EPiC Series in Built Environment
Volume 6, 2025, Pages 430–439
Proceedings of Associated Schools of Construction 61st Annual International Conference

AI-based Object Detection and Material Classification for Scan-to-BIM – A Deep Learning Framework

Rana Muhammad Irfan Anwar[1] and Salman Azhar[1]
[1]Auburn University

Building Information Modeling (BIM) is a pivotal technology in the Architecture, Engineering, and Construction (AEC) industry. It enables the creation and management of digital representations of physical and functional characteristics of buildings. The integration of deep learning technology can significantly enhance BIM's capabilities. This is particularly true for object detection and material classification. This paper explores the application of deep learning techniques, including Convolutional Neural Networks (CNNs), for the automated detection and classification of building elements and materials. We detail the workflows in training and deploying these models, encompassing data collection, preprocessing, model training, and validation. Furthermore, we discuss the integration of these models into BIM frameworks. Emphasizing the benefits such as improved accuracy, efficiency, and cost-effectiveness. There are challenges like large data requirements and computational demands. Still, the potential for deep learning to transform BIM processes is immense. This article suggests a framework as part of ongoing research to address current limitations and advance the automation of Scan-to-BIM processes. It introduces sophisticated deep-learning models for object detection and material identification within the construction environment. The proposed framework will be implemented, and future research articles will present the final results.

Keywords: AEC industry, Scan-to-BIM, Deep learning, Material classification, Object detection

Introduction

The emergence of deep learning technology has brought revolutionary changes to various industries, including the Architecture, Engineering, and Construction (AEC) field. The applications of Computer Vision (CV) and image processing systems are rising as an emerging field of research with steady growth in the AEC industry (Rashidi et al. 2016). This sector ranks as one of the most intensive fields where vision-based systems are used to facilitate decision-making processes during the construction phase (Rauch and Braml 2023). Artificial Intelligence (AI) and deep learning-based object detection and material classification can play a crucial role in developing Building Information Models (BIM). These technologies enable automatic recognition and classification of building components and materials which as a result can greatly improve the efficiency and accuracy of BIM generation.

BIM has become a cornerstone of modern practices in the AEC industry. It involves the generation and management of digital representations of the physical and functional characteristics of buildings (Azhar

2011). Although BIM processes are in place for new buildings, the majority of existing buildings and structures have not yet been maintained, refurbished, or deconstructed using BIM (Volk, Stengel, and Schultmann 2014). Integrating deep learning technology into BIM workflows, specifically for object detection and material classification, can improve the precision and efficiency of model creation. This article examines the current literature. It identifies processes, advantages, and challenges of utilizing deep learning technology for object detection and material classification within the AEC industry. Based on the gathered information this study proposes a deep learning framework for Scan-to-BIM.

Literature Review

Scan-to-BIM is a process that involves capturing the as-is conditions of a building using various scanning technologies and converting this data into a detailed BIM model. This process is crucial for ensuring accurate building information as the success of BIM depends on it (Wang, Guo, and Kim 2019). It is essential for various purposes like cost reduction, control through the project life cycle, and time savings in construction projects (Bryde, Broquetas, and Volm 2013). Accurate BIMs are necessary for construction project handover and facility management. It benefits from laser scanning technology's high measurement accuracy and speed (Yang, Cheng, and Wang 2020). It is important for better facility management in Mechanical, Electrical, and Plumbing (MEP) systems (Wang et al. 2021). Accurate BIM is necessary for heritage building modeling. It ensures geometric accuracy and semantic richness, avoiding trade-offs between visual fidelity and parametric flexibility (Radanovic, Khoshelham, and Fraser 2020). It is crucial for structural simulation in historic buildings as well. It preserves the uniqueness and authenticity of the building while considering geometric irregularities (Barazzetti et al. 2015). It ensures fit between assemblies and construction sites as well as reduces the average error between BIM and as-built conditions (Rausch and Haas 2021).

The process of Scan-to-BIM involves four key steps: identifying information requirements, determining the required scan data quality, acquiring the scan data, and reconstructing the as-is BIM (Wang et al. 2019). Capturing data for processes like Scan-to-BIM requires careful planning, execution, and methodical pre-processing to produce high-quality point clouds (Valero, Bosché, and Bueno 2022). The US GSA offers guidelines for accuracy tolerances, which range from ± 51 mm for Level of Detail (LOD) 1 to ± 3 mm for LOD 4 (US GSA 2009). Object detection involves the identification and location of objects within an image or 3D scan. Deep learning algorithms like Mask R-CNN (He et al. 2017), and YOLO (You Only Look Once) (Wan et al. 2023) have become widely used for this task due to their high accuracy and real-time detection capabilities (Nath and Behzadan 2020). Currently, object detection in the AEC industry is typically used for the purpose of safety inspection (Tang, Roberts, and Golparvar-Fard 2020), quality control (Xuehui et al. 2021), progress monitoring (Kim and Kim 2018), defect detection (Muhammad et al. 2021), equipment and material detection (Fang et al. 2018), and productivity management (Wang et al. 2022). The recognition of construction materials in scanned data at different construction sites is vital for numerous applications in the construction industry (Son et al. 2014). Project managers can maintain accurate material usage and availability records by automatically identifying and classifying materials on-site, such as concrete (Son, Kim, and Kim 2012). This helps minimize waste and ensure that materials are utilized efficiently as it can accurately identify and distinguish construction waste materials (Davis et al. 2021). Material classification is a crucial step in any vision-based system for creating accurate 3D models of as-built structures. Digital material classification uses appearance-based data to automate the generation of 3D models for construction processes (Dimitrov and Golparvar-Fard 2014). The appearance-based material classification approach is also applicable for tracking construction progress throughout the operation and maintenance phase (Han and Golparvar-Fard 2015). It allows for continuous monitoring of construction materials and ensuring that the correct materials are employed according to project specifications. Material classification in the construction industry involves using features like material reflectance, HSV color values, and surface roughness to accurately identify common building materials (Yuan, Guo, and Wang 2020a). Deep learning models can classify materials based on their visual and spectral characteristics. This is essential for various aspects of building management, including maintenance, renovation, sustainability assessments, and cost estimation. In the context of BIM, these objects typically consist of building components such as walls, windows, doors, and structural elements.

Previously, frameworks and methodologies have been developed to streamline the process with semi-automated approaches promising improvements in accuracy and efficiency. A study was performed to improve productivity and reliability in creating as-built BIMs of complex indoor structures. It used terrestrial laser scanners to reduce data size and enhance the identification and modeling efficiency (Jung et al. 2014). Similarly, another study proposed a method to optimize the number and scan positions for Scan-to-BIM procedures. It was aimed to achieve full coverage and avoid major occlusions while maintaining data completeness (Díaz-Vilariño et al. 2018). Scan-to-BIM currently relies on manual user input however it is still necessary to develop a fully automated system (Tang et al. 2010). It should be capable of scanning construction projects and buildings for data collection. This would involve employing a sophisticated deep learning model to perform object detection and determine the material of the object. Subsequently, this information could be used to create accurate BIM models. The goal of this research is to fill this gap by introducing a new framework.

Methods and Framework

The research proposes a Scan-to-BIM framework, as shown in Figure. 1, for the automatic generation of accurate BIM models from scanned and processed data.

Data Acquisition

In the AEC industry data is captured via various high-tech tools such as laser scanners, drones, robots, video cameras, etc. The framework proposes capturing comprehensive spatial and visual data of a construction project and its environment. Using state-of-the-art reality capture technologies such as laser scanners, drones, cameras, and robots.

Data Preprocessing

During this stage, it is important to prepare the data to be processed by the deep learning models. This involves various tasks such as cleaning, noise removal, data compression, formatting, and labeling. These actions are aimed at ensuring that the data is of high quality and ready for analysis by reducing errors and using standard formats.

AI Object Detection

During this important phase, the data will be split into two categories. Laser-scanned data will be used for object detection. Also, to gather parametric and geometric information about the building components. On the other hand, photogrammetric data will be utilized for material identification and classification. Together all the data combined will be used for BIM generation. It's essential to conduct a comparative analysis. It will help determine which deep learning algorithms perform best for the tasks of object detection and material classification using each type of captured data.

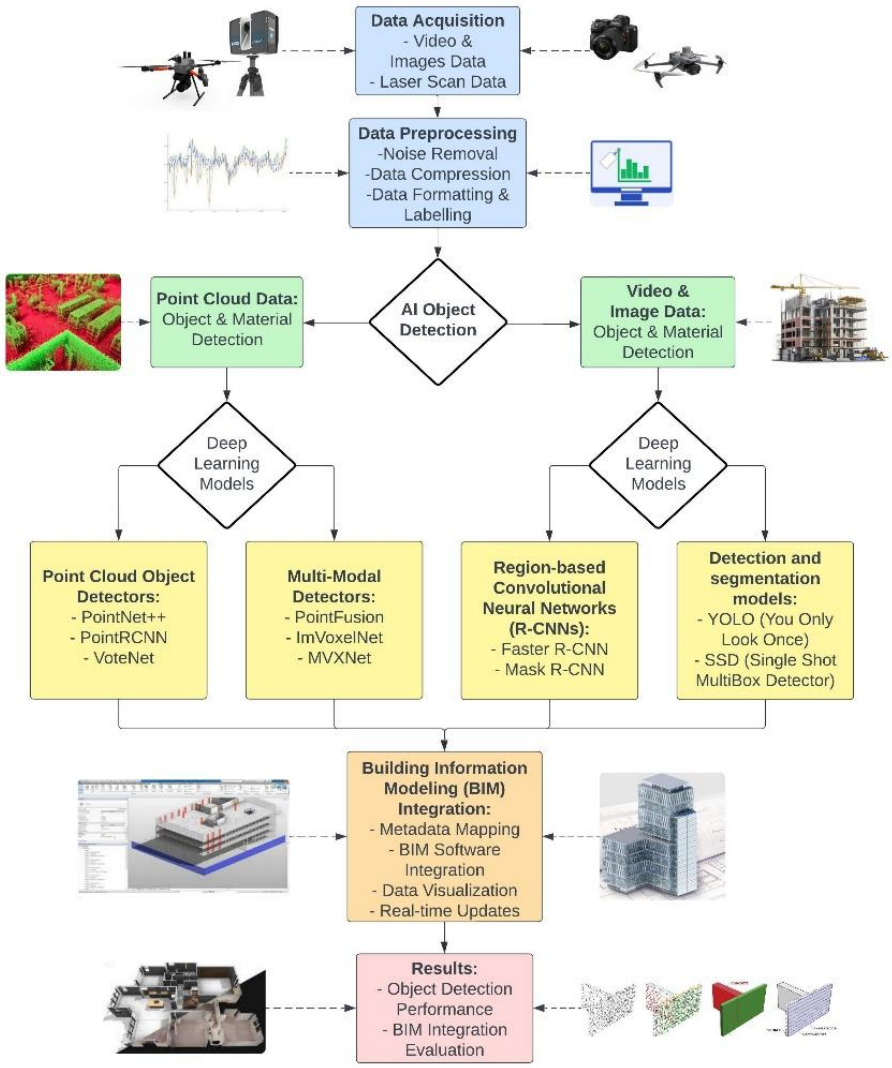

Figure 1. Developed Framework

Point Cloud Data Processing

This framework proposes some of the famous deep learning algorithms for the required purpose such as PointNet++ and PointRCNN. PointNet is a novel neural network that efficiently and effectively processes 3D point clouds for object classification, part segmentation, and scene semantic parsing (Qi et al. 2017). PointNet++ is an extension of PointNet, designed to handle the complexities of 3D point cloud data. It stands as one of the leading neural architectures for understanding point clouds (Qian et al. 2022). It processes raw point clouds directly, capturing local and global geometric features through hierarchical learning. PointNet++ performs well in occluded and cluttered environments. It captures local features through a hierarchical approach, enabling the model to understand fine-grained details in complex scenes. It leverages the full 3D spatial information, which is critical in construction sites where objects may overlap or be partially visible. It is relatively robust to variations in lighting conditions, as it does not rely on color information but on spatial configurations.

PointCNN is a generalization of Convolutional Neural Networks (CNNs) for learning features from point clouds (Li et al. 2018). PointRCNN is a Region-based CNN adapted for 3D object detection directly from point clouds. It generates proposals from raw point clouds and refines them through a two-stage process. It is a clear and efficient architecture (Luo et al. 2022). It achieves high accuracy in 3D object detection by effectively utilizing 3D spatial information and refining proposals through a two-stage process (Shi, Wang, and Li 2019). Its proposal generation mechanism can identify and differentiate between overlapping objects, making it suitable for cluttered construction sites. It allows end-to-end learning directly from point clouds, reducing preprocessing requirements. A study (Liu et al. 2022) demonstrated the highest accuracy for PointRCNN when compared to three other deep learning networks: PointPillars, SECOND, and PV-RCNN, for detecting objects using laser-scanned data. The improved PointRCNN model performs better 3D object detection in point clouds by addressing non-uniform density. It achieves competitive performance with less computational cost compared to the baseline PointRCNN (Li and Hu 2020).

Video & Image Data Analysis

Deep learning is applied for object and material detection in 2D visual data using multi-modal detectors (e.g., PointFusion, ImVoxelNet, MVXNet) that integrate various data types. Region-based Convolutional Neural Networks (R-CNNs) like Faster R-CNN and Mask R-CNN for detailed segmentation. Detection and Segmentation Models such as YOLO and SSD, focus on real-time object detection. YOLO is a popular real-time object detection algorithm that processes images in a single forward pass through a convolutional neural network, making it extremely fast (Hu, Shi, and Zhang 2021). To date, the research community has developed improved versions from YOLOv1 to YOLOv10. In the latest research by (Wang, Yeh, and Liao 2024), authors performed a comparative analysis of YOLOv9 with other train-from-scratch real-time object detectors. These comparisons demonstrated that the latest YOLOv9 has shown significant improvements in all aspects compared to existing methods. Among various object detectors, YOLO stands out as the one that strikes the best balance between accuracy and execution time (Hu et al. 2021).

BIM Integration

First, the deep learning algorithms will identify the building components such as concrete beams, columns, etc. After that material will be identified for BIM integration. These results will be processed and introduced into BIM software such as Autodesk Revit where accurate and precise models will be created using the acquired data. Revit add-in Dynamo can be used for this purpose. This modeling includes metadata mapping and software integration to provide real-time visualization and updates within the BIM environment.

Results and Discussion

The proposed framework includes evaluating object detection performance and the effectiveness of BIM integration. It will provide insights into the accuracy of object detection and the utility of integrating AI findings into BIM for construction management and planning. For measuring the performance of deep learning models metrics such as Intersection over Union (IoU) will be used. It measures the overlap between the predicted bounding box or segmentation mask and the ground truth. It is a widely adopted metric for evaluating object detection and segmentation tasks (Rezatofighi et al. 2019). Similarly, mAP is a widely used metric for evaluating the quality of object detectors (Wang 2022).

Benefits

This framework enhances the efficiency and effectiveness of AI-driven object detection in construction and architectural contexts. It provides richer insights and supports better decision-making via BIM. Today, there are several advanced deep-learning models available that are capable of achieving high precision in detecting and categorizing building elements and materials. This capability can significantly reduce errors and inconsistencies. The resulting data can be used to generate BIM models which is of immense importance in the AEC industry. To date, BIM generation is in the manual and semi-automatic phase. Automating the detection and classification processes can significantly speed up model generation, saving valuable time and cost. Reducing manual labor and minimizing errors translates into substantial cost savings for construction projects. The cost of materials is around 50% to 60% of the overall cost of construction projects (Safa et al. 2014). A realistic BIM model can be used for better management of construction materials which significantly impacts the project's financial management (Chunyaem et al. 2019). Accurate and detailed BIMs facilitate better building maintenance, renovation planning, and lifecycle management, enhancing overall building sustainability. By leveraging precise and real-time data, construction projects can achieve higher precision, efficiency, and overall success.

Challenges

Despite the numerous benefits, integrating deep learning into BIM faces several challenges. Deep learning models require large, annotated datasets for training, which can be labor-intensive and time-consuming to create. The foundational approach of image-based methods leverages the distinct visual attributes of building materials, including color, texture, roughness, and projection, to facilitate their automatic classification (Son et al. 2014). Also, image-based methods are heavily impacted by illumination conditions, which strongly affect material classification due to changes in visual characteristics caused by different lighting conditions (Yuan, Guo, and Wang 2020b). PointNet++ and PointRCNN are well-suited for handling occlusion and clutter in construction environments due to their 3D point cloud processing capabilities. They are also robust to lighting variations. On the other hand, YOLO is highly efficient for real-time applications but may have limitations in complex 3D environments. Training deep learning models is computationally intensive, necessitating powerful hardware and substantial energy consumption. PointNet++ and PointRCNN offer high accuracy and robustness in 3D space but at the cost of increased computational complexity and resource requirements. They are better suited for tasks where detailed 3D information is critical, and computational resources are available. YOLO, with its real-time processing capability, is ideal for quick detection tasks where computational efficiency and speed are prioritized over detailed 3D understanding. However, it may require supplementary techniques to address 3D-specific challenges like adopting YOLO3D. Ensuring that models generalize well across different building styles, materials, and conditions is challenging and requires diverse training data. Utilizing large, diverse datasets can help address the variability in construction materials and scenarios. These datasets should encompass a wide range of material types, textures, and environmental conditions. That will enable the trained models to generalize better to unseen data like the Site Object Detection Dataset (SODA) dataset comprising more than 20,000 images (Duan et al. 2022). Additionally, data augmentation techniques, such as Geometric Transformations (Zhao, Li, and Cheng 2022), Plankain jittering (Zini et al. 2022), or Synthetic Data Generation (Endres, Mannarapotta Venugopal, and Tran 2022), can be employed to further increase the diversity of the training data and improve the robustness of the models (Shorten and Khoshgoftaar 2019). Integrating deep learning models with existing BIM software and workflows can be complex, requiring careful consideration of data formats and interoperability standards. In the case of Autodesk Revit software add-ins like Dynamo and Dyno Browser as well as Revit API (Application Programming Interface) can be used to address this challenge.

Conclusion

Object detection and material classification using deep learning has been revolutionizing the AEC industry in various domains. These technologies automate the identification and categorization of building components and materials. Which improves the accuracy, efficiency, and cost-effectiveness of BIM generation. As deep learning technologies progress, integrating them into BIM will be crucial for driving innovation and sustainability in the AEC industry. This article is a part of ongoing research and in the future, this proposed framework will be implemented in several case studies for testing and validation purposes. The results will be presented in future articles. Also, future research and development efforts should prioritize addressing the current challenges. It will enhance the model generalization and improve the interoperability of deep learning models within BIM frameworks.

References

Azhar, Salman. 2011. *Building Information Modeling (BIM): Trends, Benefits, Risks, and Challenges for the AEC Industry*. Vol. 11.

Barazzetti, Luigi, Fabrizio Banfi, Raffaella Brumana, Gaia Gusmeroli, Mattia Previtali, and Giuseppe Schiantarelli. 2015. 'Cloud-to-BIM-to-FEM: Structural Simulation with Accurate Historic BIM from Laser Scans'. *Simulation Modelling Practice and Theory* 57:71–87. doi: 10.1016/j.simpat.2015.06.004.

Bryde, David, Martí Broquetas, and Jürgen Marc Volm. 2013. 'The Project Benefits of Building Information Modelling (BIM)'. *International Journal of Project Management* 31(7):971–80. doi: 10.1016/j.ijproman.2012.12.001.

Chunyaem, Weerayut, Chayakrit Charoensiriwath, Kriengsak Panuwatwanich, Shigeki Saito, and Patai Padungtin. 2019. 'Application of Artificial Intelligence to Automate Construction Materials Data Classification'. *Creative Construction Conference 2019* 8–13. doi: 10.3311/CCC2019-002.

Davis, Peter, Fayeem Aziz, Mohammad Tanvi Newaz, Willy Sher, and Laura Simon. 2021. 'The Classification of Construction Waste Material Using a Deep Convolutional Neural Network'. *Automation in Construction* 122:103481. doi: 10.1016/J.AUTCON.2020.103481.

Díaz-Vilariño, L., E. Frías, J. Balado, and H. González-Jorge. 2018. 'Scan Planning and Route Optimization for Control of Execution of As-Designed Bim'. Pp. 217–24 in *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*. Vol. 42. International Society for Photogrammetry and Remote Sensing.

Dimitrov, Andrey, and Mani Golparvar-Fard. 2014. 'Vision-Based Material Recognition for Automated Monitoring of Construction Progress and Generating Building Information Modeling from Unordered Site Image Collections'. *Advanced Engineering Informatics* 28(1):37–49. doi: 10.1016/J.AEI.2013.11.002.

Duan, Rui, Hui Deng, Mao Tian, Yichuan Deng, and Jiarui Lin. 2022. 'SODA: A Large-Scale Open Site Object Detection Dataset for Deep Learning in Construction'. *Automation in Construction* 142:104499. doi: 10.1016/J.AUTCON.2022.104499.

Endres, Markus, Asha Mannarapotta Venugopal, and Tung Son Tran. 2022. 'Synthetic Data Generation: A Comparative Study'. *ACM International Conference Proceeding Series* 94–102. doi: 10.1145/3548785.3548793.

Fang, Weili, Lieyun Ding, Botao Zhong, Peter E. D. Love, and Hanbin Luo. 2018. 'Automated Detection of Workers and Heavy Equipment on Construction Sites: A Convolutional Neural Network Approach'. *Advanced Engineering Informatics* 37:139–49. doi: 10.1016/j.aei.2018.05.003.

Han, Kevin K., and Mani Golparvar-Fard. 2015. 'Appearance-Based Material Classification for Monitoring of Operation-Level Construction Progress Using 4D BIM and Site Photologs'. *Automation in Construction* 53:44–57. doi: 10.1016/J.AUTCON.2015.02.007.

He, Kaiming, Georgia Gkioxari, Piotr Dollar, and Ross Girshick. 2017. 'Mask R-CNN'. Pp. 2980–88 in *Proceedings of the IEEE International Conference on Computer Vision*. Vols 2017-October. Institute of Electrical and Electronics Engineers Inc.

Hu, Jun ying, C. J. Richard Shi, and Jiang she Zhang. 2021. 'Saliency-Based YOLO for Single Target Detection'. *Knowledge and Information Systems* 63(3):717–32. doi: 10.1007/S10115-020-01538-0/FIGURES/9.

Jung, Jaehoon, Sungchul Hong, Seongsu Jeong, Sangmin Kim, Hyoungsig Cho, Seunghwan Hong, and Joon Heo. 2014. 'Productive Modeling for Development of As-Built BIM of Existing Indoor Structures'. *Automation in Construction* 42:68–77. doi: 10.1016/j.autcon.2014.02.021.

Kim, Hongjo, and Hyoungkwan Kim. 2018. '3D Reconstruction of a Concrete Mixer Truck for Training Object Detectors'. *Automation in Construction* 88:23–30. doi: 10.1016/j.autcon.2017.12.034.

Li, Jie, and Yu Hu. 2020. 'A Density-Aware PointRCNN for 3D Objection Detection in Point Clouds'. *ArXiv.Org*.

Li, Yangyan, Rui Bu, Mingchao Sun, and Baoquan Chen. 2018. 'PointCNN'. *Neural Information Processing Systems*.

Liu, Zhiyong, Xi Wang, Jiankai Zhu, Pengle Cheng, and Ying Huang. 2022. 'LiDAR and Deep Learning-Based Standing Tree Detection for Firebreaks Applications'. *Sensors 2022, Vol. 22, Page 8858* 22(22):8858. doi: 10.3390/S22228858.

Luo, Xizhao, Feng Zhou, Chongben Tao, Anjia Yang, Peiyun Zhang, and Yonghua Chen. 2022. 'Dynamic Multitarget Detection Algorithm of Voxel Point Cloud Fusion Based on PointRCNN'. *IEEE Transactions on Intelligent Transportation Systems* 23(11):20707–20. doi: 10.1109/TITS.2022.3176390.

Muhammad, Ilyas, Khaw Ying, Muthuchamy Nithish, Jin Xin, Zhao Xinge, and Chien Chern Cheah. 2021. 'Robot-Assisted Object Detection for Construction Automation: Data and Information-Driven Approach'. *IEEE/ASME Transactions on Mechatronics* 26(6):2845–56. doi: 10.1109/TMECH.2021.3100306.

Nath, Nipun D., and Amir H. Behzadan. 2020. 'Deep Convolutional Networks for Construction Object Detection Under Different Visual Conditions'. *Frontiers in Built Environment* 6. doi: 10.3389/fbuil.2020.00097.

Qi, Charles R., Hao Su, Kaichun Mo, and Leonidas J. Guibas. 2017. 'PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation'. *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017* 2017-January:77–85. doi: 10.1109/CVPR.2017.16.

Qian, Guocheng, Yuchen Li, Houwen Peng, Jinjie Mai, Hasan Abed Al Kader Hammoud, Mohamed Elhoseiny, and Bernard Ghanem. 2022. ‘PointNeXt: Revisiting PointNet++ with Improved Training and Scaling Strategies’. *Advances in Neural Information Processing Systems* 35.

Radanovic, Marko, Kourosh Khoshelham, and Clive Fraser. 2020. ‘Geometric Accuracy and Semantic Richness in Heritage BIM: A Review’. *Digital Applications in Archaeology and Cultural Heritage* 19.

Rashidi, Abbas, Mohamad Hoseyn Sigari, Marcel Maghiar, and David Citrin. 2016. ‘An Analogy between Various Machine-Learning Techniques for Detecting Construction Materials in Digital Images’. *KSCE Journal of Civil Engineering* 20(4):1178–88. doi: 10.1007/S12205-015-0726-0/METRICS.

Rauch, Lukas, and Thomas Braml. 2023. ‘Semantic Point Cloud Segmentation with Deep-Learning-Based Approaches for the Construction Industry: A Survey’. *Applied Sciences 2023, Vol. 13, Page 9146* 13(16):9146. doi: 10.3390/APP13169146.

Rausch, Christopher, and Carl Haas. 2021. ‘Automated Shape and Pose Updating of Building Information Model Elements from 3D Point Clouds’. *Automation in Construction* 124. doi: 10.1016/j.autcon.2021.103561.

Rezatofighi, Hamid, Nathan Tsoi, Junyoung Gwak, Amir Sadeghian, Ian Reid, and Silvio Savarese. 2019. ‘Generalized Intersection over Union: A Metric and a Loss for Bounding Box Regression’. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* 2019-June:658–66. doi: 10.1109/CVPR.2019.00075.

Safa, Mahdi, Arash Shahi, Carl T. Haas, and Keith W. Hipel. 2014. ‘Supplier Selection Process in an Integrated Construction Materials Management Model’. *Automation in Construction* 48:64–73. doi: 10.1016/J.AUTCON.2014.08.008.

Shi, Shaoshuai, Xiaogang Wang, and Hongsheng Li. 2019. ‘PointRCNN: 3D Object Proposal Generation and Detection from Point Cloud’. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* 2019-June:770–79. doi: 10.1109/CVPR.2019.00086.

Shorten, Connor, and Taghi M. Khoshgoftaar. 2019. ‘A Survey on Image Data Augmentation for Deep Learning’. *Journal of Big Data* 6(1):1–48. doi: 10.1186/S40537-019-0197-0/FIGURES/33.

Son, Hyojoo, Changmin Kim, Nahyae Hwang, Changwan Kim, and Youngcheol Kang. 2014. ‘Classification of Major Construction Materials in Construction Environments Using Ensemble Classifiers’. *Advanced Engineering Informatics* 28(1):1–10. doi: 10.1016/J.AEI.2013.10.001.

Son, Hyojoo, Changmin Kim, and Changwan Kim. 2012. ‘Automated Color Model–Based Concrete Detection in Construction-Site Images by Using Machine Learning Algorithms’. *Journal of Computing in Civil Engineering* 26(3):421–33. doi: 10.1061/(ASCE)CP.1943-5487.0000141.

Tang, Pingbo, Daniel Huber, Burcu Akinci, Robert Lipman, and Alan Lytle. 2010. ‘Automatic Reconstruction of As-Built Building Information Models from Laser-Scanned Point Clouds: A Review of Related Techniques’. *Automation in Construction* 19(7):829–43.

Tang, Shuai, Dominic Roberts, and Mani Golparvar-Fard. 2020. ‘Human-Object Interaction Recognition for Automatic Construction Site Safety Inspection’. *Automation in Construction* 120. doi: 10.1016/j.autcon.2020.103356.

US GSA. 2009. *GSA Building Information Modeling Guide Series: 03-GSA BIM Guide for 3D Imaging*.

Valero, Enrique, Frédéric Bosché, and Martin Bueno. 2022. 'LASER SCANNING FOR BIM'. *Journal of Information Technology in Construction* 27:486–95. doi: 10.36680/j.itcon.2022.023.

Volk, Rebekka, Julian Stengel, and Frank Schultmann. 2014. 'Building Information Modeling (BIM) for Existing Buildings - Literature Review and Future Needs'. *Automation in Construction* 38:109–27.

Wan, Dahang, Rongsheng Lu, Sailei Wang, Siyuan Shen, Ting Xu, and Xianli Lang. 2023. 'YOLO-HR: Improved YOLOv5 for Object Detection in High-Resolution Optical Remote Sensing Images'. *Remote Sensing* 15(3). doi: 10.3390/rs15030614.

Wang, Beinan. 2022. 'A Parallel Implementation of Computing Mean Average Precision'.

Wang, Boyu, Chao Yin, Han Luo, Jack C. P. Cheng, and Qian Wang. 2021. 'Fully Automated Generation of Parametric BIM for MEP Scenes Based on Terrestrial Laser Scanning Data'. *Automation in Construction* 125. doi: 10.1016/j.autcon.2021.103615.

Wang, Chien-Yao, I. Hau Yeh, and Hong-Yuan Mark Liao. 2024. 'YOLOv9: Learning What You Want to Learn Using Programmable Gradient Information'.

Wang, Qian, Jingjing Guo, and Min Koo Kim. 2019. 'An Application Oriented Scan-to-Bim Framework'. *Remote Sensing* 11(3). doi: 10.3390/rs11030365.

Wang, Xiaoyu, Hengyou Wang, Changlun Zhang, Qiang He, and Lianzhi Huo. 2022. 'A Sample Balance-Based Regression Module for Object Detection in Construction Sites'. *Applied Sciences (Switzerland)* 12(13). doi: 10.3390/app12136752.

Xuehui, An, Zhou Li, Liu Zuguang, Wang Chengzhi, Li Pengfei, and Li Zhiwei. 2021. 'Dataset and Benchmark for Detecting Moving Objects in Construction Sites'. *Automation in Construction* 122. doi: 10.1016/j.autcon.2020.103482.

Yang, Liu, Jack C. P. Cheng, and Qian Wang. 2020. 'Semi-Automated Generation of Parametric BIM for Steel Structures Based on Terrestrial Laser Scanning Data'. *Automation in Construction* 112. doi: 10.1016/j.autcon.2019.103037.

Yuan, Liang, Jingjing Guo, and Qian Wang. 2020a. 'Automatic Classification of Common Building Materials from 3D Terrestrial Laser Scan Data'. *Automation in Construction* 110. doi: 10.1016/j.autcon.2019.103017.

Yuan, Liang, Jingjing Guo, and Qian Wang. 2020b. 'Automatic Classification of Common Building Materials from 3D Terrestrial Laser Scan Data'. *Automation in Construction* 110:103017. doi: 10.1016/J.AUTCON.2019.103017.

Zhao, He, Huiqi Li, and Li Cheng. 2022. 'Data Augmentation for Medical Image Analysis'. *Biomedical Image Synthesis and Simulation: Methods and Applications* 279–302. doi: 10.1016/B978-0-12-824349-7.00021-9.

Zini, Simone, Alex Gomez-Villa, Marco Buzzelli, Bartłomiej Twardowski, Andrew D. Bagdanov, and Joost van de Weijer. 2022. 'Planckian Jitter: Countering the Color-Crippling Effects of Color Jitter on Self-Supervised Training'.