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Machine Learning for Improving Construction Productivity: A Systematic Literature Review

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Machine learning, as one of the Artificial Intelligence (AI) approaches, has been widely adopted in various fields and is now becoming one of the emerging technologies revolutionizing the construction industry. One of the machine learning applications in the construction industry is to improve construction productivity. However, the current application in this field primarily focuses on enhancing productivity within specific, isolated construction tasks, often lacking real-world applicability. Therefore, a more holistic framework aimed at enhancing productivity across the entire construction process is desired by industry professionals. To enhance readiness for constructing such a framework, a methodical examination of existing literature has been carried out to explore the status of utilizing machine learning to enhance efficiency in construction practices. This review not only identifies but also categorizes the existing machine-learning applications and practices. Additionally, it highlights limitations and potential enhancements within current machine learning techniques, offering valuable insights for future research endeavors.

Key Words: AI, Machine Learning, Construction Productivity

Introduction

Productivity is the efficient utilization of inputs to attain a desired output (Florez-Perez et al., 2022). Unfortunately, the construction industry is renowned for the challenges it faces in achieving optimal productivity, even though the construction industry transforms infrastructure and promotes economic advancement (Zhan & Pan, 2020). These challenges often prevent construction projects away from their full success, which rely on timely delivery and the efficient allocation of resources. Construction productivity trends have been analyzed by researchers in previous years and have been found that most countries have a downward trend in total productivity (Dixit et al., 2019). In one of the studies, it was found that global productivity in construction has seen a mere growth of just 1% of the annual growth rate in years between 1995 and 2014 (Barbosa et al., 2017). On the other hand, the global productivity in the economy and the manufacturing sector has seen more significant numbers, i.e. 2.7% and 3.6% each year, respectively. Thus, the need to have a better improvement in productivity growth rate in construction is obvious. To achieve this a comprehensive strategy needs to be developed including innovative techniques and a detailed and systematic analysis of existing performance data of the projects. Up until now, analysis of performance data of projects is usually considered a difficult task due to the amount of data construction projects generate and the data variation among similar construction projects. Nevertheless, propelled by the emergence of cutting-edge technologies and data-centric approaches, we possess the means to tackle these challenges, optimize construction procedures, and elevate efficiency across the construction sector.

Artificial Intelligence (AI), including machine learning, natural language processing, robotics, and expert systems, etc., holds the promise of delivering substantial advantages to the construction sector. The integration of AI into the construction industry has experienced a swift expansion, as highlighted by (Vickranth et al., 2019), with a noteworthy focus on elevating construction productivity. Additionally, machine learning has been especially standing out among AI approaches due to its ability to glean insights from past data, minimize human errors, and enable swift and efficient decision-making. Nevertheless, the current application of machine learning primarily focuses on improving productivity in specific isolated construction tasks, and the resulting models often lack practical real-world applications. Therefore, a more holistic framework aimed at enhancing productivity across the entire construction process is desired by industry professionals. On the other hand, to establish such a framework, there is a compelling need for a systematic review and analysis of existing knowledge and applications of machine learning in enhancing productivity within construction practices, intending to formulate recommendations for future research directions.

A systematic review of literature is a meticulous research approach employed to methodically collect, discern, and scrutinize existing literature encompassing various sources like books, peer-reviewed articles, conference proceedings, and more, all related to a particular topic (Carrera-Rivera et al., 2022; Pati & Lorusso, 2017; Kitchenham & Charters, 2007; Kitchenham et al., 2009). Such a systematic review method has been used to analyze the latest literature (between 2019 and 2023) on machine learning approaches intended to improve productivity in construction practices. The aim is to prepare for the development of a comprehensive framework that addresses construction productivity.

Methodology

The methodology employed in this paper follows the established research framework as outlined by (Z. Gao & Sultan, 2023) using the Scopus database. The questions that emerged from this process are as follows:

1) How can advancements in productivity within construction be classified by utilizing machine learning?
2) How can current frameworks be enhanced?

During the process, to ensure a wide range of data, the initial search round deliberately avoided using the term “productivity”. Instead, it relied on the keywords “machine learning in construction” and/or “deep learning in construction”. Here, the term 'Machine Learning in Construction' serves as a broad category covering various techniques for construction-related tasks. This overarching terminology encompasses conventional machine learning algorithms with deep learning in construction acknowledged as one of its subsets. This is to accurately represent a clear hierarchical relationship between machine and deep learning. Subsequently, various refinements were applied, linking these initial keywords to "productivity" for the set of articles displayed by the search engine. This systematic selection process led to the inclusion of 80 articles from a variety of journals published during the mentioned years. Conference papers were not considered in this review.

Identified AI Approaches for Productivity

Machine learning predicts outcomes through training on existing data, while its subset, deep learning, autonomously learns from extensive datasets (Khallaf & Khallaf, 2021). Moreover, machine learning includes supervised learning, unsupervised learning, and reinforcement learning (Y. Xu et al., 2021). Table 1-5 provides a summary of the key machine learning algorithms, containing insights into their specific applications in the construction practices of productivity, datasets used, the performance of the models, and limitations in the framework that was used. The rationale for organizing Tables 1 to 5 around specific machine learning algorithms is to offer readers a comprehensive understanding of the application of each algorithm, thereby ensuring clarity and a nuanced understanding in addressing productivity challenges. This approach is driven by the aims of this study, which is to identify machine learning approaches and establish subfields dedicated to enhancing productivity throughout the entire construction process. The outcome of this study lays the groundwork for our future study, wherein we plan to develop a comprehensive machine learning-based framework addressing all aspects of productivity in construction projects as a whole and which aims to enhance the overall productivity of construction projects.

The main machine learning approaches for enhancing construction productivity include five (5) methods: 1-Logistic Regression, 2-Decision Tree, 3-Random Forest, 4-K Nearest Neighbor, and 5-Support Vector. Machine. These five approaches are all supervised machine learning. The deep learning methods have been also explored but not presented in this paper.

Table 1. Logistic Regression (LR (Logistic)) for Improving Productivity in Construction.

References	Application	Dataset	Performance	Improvements in Framework
(Sadatnya et al., 2023)	Prediction of work crew productivity (WCP)	A dataset containing project activities' data points from daily work reports (DWR)	Accuracy-76.2% Precision-77.9% F1 score-76.63%	Errors and more features in DWRs, comparison with other frameworks.
(Florez-Perez et al., 2022)	Prediction of the level of productivity of construction workers	A construction project's site condition and workers data gathered manually	Accuracy-87.2%	Larger dataset with advanced classification algorithms
(Sanhudo et al., 2021)	Classification of construction workers' activities	Data was acquired as activity-circuit, with accelerometers placed on six workers.	Accuracy-78.10%	Model validation in real-world scenarios, worker's other activities be included
(Khalef & El-Adaway, 2021)	Classification and prediction of contractual changes during projects of the airport improvement program	Previously recorded contractual changes by the FAA	Accuracy-84.03%	NLP for text sentiments and/or ontology, consider contracts from other construction fields
(Xie et al., 2020)	Prediction temp. changes when pouring and curing concrete in varying conditions	Used radio frequency identification sensors for measuring temperature	Accuracy-61.16%	Larger dataset with varieties of sensing data
(Hu & Castro-Lacouture, 2019)	Prediction of relevant and irrelevant issues in BIM-enabled clash detection in design and construction	Previous literature, experts' interviews, and real-life construction project data	Accuracy-70%	Larger dataset, improved data collection process

Table 2. Decision Tree (DT) for Improving Productivity in Construction.

References	Applications	Dataset	Performance	Improvements in Framework
(Sadatnya et al., 2023)	Prediction of work crew productivity (WCP)	A dataset containing project activities' data points from daily work reports (DWR)	Accuracy-94.5% Precision-85.3% F1 score-84.95%	Errors and more features in DWRs, comparison with other frameworks.
(Lu et al., 2021)	Estimation of waste generated by construction activities	Identified factors affecting waste generation; data gathered from authorities	R^2-85.3% (training) R^2-75.6% (testing)	Larger dataset, model validation in a real-world scenario
(Sanhudo et al., 2021)	Classification of construction workers' activities	Data was acquired as activity-circuit, with accelerometers placed on six workers	Accuracy-78.14%	Model validation in real-world scenarios, worker's other activities be included
(Hu & Castro-Lacouture, 2019)	Prediction of issues in clash detection	Previous literature, experts' interviews, and real-life construction project data	Accuracy-77%	Larger dataset, improved data collection process

Table 3. Random Forest (RF) for Improving Productivity in Construction.

References	Applications	Dataset	Performance	Improvements in Framework
(Sadatnya et al., 2023)	Prediction of work crew productivity (WCP)	A dataset containing project activities' data points from daily work reports (DWR)	Accuracy-96.9% Precision-92.4% F1 score-92.35%	Errors and more features in DWRs, comparison with other frameworks.
(C. Xu et al., 2021)	Prediction of tunnel boring machine's operating parameters to improve its control and efficiency	A tunnel boring machine's daily data containing its operational points recorded every second during a tunneling project	Accuracy~89% (Adv. Rate) Accuracy~87% (Torque) Accuracy~92% (Thrust) Accuracy~98% (Rotation)	A larger and more diverse dataset
(Sanhudo et al., 2021)	Classification of construction workers' activities	Data was acquired as activity-circuit, with accelerometers placed on six workers	Accuracy-90%	Model validation in real-world scenarios, worker's other activities be included
(Khalef & El-Adaway, 2021)	Classification and prediction of airport improvement program's projects contract changes	Previously recorded contractual changes by the FAA	Accuracy-87.45%	NLP for text sentiments and/or ontology, contracts from other fields also.
(Huber & Imhof, 2019)	Prediction of collusion of firms and bid-rigging in the bidding process	Previously recorded bidding and tendering data by authorities	Rate of Correct Classification-84%	Larger dataset
(Hu & Castro-Lacouture, 2019)	Prediction of issues in clash detection	Previous literature, experts' interviews, and real-life construction project data	Accuracy-79%	Larger dataset, improved data collection process

Table 4. K Nearest Neighbor (KNN) for Improving Productivity in Construction.

References	Application	Dataset	Performance	Improvements in Framework
(Sadatnya et al., 2023)	Prediction of work crew productivity (WCP)	A dataset containing project activities' data points from daily work reports (DWR)	Accuracy-99.5% Precision-81.3% F1 score-81.4%	Errors and more features in DWRs, comparison with other frameworks.
(Florez-Perez et al., 2022)	Prediction of the level of productivity of construction workers	A construction project's site condition and workers data gathered manually	Accuracy-97.7%	Larger dataset with advanced classification algorithms
(Sanhudo et al., 2021)	Classification of construction workers' activities	Data was acquired as activity-circuit, with accelerometers placed on six workers	Accuracy-93.69%	Model validation in real-world scenarios, worker's other activities be included
(Ayhan et al., 2021)	Prediction of the occurrences of disputes during construction	Construction project data gathered from project team members of various firms	Accuracy-87.69%	Larger dataset, attributes for dispute identification be assessed objectively as well, and more ML techniques
(Khalef & El-Adaway, 2021)	Classification and prediction of airport improvement program's projects contract changes	Previously recorded contractual changes by the FAA	Accuracy-58.17%	NLP for text sentiments and/or ontology, consider contracts from other construction fields

Table 5. Support Vector Machine (SVM) for Improving Productivity in Construction.

References	Application	Dataset	Performance	Improvements in Framework
(Sadatnya et al., 2023)	Prediction of work crew productivity (WCP)	A dataset containing project activities' data points from daily work reports (DWR)	Accuracy-98.7% Precision-81.5% F1 score-81.5%	Errors and more features in DWRs, comparison with other frameworks.
(Florez-Perez et al., 2022)	Prediction of the level of productivity of construction workers	A construction project's site condition and workers data gathered manually	Accuracy-95.8%	Larger dataset with advanced classification algorithms
(M.-K. Kim et al., 2021)	Diameter classification and reinforced bar spacing estimation	Terrestrial laser scanning for varied diameter reinforced bars	Accuracy-78.7%	Prediction of small dia. rebars be improved
(C. Xu et al., 2021)	Prediction of tunnel boring machine's operating parameters to improve its control and efficiency	A tunnel boring machine's daily data containing its operational points recorded every second during a tunneling project	Accuracy~87% (Rate) Accuracy~59% (Torque) Accuracy~62% (Thrust) Accuracy~98% (Rotation)	A larger and more diverse dataset
(Ayhan et al., 2021)	Prediction of the occurrences of disputes during construction	Construction project data gathered from project team members of various firms	Accuracy-89.91% (Poly. Kernel) Accuracy-90.46% (RBF Kernel)	A larger dataset, attributes for dispute identification to be assessed, and more ML techniques
(Khalef & El-Adaway, 2021)	Classification and prediction of airport improvement program's projects contract changes	Previously recorded contractual changes by the FAA	Accuracy-82.51%	NLP for text sentiments and/or ontology, consider contracts from other construction fields

(Rashid & Louis, 2020)	Identification of common activities in modular construction	Audio recording generated in modular construction factory	Accuracy-96.48% Precision-96.68% Recall-96.73% F1-Score-96.64%	Identify simultaneous multiple activities, source with microphone arrays, value-adding activities with less sound
(Tien Bui et al., 2019)	Prediction of shear strength of soil for road construction projects	Soil investigation data done during the pre-construction phase of a highway as a case study	R^2-88.5%	A larger dataset should tell the level of importance of each feature

Table 6 sums up the identified machine learning approaches used on specific topics for construction productivity improvement. These topics have led to the generation of four sub-fields: 1-Construction Personnel, 2-Construction Machinery, and automation, 3-Disputes Resolution, and 4-Quality Assurance and predicting Defects.

Table 6. Identified machine learning Approaches for Improving Productivity in Construction.

References	Machine Learning Approach	Topics
(Sadatnya et al., 2023)	LR (Logistic), DT, RF, KNN, SVM	Work Crew Productivity
(Florez-Perez et al., 2022)	LR (Logistic), KNN, SVM, DNN	Worker Productivity Level
(Wei et al., 2022)	Mask R-CNN	Auto Progress of In-door Construction
(Sherafat et al., 2022)	CNN	Determining Machinery from its Sound
(Xiao et al., 2022)	Mask R-CNN	Off-Site Worker Tracking
(Z. Zhang et al., 2022)	Mask R-CNN	Auto characterization of Sand
(H. Kim et al., 2022)	CNN	Auto Concrete Cracks Detection
(Assadzadeh et al., 2022)	HRNet	Data to Estimate Excavator Poses
(Arashpour et al., 2022)	DNN	Monitoring Heavy Machinery
(W. Gao et al., 2022)	LSTM + BiLSTM + GRU	Commands to Architects
(Lu et al., 2021)	LR (Linear), DT, ANN	Construction Waste
(Sanhudo et al., 2021)	LR (Logistic), DT, RF, KNN, AdaBoost, GBM, ANN	Worker Activities
(Khalef & El-Adaway, 2021)	LR (Logistic), RF, KNN, SVM, XGBoost, ANN	Contractual Changes
(C. Xu et al., 2021)	RF, SVM	TBM Operating Parameters
(M.-K. Kim et al., 2021)	NB, SVM	Diameter & Spacing in Rebars
(Ayhan et al., 2021)	NB, KNN, SVM, AdaBoost	Occurrence of Construction Disputes
(Asteris et al., 2021)	GPR, ANN	Compressive Strength of Concrete
(Yang et al., 2021)	CNN	Classify Rocks during TBM
(Qin et al., 2021)	Mask R-CNN	Lining Elements During Inspection
(Xiao et al., 2021)	CNN	Conversion of Long to Concise Videos
(Hong et al., 2021)	CycleGAN + Mask R-CNN	Data for Future Algorithms
(Kassem et al., 2021)	DNN	Productivity of Excavators
(R. Zhang & El-Gohary, 2021)	LSTM+CRF	Extract Info. from regulatory Bodies
(Wu et al., 2021)	BiLSTM + CRF	Constraints for AWP
(Xie et al., 2020)	LR (Logistic)	Temp. Changes in Concrete Curing
(Rashid & Louis, 2020)	SVM	Activities in Modular Construction
(Mishra et al., 2020)	ANN	Compressive Strength of Brick Masonry
(Lau Hiu Hoong et al., 2020)	CNN	Recycle of Inert Waste
(Jiang & Bai, 2020)	CNN	Estimate Elevation of Site
(Yin et al., 2020)	YOLOv3	Defects in Sewer Pipes
(Hu & Castro-Lacouture, 2019)	LR (Logistic), DT, RF, NB	BIM-enabled clash detection
(Huber & Imhof, 2019)	RF	Rigging in Bidding
(Tien Bui et al., 2019)	SVM	Shear Strength of Soil

Discussion

It can be concluded that supervised machine learning (LR, DT, RF, KNN, and SVM) is the most widely used machine learning for productivity improvement in construction. However, the ability of supervised machine learning algorithms to predict and assist in decision-making regarding construction productivity aspect is underscored by its models' dependence on labeled datasets. Supervised learning depends on historical data with predetermined target variables, enabling models to determine patterns and make precise predictions or classifications. The training of machine learning models with labeled datasets provides capability and usage across various construction scenarios with better performance of models, as reflected in the accuracies reported in Tables 1-5. These high accuracies validate the effectiveness of supervised learning/labeled datasets, underscoring their significance in achieving precise predictions.

A nuanced approach is required for selecting machine learning algorithms to address construction productivity issues due to the observed variations in models' performance, as shown by varying performances in Tables 1-5. For instance, DT exhibited high accuracy in predicting work crew productivity, aligning with the interpretability and simplicity of DTs in certain scenarios. Alternatively, RF excelled in predicting tunnel boring machine operating parameters, utilizing the ensemble approach to enhance accuracy and robustness. These variations underscore the nuanced strengths of each algorithm and stress the importance of tailoring approaches based on the unique nature of the construction productivity task/issue at hand. This task-specific selection of algorithms is critical for optimizing performance and addressing the intricacies of diverse construction scenarios.

The emphasis on larger and diverse datasets, particularly in RF and SVM applications, originates from the rationale that comprehensive datasets enhance model training and generalization. This emphasis aligns with the data reported in Tables 1-5, demonstrating that larger datasets provide models with a broader range of examples, enabling them to capture a more extensive spectrum of patterns and nuances in construction data. As illustrated by the reported high accuracies, it reinforces the significance of extensive datasets in ensuring that algorithms perform well across various construction scenarios. Despite the vast potential of machine learning in enhancing construction productivity, challenges, such as the limited availability of comprehensive datasets for model training, have been identified within the construction industry and need to be addressed. The effectiveness of machine learning models is intricately linked to the quality and quantity of the data used. Hence, exploring comprehensive, automated data collection methods becomes crucial to overcome existing limitations. The ongoing optimization of machine learning models with improved data signifies a continuous effort toward the full integration of machine learning into the construction industry.

Table 6, outlining various machine learning approaches used to enhance construction productivity, has led to the identification of four key sub-fields: 1-Construction Personnel, 2-Construction Machinery & Automation, 3-Disputes Resolution, and 4-Quality Assurance & Predicting Defects. These sub-fields have emerged from applying machine learning in specific areas of construction. This breakdown into sub-fields not only demonstrates the diverse applications of machine learning but also establishes focused areas for further research and development. It lays the groundwork for future research work, wherein we plan to develop a comprehensive machine learning-based framework addressing all aspects of productivity in construction projects as a whole, aiming to improve the overall productivity of construction projects.

Looking ahead, the identified machine learning approaches and subfields provide a foundation for future research directions. Continuous investigation needs to be done so that specific models be implemented in those situations where they can perform better because of the variability in the performance of algorithms.

Conclusion

The detailed analysis of existing literature has effectively identified important machine learning approaches to improve and enhance construction productivity, resulting in the formation of a methodical classification (1-Construction Personnel, 2-Construction Machinery, and automation, 3-Disputes Resolution, and 4-Quality Assurance and predicting Defects) which improve the productivity of the entire construction process as a whole. Machine learning methods have surfaced as widely favored options for advancing productivity in the construction sector. Recognizing the potential of these techniques, our findings conclude the necessity for a comprehensive machine learning-based framework. Such a framework, covering all aspects of productivity in the entire construction process as a whole, holds the promise of significantly enhancing overall project efficiency. This study not only contributes to a structured categorization and identification of key machine learning techniques but also emphasizes the critical need for a unified framework and the imperative role of comprehensive datasets in advancing the application of machine learning for enhanced construction productivity.

However, we acknowledge a prevailing challenge which is the limited availability of construction data, resulting in smaller datasets for training machine learning models. This limitation hampers the generalizability of developed models. To overcome this obstacle, the construction industry must prioritize the creation of larger, more comprehensive datasets. Although not presented in this paper, the emergence of deep learning signals a transformative shift in addressing complex construction productivity issues. These approaches offer sophisticated solutions for tasks requiring intricate pattern recognition and temporal understanding but need further investigation into their potential applications across diverse construction scenarios. Such an endeavor is essential for the practical and effective application of machine learning in the field, ensuring that models are robust and applicable across diverse construction scenarios.

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References

Arashpour, M., Kamat, V., Heidarpour, A., Hosseini, M. R., & Gill, P. (2022). Computer vision for anatomical analysis of equipment in civil infrastructure projects: Theorizing the development of regression-based deep neural networks. *Automation in Construction*, *137*. https://doi.org/10.1016/j.autcon.2022.104193

Assadzadeh, A., Arashpour, M., Brilakis, I., Ngo, T., & Konstantinou, E. (2022). Vision-based excavator pose estimation using synthetically generated datasets with domain randomization. *Automation in Construction*, *134*. https://doi.org/10.1016/j.autcon.2021.104089

Asteris, P. G., Skentou, A. D., Bardhan, A., Samui, P., & Pilakoutas, K. (2021). Predicting concrete compressive strength using hybrid ensembling of surrogate machine learning models. *Cement and Concrete Research*, *145*. https://doi.org/10.1016/j.cemconres.2021.106449

Ayhan, M., Dikmen, I., & Talat Birgonul, M. (2021). Predicting the Occurrence of Construction Disputes Using Machine Learning Techniques. *Journal of Construction Engineering and Management*, *147*(4). https://doi.org/10.1061/(ASCE)CO.1943-7862.0002027

Barbosa, F., Woetzel, J., Mischke, J., Ribeirinho, M. J., Sridhar, M., Parsons, M., Bertram, N., & Brown, S. (2017). *Reinventing Construction: A Route to Higher Productivity*.

Carrera-Rivera, A., Ochoa, W., Larrinaga, F., & Lasa, G. (2022). How to conduct a systematic literature review: A quick guide for computer science research. *MethodsX*, *9*, 101895. https://doi.org/10.1016/J.MEX.2022.101895

Dixit, S., Mandal, S. N., Thanikal, J. V, & Saurabh, K. (2019). Evolution of studies in construction productivity: A systematic literature review (2006–2017). *Ain Shams Engineering Journal*. https://api.semanticscholar.org/CorpusID:133563824

Florez-Perez, L., Song, Z., & Cortissoz, J. C. (2022). Using machine learning to analyze and predict construction task productivity. *Computer-Aided Civil and Infrastructure Engineering*. https://doi.org/10.1111/mice.12806

Gao, W., Zhang, X., He, Q., Lin, B., & Huang, W. (2022). Command prediction based on early 3D modeling design logs by deep neural networks. *Automation in Construction*, *133*. https://doi.org/10.1016/j.autcon.2021.104026

Gao, Z., & Sultan, A. (2023). AI for Improving Construction Safety: A Systematic Literature Review. *EPiC Series in Built Environment*, *4*, 354–362. https://doi.org/10.29007/JTKN

Hong, Y., Park, S., Kim, H., & Kim, H. (2021). Synthetic data generation using building information models. *Automation in Construction*, *130*. https://doi.org/10.1016/j.autcon.2021.103871

Huber, M., & Imhof, D. (2019). Machine learning with screens for detecting bid-rigging cartels. *International Journal of Industrial Organization*, *65*, 277–301. https://doi.org/10.1016/j.ijindorg.2019.04.002

Hu, Y., & Castro-Lacouture, D. (2019). Clash Relevance Prediction Based on Machine Learning. *Journal of Computing in Civil Engineering*, *33*(2). https://doi.org/10.1061/(ASCE)CP.1943-5487.0000810

Jiang, Y., & Bai, Y. (2020). Estimation of Construction Site Elevations Using Drone-Based Orthoimagery and Deep Learning. *Journal of Construction Engineering and Management*, *146*(8). https://doi.org/10.1061/(ASCE)CO.1943-7862.0001869

Kassem, M., Mahamedi, E., Rogage, K., Duffy, K., & Huntingdon, J. (2021). Measuring and benchmarking the productivity of excavators in infrastructure projects: A deep neural network approach. *Automation in Construction*, *124*. https://doi.org/10.1016/j.autcon.2020.103532

Khalef, R., & El-Adaway, I. H. (2021). Automated Identification of Substantial Changes in Construction Projects of Airport Improvement Program: Machine Learning and Natural Language Processing Comparative Analysis. *Journal of Management in Engineering*, *37*(6). https://doi.org/10.1061/(ASCE)ME.1943-5479.0000959

Khallaf, R., & Khallaf, M. (2021). Classification and analysis of deep learning applications in construction: A systematic literature review. *Automation in Construction*, *129*. https://doi.org/10.1016/j.autcon.2021.103760

Kim, H., Sim, S.-H., & Spencer, B. F. (2022). Automated concrete crack evaluation using stereo vision with two different focal lengths. *Automation in Construction*, *135*. https://doi.org/10.1016/j.autcon.2022.104136

Kim, M.-K., Thedja, J. P. P., Chi, H.-L., & Lee, D.-E. (2021). Automated rebar diameter classification using point cloud data-based machine learning. *Automation in Construction*, *122*. https://doi.org/10.1016/j.autcon.2020.103476

Kitchenham, B., Kitchenham, B., & Charters, S. (2007). *Guidelines for performing systematic literature reviews in software engineering*.

Kitchenham, B., Pearl Brereton, O., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009). Systematic literature reviews in software engineering – A systematic literature review. *Information and Software Technology*, *51*(1), 7–15. https://doi.org/10.1016/J.INFSOF.2008.09.009

Lau Hiu Hoong, J. D., Lux, J., Mahieux, P.-Y., Turcry, P., & Aït-Mokhtar, A. (2020). Determination of the composition of recycled aggregates using a deep learning-based image analysis. *Automation in Construction*, *116*. https://doi.org/10.1016/j.autcon.2020.103204

Lu, W., Lou, J., Webster, C., Xue, F., Bao, Z., & Chi, B. (2021). Estimating construction waste generation in the Greater Bay Area, China using machine learning. *Waste Management*, *134*, 78–88. https://doi.org/10.1016/J.WASMAN.2021.08.012

Mishra, M., Bhatia, A. S., & Maity, D. (2020). Predicting the compressive strength of unreinforced brick masonry using machine learning techniques validated on a case study of a museum through nondestructive testing. *Journal of Civil Structural Health Monitoring*, *10*(3), 389–403. https://doi.org/10.1007/s13349-020-00391-7

Pati, D., & Lorusso, L. N. (2017). How to Write a Systematic Review of the Literature. *HERD: Health Environments Research & Design Journal*, *11*(1), 15–30. https://doi.org/10.1177/1937586717747384

Qin, H., Zhang, D., Tang, Y., & Wang, Y. (2021). Automatic recognition of tunnel lining elements from GPR images using deep convolutional networks with data augmentation. *Automation in Construction*, *130*. https://doi.org/10.1016/j.autcon.2021.103830

Rashid, K. M., & Louis, J. (2020). Activity identification in modular construction using audio signals and machine learning. *Automation in Construction*, *119*. https://doi.org/10.1016/j.autcon.2020.103361

Sadatnya, A., Sadeghi, N., Sabzekar, S., Khanjani, M., Tak, A. N., & Taghaddos, H. (2023). Machine learning for construction crew productivity prediction using daily work reports. *Automation in Construction*, *152*. https://doi.org/10.1016/j.autcon.2023.104891

Sanhudo, L., Calvetti, D., Martins, J. P., Ramos, N. M. M., Mêda, P., Gonçalves, M. C., & Sousa, H. (2021). Activity classification using accelerometers and machine learning for complex construction worker activities. *Journal of Building Engineering*, *35*. https://doi.org/10.1016/j.jobe.2020.102001

Sherafat, B., Rashidi, A., & Asgari, S. (2022). Sound-based multiple-equipment activity recognition using convolutional neural networks. *Automation in Construction*, *135*. https://doi.org/10.1016/j.autcon.2021.104104

Tien Bui, D., Hoang, N.-D., & Nhu, V.-H. (2019). A swarm intelligence-based machine learning approach for predicting soil shear strength for road construction: a case study at Trung Luong National Expressway Project (Vietnam). *Engineering with Computers*, *35*(3), 955–965. https://doi.org/10.1007/s00366-018-0643-1

Vickranth, V., Bommareddy, S. S. R., & Premalatha, V. (2019). Application of lean techniques, enterprise resource planning, and artificial intelligence in construction project management. *International Journal of Recent Technology and Engineering*, *7*(6C2), 147–153.

Wei, W., Lu, Y., Zhong, T., Li, P., & Liu, B. (2022). Integrated vision-based automated progress monitoring of indoor construction using mask region-based convolutional neural networks and BIM. *Automation in Construction*, *140*. https://doi.org/10.1016/j.autcon.2022.104327

Wu, C., Wang, X., Wu, P., Wang, J., Jiang, R., Chen, M., & Swapan, M. (2021). Hybrid deep learning model for automating constraint modeling in advanced working packaging. *Automation in Construction*, *127*. https://doi.org/10.1016/j.autcon.2021.103733

Xiao, B., Xiao, H., Wang, J., & Chen, Y. (2022). Vision-based method for tracking workers by integrating deep learning instance segmentation in off-site construction. *Automation in Construction*, *136*. https://doi.org/10.1016/j.autcon.2022.104148

Xiao, B., Yin, X., & Kang, S.-C. (2021). Vision-based method of automatically detecting construction video highlights by integrating machine tracking and CNN feature extraction. *Automation in Construction*, *129*. https://doi.org/10.1016/j.autcon.2021.103817

Xie, H., Shi, W., Issa, R. R. A., Guo, X., Shi, Y., & Liu, X. (2020). Machine Learning of Concrete Temperature Development for Quality Control of Field Curing. *Journal of Computing in Civil Engineering*, *34*(5). https://doi.org/10.1061/(ASCE)CP.1943-5487.0000916

Xu, C., Liu, X., Wang, E., & Wang, S. (2021). Prediction of tunnel boring machine operating parameters using various machine learning algorithms. *Tunnelling and Underground Space Technology*, *109*. https://doi.org/10.1016/j.tust.2020.103699

Xu, Y., Zhou, Y., Sekula, P., & Ding, L. (2021). Machine learning in construction: From shallow to deep learning. *Developments in the Built Environment*, *6*. https://doi.org/10.1016/j.dibe.2021.100045

Yang, Z., He, B., Liu, Y., Wang, D., & Zhu, G. (2021). Classification of rock fragments produced by tunnel boring machine using convolutional neural networks. *Automation in Construction*, *125*. https://doi.org/10.1016/j.autcon.2021.103612

Yin, X., Chen, Y., Bouferguene, A., Zaman, H., Al-Hussein, M., & Kurach, L. (2020). A deep learning-based framework for an automated defect detection system for sewer pipes. *Automation in Construction*, *109*. https://doi.org/10.1016/j.autcon.2019.102967

Zhang, R., & El-Gohary, N. (2021). A deep neural network-based method for deep information extraction using transfer learning strategies to support automated compliance checking. *Automation in Construction*, *132*. https://doi.org/10.1016/j.autcon.2021.103834

Zhang, Z., Yin, X., & Yan, Z. (2022). Rapid data annotation for sand-like granular instance segmentation using mask-RCNN. *Automation in Construction*, *133*. https://doi.org/10.1016/j.autcon.2021.103994

Zhan, W., & Pan, W. (2020). Formulating Systemic Construction Productivity Enhancement Strategies. *Journal of Construction Engineering and Management*, *146*(8), 5020008. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001886