2024; Sun et al., 2023)
Detection and Correction of Misalignments	Ensuring accurate detection of misalignments and transmitting this information for corrective action remains a challenge.	(Oguntoye et al., 2023; Xie et al., 2024)
Complexity in Planning and Control	Planning and controlling production processes, especially in SMEs, is challenging and requires significant expertise.	(Princz et al., 2023; Sun et al., 2023)
Systematic Implementation	There is a need for systematic approaches to implementing intelligent progress-tracking technologies and addressing existing gaps in literature and practical applications.	(Koulalis et al., 2022; Princz et al., 2023)
Limited Applications	Despite advancements, the application of computer vision in the construction industry, particularly in Digital Twins, remains limited.	(Koulalis et al., 2022)
Integration with Existing Models	Combining CV with existing 3D reference models and visual sensor data presents challenges in data compatibility and integration.	(Koulalis et al., 2022)
Variations in Image Capture	Differences in image quality, lighting, and angles can affect the accuracy of PPE detection systems.	(Arfan et al., 2023; Jiang et al., 2023)
Synergy Between CV and CPM	There is a lack of synergy between CV technologies and construction progress monitoring practices, highlighting the need for more research and integration.	(Moragane et al., 2024)
Complex Industry Challenges	The construction industry faces challenges including cost overruns, time delays, health and safety issues, productivity, and labour shortages, complicating computer vision adoption.	(Abioye et al., 2021; Sun et al., 2023)
Integration of Multiple Technologies	Combining CV, AR, GPS, and IMU sensor data to achieve effective real-time verification and management is complex and requires seamless integration.	(Ma, 2023; Nguyen et al., 2024)
High Complexity of High-Rise Buildings	The complexity and scale of high-rise buildings pose significant challenges for automation and robotic systems, requiring advanced solutions for effective implementation.	(Sun et al., 2023)
Labor Productivity and Safety Issues	Addressing issues like low labour productivity, labour shortages, and high worker safety risks through automation and robotics involves overcoming technical and practical challenges.	(Sivakumar et al., 2024)
Accuracy of 3D Models	Ensuring the accuracy and detail of 3D reconstructions is challenging, particularly when dealing with complex construction sites and varying environmental conditions.	(Katsatos et al., 2023)
Data Acquisition and Processing	Acquiring high-quality data from challenging construction environments and processing it effectively for 3D reconstruction can be complex and resource intensive.	(J. Liu et al., 2022; Rodrigo et al., 2024)
Recognition Logic	Establishing effective recognition logic for distinguishing construction workers and their activities is challenging, especially in complex or cluttered environments.	(Jiang et al., 2023; Li et al., 2024)
Complex Environments	Sophisticated computer vision models are needed to accurately detect and classify activities in complex and dynamic construction environments.	(Arfan et al., 2023; Oguntoye et al., 2023)

Challenge	Description	References
Integration of Multiple Models	Combining multiple deep learning algorithms for comprehensive analysis adds complexity and requires careful integration and optimisation.	(Li et al., 2024; J. Liu et al., 2022)
Inadequate Model Performance	Existing models may not perform well in diverse and complex construction environments, requiring further refinement.	(Sivakumar et al., 2024)
Limited Application Scenarios	The practical application of deep learning models in construction safety management scenarios is still limited, with room for improvement in real-world applications.	(J. Liu et al., 2022)
Accuracy Improvement	Improving accuracy in computer vision applications requires addressing challenges related to data quality, processing techniques, and real-world applicability.	(Duan et al., 2022; Senthilnathan & Raphael, 2022)
Integration Complexity	Integrating computer vision systems with existing construction technologies presents challenges in ensuring seamless operation and data compatibility.	(Nguyen et al., 2024)
Training Image Generation	Generating diverse and representative training images is crucial for developing robust computer vision models for construction applications.	(Li et al., 2024)
Model Performance	The performance of CV models can be affected by data quality and environmental factors, requiring continuous improvement.	(Duan et al., 2022; Sivakumar et al., 2024)
Adoption Barriers	Barriers to adopting CV technologies include cost, complexity, and resistance to change within the construction industry.	(Rodrigo et al., 2024)
High Clutter and Diversity	High levels of clutter and diversity in construction environments pose challenges for accurate object detection and classification.	(Arfan et al., 2023)
Accuracy in Detection	Achieving high accuracy in object detection and classification requires addressing challenges related to data quality and system calibration.	(Arfan et al., 2023; Jiang et al., 2023)
Adverse Weather Conditions	Adverse weather conditions can affect the performance of CV systems, requiring robust solutions to handle environmental variability.	(Mahmud et al., 2023)
Complex Site Environments	Complex site environments present challenges for CV systems, requiring advanced methods for accurate analysis and monitoring.	(Kamari & Ham, 2021; Mahmud et al., 2023)
Dataset Complexity	Managing the complexity of datasets for CV applications involves addressing issues related to diversity and volume.	(Duan et al., 2022; J. Liu et al., 2022)
Access to Relevant Datasets	Accessing and utilising relevant datasets is essential for developing and applying effective CV solutions.	(Duan et al., 2022; J. Liu et al., 2022)
Data Collection and Calibration	Collecting and calibrating data for CV systems requires careful attention to ensure accuracy and reliability.	(Akinsemoyin et al., 2023; Hassan et al., 2024)
Accuracy and Stability	Achieving accuracy and stability in CV systems requires addressing challenges related to data variability and processing techniques.	(Ma, 2023; Senthilnathan & Raphael, 2022)
Real-Time Processing	Real-time processing capabilities are essential for effective pose reconstruction and application of CV systems in construction.	(Moohialdin et al., 2023; Schüle et al., 2024)
Dynamic Work Environments	Dynamic work environments in construction present challenges for CV systems, requiring adaptability and robustness in their design.	(Akinsemoyin et al., 2023; Moohialdin et al., 2023)
Defects and Deformities Detection	Detecting defects and deformities in construction materials and structures using CV requires advanced techniques and accurate models.	(Senthilnathan & Raphael, 2022)

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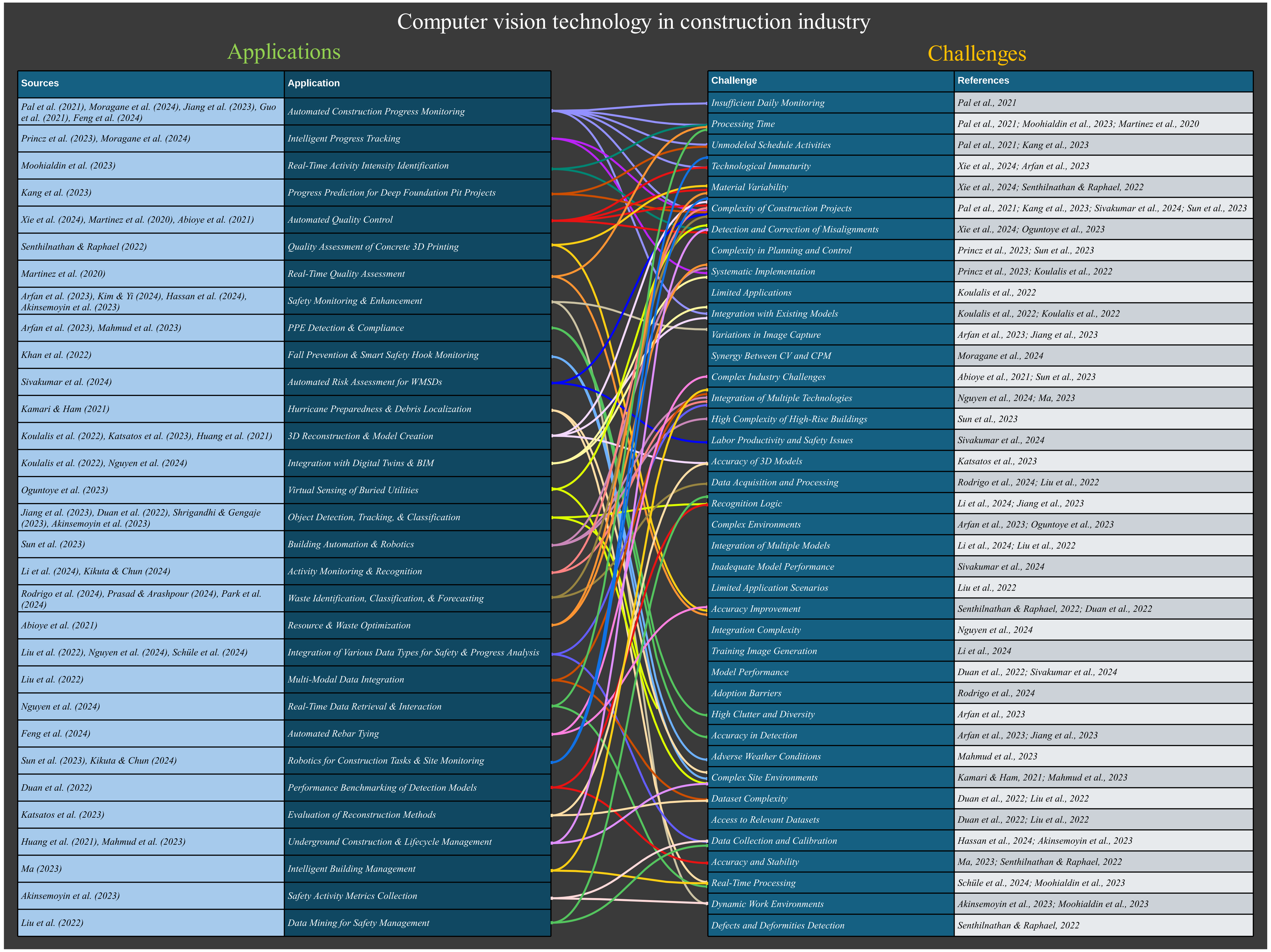

Figure 4: Framework of applications and challenges of computer vision in the construction industry

As per Figure 4, Automated Construction Progress Monitoring has the highest challenges, which are Insufficient Daily Monitoring, Processing Time, Unmodeled Schedule Activities, Technological Immaturity, Complexity in Planning and Control, and Integration with Existing Models. It illustrates Automated Construction Progress Monitoring is the most significant application with many barriers. Then with four challenges, Automated Quality Control takes the second significant application having challenges: Technological Immaturity, Material Variability, Complexity of Construction Projects, and Detection and Correction of Misalignments. Then 3D Reconstruction and Model Creation, Object Detection, Tracking, and Classification, and Building Automation and Robotics take the third place by having three challenges per each, meaning similar significance. On the other hand, all other applications have two challenges each showing their lesser significance compared to others.

This framework will be useful and act as a guiding tool for construction stakeholders in decision-making stages. Since the framework shows the challenges which might arise in applying the selected computer vision technologies in construction projects, it will guide them to take precautionary measures and warnings while selecting CV technologies for their project.

4. CONCLUSIONS

The study brings out the fact that computer vision in construction such as monitoring of projects and their progress, tracking of quality, safety, and 3D reconstruction provides a considerable plus point. These technologies enhance the means of tracking the construction progress in real-time, quality control and assurance, handling safety issues and site visualisation. They have direct benefits in that they increase productivity, decrease rates of mistakes, and raise the effectiveness of projects since they yield insight that can be very hard to come by otherwise. However, the study reveals some of the key issues that are bound to arise when using computer vision in construction projects. The challenges include relatively young technologies and the level of difficulty when incorporating such technologies into the existing systems. Certain challenges that arise include fluctuations in the construction material, time needed to process the items, and precision of the 3D models. The research stresses that these issues must be solved before CV is fully realised in the construction industry.

This study's framework presents the mapping between computer vision applications and their corresponding challenges, which can be helpful for the construction stakeholders. it highlights that Automated Construction Progress Monitoring has the highest challenges compared to other computer vision applications. The assessment of the barriers that are expected to be experienced when implementing each of the contexts will enable the stakeholders to avoid pitfalls that may be detrimental to their cause.

However, this study has the following limitations. The SLR is limited to the published research, which might not reflect all the present and future technologies and uses of computer vision in construction. This exclusion of recent sources might result in missing earlier advancements and basic research performed in the field. Thirdly, the paper only focuses on the literature published in English, which in the authors' contribution could mean that important information from other languages is overlooked. The framework that has been established is founded upon established challenges and applications; these may change as new technology is found or new problems are required to be solved. Therefore, based on the above limitations, several points for future research are suggested to broaden the knowledge of the article. As for the type of studies, the research could follow the developmental changes in CV systems and their effects on construction projects. Including, whether research should encompass both local and international publications, and whether the research should be limited to only English articles or should it encompass international outlooks as well could present a clearer view of the advancements.

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