YOLO and Faster R-CNN Object Detection in Architecture, Engineering and Construction (AEC): Applications, Challenges, and Future Prospects

Article *in* SSRN Electronic Journal · January 2023

DOI: 10.2139/ssrn.4624204

3 authors:

Nitin Rane
University of Mumbai

Saurabh Purushottam Choudhary
Vivekanand Education Society's College of Architecture

Jayesh Rane
Pillai Hoc College Of Engineering And Technology

YOLO and Faster R-CNN object detection in Architecture, Engineering and Construction (AEC): applications, challenges, and future prospects

[*1] Nitin Liladhar Rane [2] Saurabh P. Choudhary [3] Jayesh Rane

[*1,2,3] University of Mumbai, Mumbai, India

[*1] Email: nitinrane33@gmail.com

Abstract:

Object detection plays a crucial role in transforming the Architecture, Engineering, and Construction (AEC) industry, enhancing project efficiency, safety, and overall productivity. This study explores the applications, challenges, and future potential of two cutting-edge object detection algorithms, namely You Only Look Once (YOLO) and Faster Region-based Convolutional Neural Networks (Faster R-CNN), within the realm of AEC. The research comprehensively investigates the diverse applications of YOLO and Faster R-CNN in AEC, including real-time site monitoring, structural integrity assessment, safety protocol enforcement, automated progress tracking, and quality control. These algorithms have propelled the AEC industry forward, enabling advancements in autonomous inspection, defect detection, and resource management. Consequently, these innovations have enhanced decision-making processes and optimized project lifecycles. Nevertheless, integrating object detection technologies in AEC presents challenges. This paper meticulously examines hurdles such as data annotation complexities, algorithmic limitations, and computational resource demands. It also delves into ethical considerations, data privacy, and cybersecurity concerns, shedding light on the ethical implications associated with the widespread adoption of these technologies in the industry. Looking ahead, the paper outlines the future prospects of YOLO and Faster R-CNN in AEC and discusses potential solutions to existing challenges. These solutions include the development of more robust algorithms, streamlined data annotation processes, and advancements in edge computing. Moreover, the study explores emerging trends like Explainable AI (XAI) and Generative Adversarial Networks (GANs), envisioning their integration with object detection for even more sophisticated applications in AEC. This study provides valuable insights to researchers, practitioners, and policymakers, paving the way for a more efficient, innovative, and ethically responsible AEC sector.

Keywords: Object Detection, YOLO, Faster R-CNN, Deep Learning, Construction industry, Architecture, Object recognition.

Introduction

In recent years, the fields of Architecture, Engineering, and Construction (AEC) have undergone a significant transformation, driven by technological advancements. Notably, computer vision and deep learning techniques have emerged as powerful tools, reshaping the practices of professionals in the AEC industry, from the way they perceive and design buildings and infrastructure to how they construct them [1-5]. Within the realm of computer vision, one key area of focus is object detection, a foundational task with numerous applications in AEC, spanning safety monitoring to progress tracking. State-of-the-art object detection algorithms, such as You Only Look Once (YOLO) and Faster R-CNN, have attracted considerable attention for their ability to accurately and efficiently detect objects in real-time [6-9]. This research delves into the applications, challenges, and future prospects of YOLO and Faster R-CNN object detection methods within the context of Architecture, Engineering, and Construction.

The AEC industry, historically reliant on manual methods and 2D drawings, is currently undergoing a fundamental shift with the integration of digital technologies. Building Information Modeling (BIM) has revolutionized the process of designing, constructing, and operating buildings, providing a collaborative platform for professionals from various disciplines [10-14]. Within this digital landscape, there has been a growing demand for efficient and dependable object detection methods. Object detection, the task of identifying and locating objects within images or videos, has found diverse applications in AEC, including safety management, quality control, inventory tracking, and site monitoring [15-20]. As construction sites become increasingly complex, the need for automation and real-time analysis has led to the exploration of advanced object detection techniques, resulting in the adoption of deep learning algorithms like YOLO and Faster R-CNN.

You Only Look Once, or YOLO, represents a breakthrough in object detection algorithms. Unlike conventional methods that involve multiple stages, YOLO approaches object detection as a regression problem, simultaneously predicting bounding boxes and class probabilities while spatially partitioning an image. This real-time processing capability makes YOLO an appealing choice for AEC applications, where timely decision-making is critical [21-24]. YOLO's capacity to process images swiftly without compromising accuracy has made it indispensable in scenarios like construction site monitoring, where real-time detection of safety hazards or unauthorized personnel can prevent accidents and enhance security measures [22,24]. Faster R-CNN, another cutting-edge object detection algorithm, introduced the concept of Region Proposal Networks (RPN) to generate potential object bounding box proposals. This innovation significantly improved the accuracy of object localization. Faster R-CNN combines deep convolutional neural networks with RPNs, enabling precise object detection and classification. In the realm of AEC, Faster R-CNN finds applications in various domains, such as progress tracking, where it can analyze construction site images to assess the completion status of different elements, ensuring projects adhere to schedules and budgets [25-29]. The algorithm's robustness and accuracy make it invaluable for tasks demanding high precision, such as detecting structural defects or monitoring equipment on construction sites [27,28-29]. Figure 1 shows the co-occurrence analysis of the keywords in literature.

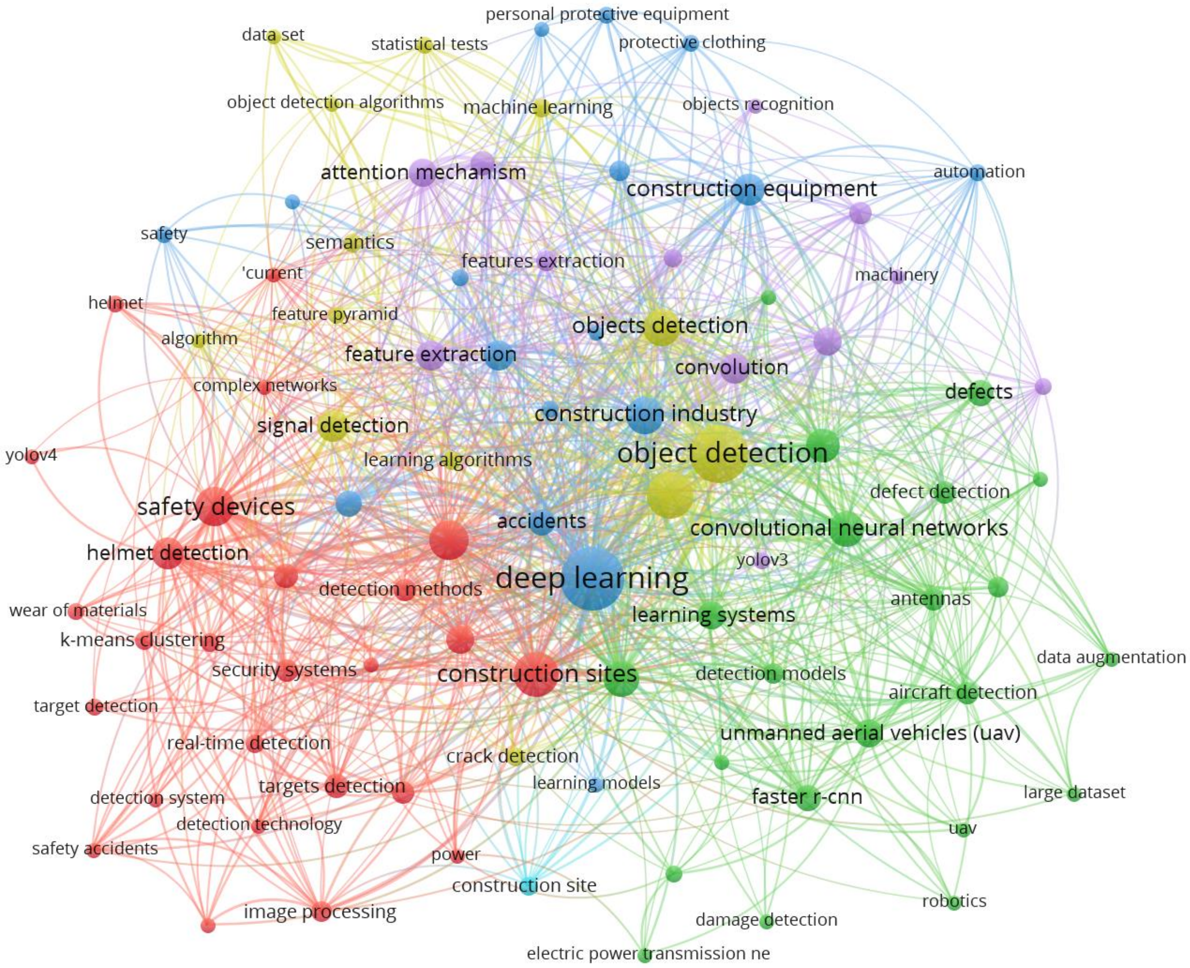

Figure 1 Co-occurrence analysis of the keywords in literature

Despite the remarkable performance of YOLO and Faster R-CNN in object detection tasks, several challenges persist in their application within the AEC industry [30-35]. One of the primary challenges lies in adapting these algorithms to handle the diverse and dynamic environmental conditions encountered on construction sites. Variability in lighting, weather, and occlusions poses challenges to the algorithms' reliability, requiring innovative solutions to enhance their robustness. Additionally, the availability of annotated data, a fundamental requirement for training deep learning models, remains a challenge in the AEC domain. Annotating construction site images with the level of detail necessary for training deep neural networks is a time-consuming and resource-intensive task, limiting the scalability of object detection applications.

Looking ahead, the integration of YOLO and Faster R-CNN object detection methods in the AEC industry holds immense potential [23,27,28]. As these algorithms continue to evolve, addressing the challenges related to environmental variability and data annotation will be pivotal. Collaborative efforts between researchers, industry professionals, and policymakers are essential to overcome these hurdles. Moreover, the combination of object detection with other emerging technologies such as augmented reality (AR) and unmanned aerial vehicles (UAVs) opens new avenues for applications in construction site visualization, remote monitoring, and project management. The synergy between object detection algorithms like YOLO and Faster R-CNN and the AEC industry has the power to revolutionize traditional practices, enhancing efficiency, safety, and overall project outcomes. This research paper explores the current landscape, challenges, and future prospects of these algorithms in the context of Architecture, Engineering, and Construction, shedding light on their transformative potential and inspiring further research and innovation in this exciting intersection of technology and industry.

Methodology

This research paper extensively explored the applications, challenges, and future prospects of YOLO (You Only Look Once) and Faster R-CNN (Region-based Convolutional Neural Networks) object detection techniques within the field of Architecture, Engineering, and Construction (AEC). The methodology primarily involved a thorough literature review, which encompassed a systematic analysis of existing research studies, scholarly articles, conference proceedings, and relevant publications related to object detection methods in the AEC industry. To compile relevant data, various academic databases such as IEEE Xplore, PubMed, Google Scholar, and Scopus were meticulously searched for peer-reviewed articles published. The search employed keywords and phrases like "object detection in construction," "deep learning in architecture," "AEC industry applications," and "YOLO and Faster R-CNN in Engineering." The inclusion criteria focused on studies centered on YOLO and Faster R-CNN object detection methods, their applications in AEC, challenges faced, and future research directions.

The gathered literature was systematically reviewed, categorized, and analyzed to identify prevalent themes, trends, and research gaps. Key findings, methodologies, and outcomes from each study were extracted and synthesized, offering a comprehensive overview of the state-of-the-art in YOLO and Faster R-CNN object detection techniques within the AEC domain. The analysis delved into challenges encountered in real-world implementations, comparative evaluations of the two methods, and potential avenues for future research and development. The synthesized information was critically evaluated to derive meaningful conclusions and insights regarding the effectiveness, limitations, and practical implications of YOLO and Faster R-CNN in AEC applications. Comparative analyses were conducted to highlight the strengths and weaknesses of each method, considering factors such as accuracy, speed, and scalability. The findings were interpreted in the context of existing literature, establishing connections between different studies to present a cohesive narrative on the topic.

Results and discussion

Significance of object detection in the AEC industry

Within the rapidly evolving landscape of the Architecture, Engineering, and Construction (AEC) industry, the adoption of cutting-edge technologies is crucial to ensure efficiency, accuracy, and safety in construction projects. Object detection, a key component of computer vision, has emerged as a transformative technology with profound implications in the AEC sector [17,18,20]. This section delves into the pivotal role of object detection in revolutionizing various facets of construction, highlighting its transformative impact on site analysis, safety protocols, project monitoring, design, and resource management.

Comprehensive Site Analysis and Surveying:

Object detection technology revolutionizes site analysis and surveying by automating the identification and classification of objects within construction sites. Drones equipped with object detection algorithms capture highresolution images, enabling precise mapping of the site. This automation provides engineers and project managers with valuable insights into existing structures, natural elements, and utilities. By expediting the decision-making process, object detection informs choices regarding site layout, drainage planning, and environmental considerations, leading to more informed and efficient decisions.

Enhanced Safety Protocols:

Safety is paramount in the AEC industry, and object detection technology ensures the well-being of construction workers. Wearable devices, integrated with object detection capabilities, monitor workers' activities in real-time. These devices can identify safety breaches, such as unauthorized access to hazardous zones or absence of appropriate safety gear, triggering immediate alerts for swift intervention. By automating safety monitoring, object detection significantly reduces the risk of accidents, creating a safer work environment.

Accurate Progress Monitoring and Quality Control:

Object detection technology offers a precise and efficient method for monitoring construction progress and maintaining quality standards. By analyzing on-site images and videos, object detection algorithms identify specific construction elements and compare them against the project’s Building Information Model (BIM). Early detection of deviations from the planned construction allows for timely corrections, ensuring adherence to the highest quality standards. This accuracy in progress monitoring prevents costly errors and rework, saving both time and resources.

Innovative Design and Planning:

In architectural design, object detection technology provides architects with a wealth of data influencing their creative process. Analysis of existing structures and environments offers insights into spatial constraints and architectural features. Object detection algorithms identify historical or cultural elements, enabling seamless integration into designs. This data-driven approach enhances the design process, ensuring the final structure harmonizes with its surroundings and fulfills the client's vision effectively.

Optimized Resource Management:

Efficient resource management is pivotal in construction projects, and object detection technology revolutionizes inventory management and material tracking. RFID tags or QR codes on construction materials can be scanned using object detection algorithms, providing real-time information about inventory levels. Automation in inventory management prevents overstocking or shortages, ensuring optimal resource utilization. By minimizing errors and optimizing resource usage, object detection significantly contributes to cost savings in the AEC industry.

The significance of object detection in the AEC industry lies in its ability to automate critical processes, enhance safety measures, provide real-time insights, maintain high-quality standards, and optimize resource utilization. By leveraging object detection technology, construction professionals can navigate modern construction projects with unprecedented efficiency and precision, ultimately shaping a safer, more streamlined, and innovative future for the AEC industry.

Applications of YOLO and Faster R-CNN object detection in the AEC industry

Recent years have brought about a notable transformation in the Architecture, Engineering, and Construction (AEC) industry, largely attributed to technological advancements. One of the key technological innovations driving this change is object detection algorithms [16,19]. These algorithms have significantly improved efficiency, accuracy, and safety within the industry. Notably, YOLO (You Only Look Once) and Faster R-CNN (Region-based Convolutional Neural Networks) have emerged as leading object detection algorithms, capturing widespread attention due to their outstanding performance and versatility [22,24,26,28]. This section explores the applications of YOLO and Faster R-CNN in the AEC sector, shedding light on how these algorithms are reshaping processes and fuelling progress.

Construction Site Safety and Monitoring:

Utilizing YOLO and Faster R-CNN algorithms proves pivotal in bolstering safety protocols at construction sites [36-39]. Equipping cameras with these algorithms allows for real-time safety monitoring. They proficiently detect the presence of safety gear like helmets, gloves, and harnesses on workers and monitor their positions and movements, ensuring compliance with safety guidelines. Moreover, these algorithms adeptly identify potential hazards such as unsecured scaffolding, exposed wires, or debris, enabling timely alerts to safety personnel and immediate corrective actions to prevent accidents and injuries.

Progress Tracking and Documentation:

In construction site management, YOLO and Faster R-CNN algorithms facilitate precise progress tracking. They identify and monitor the completion of specific construction phases by detecting installed elements like beams, columns, and walls, enabling construction managers to align progress with project schedules. Furthermore, such algorithms automate documentation by recognizing completed tasks and milestones, streamlining the process of generating progress reports [39-45]. This automation saves time, reduces human errors, and ensures the accuracy and reliability of project records.

Material and Equipment Tracking:

Construction projects involve the movement and usage of diverse materials and equipment [46-53]. YOLO and Faster R-CNN algorithms, when integrated with RFID tags, barcodes, or QR codes, enable real-time tracking of these resources. They identify and track the movement of construction materials, ensuring accurate delivery and optimal usage. Similarly, essential equipment like cranes and excavators can be monitored, preventing theft, optimizing usage, and ensuring timely maintenance. Real-time tracking enhances project efficiency, reduces costs, and minimizes delays caused by misplaced or unavailable resources.

Facility Management and Maintenance:

After project completion, YOLO and Faster R-CNN algorithms remain invaluable in facility management. They conduct regular inspections by analyzing images or video feeds, identifying wear and tear, structural issues, or damaged equipment. Early detection of maintenance needs allows proactive repairs, ensuring smooth facility operation and contributing to long-term infrastructure durability [54-57]. Facility managers can schedule maintenance activities based on the algorithms' data, preventing unexpected breakdowns and ensuring a safe environment for occupants.

Design and Planning:

During the design phase, architects and engineers rely on YOLO and Faster R-CNN algorithms to analyze images or scans of existing structures. These algorithms help identify and classify structural elements, enabling informed decisions on renovations, expansions, or modifications. This detailed analysis contributes to well-informed, practical designs, ensuring seamless integration with the existing environment. Table 1 shows the applications of YOLO and Faster R-CNN object detection in the AEC industry.

Augmented Reality (AR) and Virtual Reality (VR) Applications:

In AR applications, YOLO and Faster R-CNN algorithms enable the overlay of digital information onto physical structures, enhancing visualization of proposed designs on existing buildings. In VR environments, these algorithms enhance realism by accurately detecting and representing objects, creating immersive virtual experiences for stakeholders [58-62]. These applications aid in detailed walkthroughs, design evaluations, and simulations, enabling stakeholders to comprehend the project thoroughly before actual construction commences.

Automated Defect Detection:

Quality control is paramount, and YOLO and Faster R-CNN algorithms facilitate automated defect detection [63-67]. By analyzing images or scans, such algorithms swiftly identify defects such as cracks in concrete or structural deformities [68-73]. Automated defect detection ensures construction materials meet quality standards. Early identification enables prompt corrective measures, ensuring the overall quality and safety of the project.

Table 1 Applications of YOLO and Faster R-CNN object detection in the AEC industry

Application	**Description**	**YOLO Implementation**	**Faster R-CNN Implementation**	**Advantages**	**Challenges**
BIM (Building Information Modeling)	3D modeling and visualization of buildings and infrastructure projects.	Real-time object detection for creating BIM models from images and videos.	Integration into BIM software for accurate object recognition and modeling.	Real-time processing, Efficient resource use, Wide range of applications	Limited accuracy for complex structures, Limited scalability for large projects
Site Safety Monitoring	Monitoring and ensuring safety protocols on construction sites.	Real-time detection of safety violations such as unauthorized access and helmet detection.	Accurate detection of safety gear and potential hazards on construction sites.	Enhances safety compliance, Reduces accidents and liabilities, Remote monitoring	Weather and lighting conditions affecting accuracy, Privacy concerns due to surveillance
Construction Progress Monitoring	Tracking construction progress and comparing it with project timelines.	Monitoring construction activities and tracking completion status of different elements.	Detection of completed vs. pending tasks for progress assessment.	Real-time progress tracking, Automatic reporting, Improved project scheduling	Integration challenges, Data synchronization issues
Defect Detection	Identifying defects in construction materials and structures.	Real-time detection of defects such as cracks and deformations.	Detailed analysis of defects and severity, aiding in quick repairs.	Early defect detection, Reduced maintenance costs, Improved structural integrity	Training for specific defect types, Limited micro-level defect detection
Material Tracking and Management	Monitoring the movement and usage of construction materials.	Real-time tracking of materials on construction sites.	Identifying materials and tracking usage patterns for inventory management.	Efficient resource allocation, Reduced material wastage, Enhanced supply chain management	Barcode variations affecting accuracy, Integration with inventory systems
Environmental Monitoring	Monitoring environmental parameters on construction sites.	Detecting pollutants, emissions, and other environmental hazards in real-time.	Identifying environmental sensors and status for accurate data collection.	Timely detection of environmental issues, Compliance with regulations,	Limited detectable parameters, Calibration and sensor maintenance

				Improved site sustainability	
Augmented Reality (AR) in Design	Integrating virtual models with the real environment during the design phase.	Identifying physical elements in real-time for seamless integration of virtual and real-world elements.	Ensures accurate alignment of AR objects with physical structures for immersive experiences.	Enhanced design visualization, Improved collaboration, Real-time feedback	AR hardware limitations, Calibration and synchronization challenges

Environmental Monitoring:

Construction projects have environmental impacts, and these algorithms could monitor factors like air quality, noise levels, and water pollution [73-79]. Integrating sensors and cameras with YOLO or Faster R-CNN can help construction sites monitor their environmental impact, ensuring compliance with regulations.

Energy Efficiency Analysis:

YOLO and Faster R-CNN algorithms can analyze thermal images of buildings, detecting heat leaks, insulation gaps, or inefficient HVAC systems. This analysis contributes to energy audits, identifying areas for efficiency improvements and promoting the design of eco-friendly buildings, reducing long-term operational costs.

Predictive Maintenance:

Apart from identifying current defects, these algorithms can predict equipment or structure failures by analyzing historical data and detecting patterns. This proactive approach prevents costly downtime and extends machinery and infrastructure lifespan [80-83].

Documentation and Compliance Verification:

Automating the verification of construction activities' compliance with regulatory standards and project specifications is possible using these algorithms. By comparing real-time site conditions with plans and safety regulations, discrepancies can be identified, ensuring the construction aligns with legal requirements.

Disaster Response and Recovery:

In natural disasters, drones equipped with object detection algorithms can assess damage to buildings and infrastructure swiftly. This assessment helps emergency responders prioritize efforts and allocate resources effectively during disaster response.

YOLO and Faster R-CNN object detection algorithms have diverse applications in the AEC industry. From enhancing safety and monitoring progress to tracking resources, streamlining facility management, aiding in design, and enabling immersive AR and VR experiences, these algorithms significantly enhance various aspects of construction projects [17,19,20]. Their ability to automate tasks, improve accuracy, and provide real-time insights establishes them as indispensable tools in modern construction practices.

Challenges in Object Detection in AEC

Detecting objects is a fundamental task in computer vision, particularly within the Architecture, Engineering, and Construction (AEC) industry, where it finds diverse applications such as site monitoring, safety analysis, and progress tracking. YOLO (You Only Look Once) and Faster R-CNN (Region-based Convolutional Neural Networks) are prominent object detection algorithms employed in AEC [21,24,26,29]. However, these algorithms encounter several challenges when applied in real-world AEC scenarios.

Accuracy and Precision:

Achieving high accuracy and precision is a significant challenge in object detection within the AEC industry [17,20]. Construction sites exhibit objects of varying sizes, shapes, and textures. YOLO and Faster R-CNN must accurately identify these objects despite these differences. Precise detection is crucial, as misidentifying objects can lead to errors in project monitoring and safety analysis.

Scale Variation:

Construction sites feature objects at different scales, from small nuts and bolts to large construction equipment. Detecting objects across this wide range of scales is a challenge. YOLO and Faster R-CNN need to adapt to different scales while maintaining accuracy, a complex problem that researchers are addressing.

Occlusions and Clutter:

Dynamic construction environments often involve objects partially or fully obscured by other structures, objects, or environmental elements, leading to challenges in accurate identification. Additionally, clutter such as debris further complicates detection. YOLO and Faster R-CNN must robustly handle occlusions and clutter to be effective in real-world AEC scenarios.

Real-time Processing:

Timely detection of hazards is crucial in AEC applications, necessitating real-time processing. YOLO and Faster R-CNN must efficiently process images to meet these requirements. Achieving high accuracy in real-time scenarios demands optimized algorithms and hardware acceleration techniques without compromising precision.

Limited Training Data:

Training these deep learning models requires extensive annotated data. However, collecting diverse and extensive datasets in the AEC domain is challenging. Limited training data can lead to overfitting, where the model performs well on training data but fails to generalize to unseen data, posing a significant challenge.

Adapting to Weather Conditions:

Construction sites are exposed to various weather conditions, impacting object visibility. Adapting algorithms to work effectively under different weather conditions, such as rain or fog, is a challenge. Raindrops or fog can obscure objects, making detection difficult, necessitating robustness to adverse weather conditions.

Integration with Other Technologies:

Object detection in AEC often integrates with technologies like LiDAR and GPS. Seamless interoperability and compatibility with other systems add complexity to integration, requiring YOLO and Faster R-CNN to work harmoniously with these technologies.

Anomaly Detection:

Apart from predefined objects, AEC applications require identifying anomalies or unusual events on construction sites. Adapting YOLO and Faster R-CNN to effectively identify anomalies while maintaining low false positive rates is a challenge.

Cost and Resource Constraints:

Implementing sophisticated object detection algorithms demands significant computational resources, which might not always align with budget constraints and hardware availability in real-world AEC scenarios.

Ethical and Privacy Concerns:

Respecting privacy regulations and ethical considerations while implementing object detection systems on construction sites is paramount [84-90]. Balancing surveillance and safety needs with privacy concerns poses a challenge in designing and configuring these algorithms.

While YOLO and Faster R-CNN exhibit impressive capabilities, addressing these challenges is crucial for their successful implementation in the AEC industry. Ongoing efforts by researchers and practitioners aim to enhance the accuracy, robustness, and efficiency of these algorithms, paving the way for safer, more efficient, and technologically advanced construction practices [90-95].

Potential advances in object detection algorithms for AEC

Despite the challenges encountered, there are multiple potential advancements in object detection algorithms tailored for AEC applications, which can effectively tackle current limitations and bolster their capabilities [96-104].

Data Augmentation and Synthetic Data Generation: Researchers are currently exploring methods for augmenting existing datasets and creating synthetic data. Techniques like rotation, scaling, and flipping can diversify the training data, resulting in more robust models. The use of computer graphics for synthetic data generation can create lifelike training samples, reducing the necessity for labor-intensive manual labeling.

Transfer Learning: This approach entails training a model on a large dataset and then fine-tuning it for a specific task using a smaller dataset. This can significantly reduce the need for extensive labeled data for each unique AEC application. Pre-trained models can be adapted and fine-tuned for specific construction scenarios, saving both time and resources.

Multimodal Sensor Fusion: The integration of data from various sensors, such as LiDAR, cameras, and IoT devices, can offer a more comprehensive understanding of the construction environment. Multimodal sensor fusion allows object detection algorithms to leverage the strengths of different sensors, leading to improved accuracy and reliability, especially in challenging conditions.

Real-time Processing and Edge Computing: Advancements in hardware, including Graphics Processing Units (GPUs) and specialized AI chips, now allow for real-time data processing at the edge. Edge computing reduces latency and enables object detection algorithms to operate in real-time, making them suitable for applications where immediate responses are critical, such as safety monitoring and equipment tracking.

Explainable AI (XAI): Understanding the decisions made by object detection algorithms is vital for earning the trust of construction professionals and stakeholders. Explainable AI techniques offer insights into the model's decision-making process, making it easier to interpret and validate results. This transparency is crucial for building confidence in the technology.

Collaborative Robotics (Cobots): Object detection algorithms can be integrated with collaborative robotic systems to enhance automation in construction tasks. Cobots equipped with advanced sensors and object detection capabilities can work alongside human workers, increasing efficiency and safety on construction sites. These systems can detect and respond to the presence of workers or obstacles in real-time, preventing accidents and improving overall productivity.

Human-AI Collaboration: In complex construction projects, human expertise remains invaluable [105-109]. Object detection algorithms can be designed to work collaboratively with human professionals, assisting them in tasks that require pattern recognition and analysis. Human-AI collaboration can leverage the strengths of both humans and machines, leading to more accurate and efficient outcomes.

Future developments in object detection algorithms for AEC

Looking ahead, several exciting developments are anticipated in the field of object detection algorithms for AEC applications. Such developments have the potential to reshape the industry and unlock new possibilities for construction professionals [109-114].

Advanced Semantic Segmentation: Semantic segmentation algorithms go beyond object detection and classify each pixel in an image or point cloud into specific categories. Advancements in semantic segmentation techniques will enable a more detailed understanding of the construction environment, allowing for precise identification of objects and their attributes. This level of granularity is crucial for tasks like material tracking and quality control.

3D Object Detection and Recognition: Future developments will focus on extending object detection capabilities to 3D environments [115-121]. 3D object detection algorithms can analyze point clouds and voxel grids, providing accurate spatial information about objects in the construction site. This advancement is essential for applications like clash detection and construction progress monitoring in complex 3D structures.

Unsupervised and Self-Supervised Learning: These techniques allow algorithms to learn from unlabeled or partially labeled data. They can discover patterns and relationships in the data without explicit supervision, making them valuable for AEC applications where obtaining large labeled datasets is challenging. Unsupervised learning algorithms can identify anomalies and irregularities in construction sites, aiding in safety and quality inspections.

Edge AI and IoT Integration: The integration of AI algorithms with IoT devices and edge computing systems will become more seamless [122-130]. Edge AI platforms will process data locally on construction sites, reducing the need for extensive data transmission and enhancing real-time decision-making. IoT devices equipped with sensors and cameras will collect data, which will be processed by object detection algorithms at the edge, improving overall efficiency and responsiveness.

Robustness and Adaptability: Future object detection algorithms will be designed to adapt to dynamic and changing construction environments. These algorithms will be robust against variations in lighting, weather conditions, and occlusions. Adaptive algorithms can recalibrate themselves based on the environment, ensuring consistent performance in different scenarios. Robust and adaptable object detection systems are essential for real-world applications where construction sites are inherently unpredictable.

AI-driven Predictive Analytics: Object detection algorithms, coupled with predictive analytics, can forecast potential issues and risks on construction sites. By analyzing historical data and real-time information from object detection systems, AI models can predict equipment failures, optimize construction schedules, and anticipate safety hazards. Predictive analytics powered by object detection algorithms enable proactive decision-making, leading to cost savings and improved project outcomes.

Ethical and Social Implications: As object detection algorithms become more prevalent in the AEC industry, addressing ethical and social implications is crucial. Ensuring fairness and avoiding biases in algorithmic decisions are essential considerations. Ethical frameworks and guidelines will be developed to govern the use of AI in construction, promoting responsible and inclusive practices. Additionally, there will be a focus on educating construction professionals about the ethical implications of AI technologies, fostering awareness and understanding within the industry.

Conclusions

This research provides a thorough investigation into the utilization of sophisticated object detection methods within the Architecture, Engineering, and Construction (AEC) industry. The study delves into the practical applications, hurdles, and potential future advancements of employing YOLO (You Only Look Once) and Faster R-CNN (Region-based Convolutional Neural Networks) in the context of AEC, shedding light on their transformative impact on the planning, execution, and management of construction projects. The paper demonstrates the vast scope of applications for object detection algorithms, particularly YOLO and Faster R-CNN, in the AEC sector. These algorithms offer real-time solutions for tasks ranging from site monitoring and safety management to quality control and progress tracking. By facilitating automated detection and analysis of objects and activities within construction sites, these technologies empower AEC professionals to make informed decisions based on data, mitigate risks, and optimize resource allocation. This not only saves time and resources but also elevates the safety and quality standards of construction projects, leading to better outcomes for all stakeholders involved.

Nevertheless, the paper also emphasizes several challenges associated with implementing YOLO and Faster R-CNN in the AEC domain. One major obstacle is the requirement for high-quality, extensive datasets specifically annotated for construction sites. Training these algorithms necessitates diverse and representative data to ensure their accuracy and reliability in real-world scenarios. Additionally, integrating these technologies into existing workflows and processes poses a challenge, requiring not only technical expertise but also shifts in organizational culture and mindset. Addressing concerns related to privacy, data security, and ethical considerations is crucial to establish trust among stakeholders and ensure responsible use of these technologies. Despite these challenges, the future prospects of YOLO and Faster R-CNN object detection in AEC are promising. Advancements in technology are expected to enhance the sophistication, accuracy, and efficiency of these algorithms. Ongoing research and development endeavors are likely to tackle existing challenges, paving the way for seamless integration of these technologies into the AEC industry. The advent of 5G technology and the proliferation of Internet of Things (IoT) devices are anticipated to augment object detection algorithms by providing high-speed, low-latency connectivity and a wealth of data from various sensors and devices on construction sites. This convergence of technologies will further optimize the performance of YOLO and Faster R-CNN, enabling real-time collaboration, decision-making, and problem-solving in the AEC sector. The future of AEC with YOLO and Faster R-CNN object detection shines brightly, promising a paradigm shift that will redefine the way construction projects are conceived, executed, and delivered, ultimately benefiting society at large.

References

[1] Akinosho, T. D., Oyedele, L. O., Bilal, M., Ajayi, A. O., Delgado, M. D., Akinade, O. O., & Ahmed, A. A. (2020). Deep learning in the construction industry: A review of present status and future innovations. Journal of Building Engineering, 32, 101827.

[2] Alaloul, W. S., & Qureshi, A. H. (2021). Material classification via machine learning techniques: construction projects progress monitoring. In Deep Learning Applications. IntechOpen.

[3] Kim, J. M., Bae, J., Son, S., Son, K., & Yum, S. G. (2021). Development of model to predict natural disaster-induced financial losses for construction projects using deep learning techniques. Sustainability, 13(9), 5304.

[4] Egwim, C. N., Alaka, H., Toriola-Coker, L. O., Balogun, H., & Sunmola, F. (2021). Applied artificial intelligence for predicting construction projects delay. Machine Learning with Applications, 6, 100166.

[5] Rahimian, A., Hosseini, M. R., Martek, I., Taroun, A., Alvanchi, A., & Odeh, I. (2022). Predicting communication quality in construction projects: A fully-connected deep neural network approach. Automation in Construction, 139, 104268.

[6] Diwan, T., Anirudh, G., & Tembhurne, J. V. (2023). Object detection using YOLO: Challenges, architectural successors, datasets and applications. multimedia Tools and Applications, 82(6), 9243-9275.

[7] Liu, C., Tao, Y., Liang, J., Li, K., & Chen, Y. (2018, December). Object detection based on YOLO network. In 2018 IEEE 4th information technology and mechatronics engineering conference (ITOEC) (pp. 799-803). IEEE.

[8] Fang, W., Wang, L., & Ren, P. (2019). Tinier-YOLO: A real-time object detection method for constrained environments. IEEE Access, 8, 1935-1944.

[9] Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. Advances in neural information processing systems, 28.

[10] Moses, T., Heesom, D., & Oloke, D. (2020). Implementing 5D BIM on construction projects: Contractor perspectives from the UK construction sector. Journal of Engineering, Design and Technology, 18(6), 1867-1888.

[11] Wong, J., Wang, X., Li, H., & Chan, G. (2014). A review of cloud-based BIM technology in the construction sector. Journal of information technology in construction, 19, 281-291.

[12] Panteli, C., Polycarpou, K., Morsink-Georgalli, F. Z., Stasiuliene, L., Pupeikis, D., Jurelionis, A., & Fokaides, P. A. (2020). Overview of BIM integration into the construction sector in European member states and European Union Acquis. In IOP Conference Series: Earth and Environmental Science (Vol. 410, No. 1, p. 012073). IOP Publishing.

[13] Krasovskaya, O. A., Vyaznikov, V. E., & Mamaeva, A. I. (2021, November). Application of bim technologies as it projects for digital transformation in industry. In International Scientific and Practical Conference Digital and Information Technologies in Economics and Management (pp. 104-116). Cham: Springer International Publishing.

[14] Porwal, A., & Hewage, K. N. (2013). Building Information Modeling (BIM) partnering framework for public construction projects. Automation in construction, 31, 204-214.

[15] Liu, C., ME Sepasgozar, S., Shirowzhan, S., & Mohammadi, G. (2022). Applications of object detection in modular construction based on a comparative evaluation of deep learning algorithms. Construction Innovation, 22(1), 141-159.

[16] Kim, D., Kong, J., Lim, J., & Sho, B. (2020). A study on data collection and object detection using faster R-CNN for application to construction site safety. Journal of the Korean Society of Hazard Mitigation, 20(1), 119-126.

[17] Hevesi, P., Devaraj, R. C., Tschöpe, M., Petter, O., Elfert, J. N., Rey, V. F., ... & Lukowicz, P. (2021). Towards Construction Progress Estimation Based on Images Captured on Site. In Industrial IoT Technologies and Applications: 4th EAI International Conference, Industrial IoT 2020, Virtual Event, December 11, 2020, Proceedings 4 (pp. 141-161). Springer International Publishing.

[18] Lukowicz, P. (2021, March). Towards Construction Progress Estimation Based on Images Captured on Site. In Industrial IoT Technologies and Applications: 4th EAI International Conference, Industrial IoT 2020, Virtual Event, December 11, 2020, Proceedings (Vol. 365, p. 141). Springer Nature.

[19] Shrigandhi, M. N., & Gengaje, S. R. (2022, February). Systematic Literature Review on Object Detection Methods at Construction Sites. In International Conference on Expert Clouds and Applications (pp. 709-724). Singapore: Springer Nature Singapore.

[20] Mostafa, K., & Hegazy, T. (2021). Review of image-based analysis and applications in construction. Automation in Construction, 122, 103516.

[21] Del Savio, A. A., Luna, A., Cárdenas-Salas, D., Vergara Olivera, M., & Urday Ibarra, G. (2021). The use of artificial intelligence to identify objects in a construction site.

[22] Bhokare, S., Goyal, L., Ren, R., & Zhang, J. (2022). Smart construction scheduling monitoring using yolov3-based activity detection and classification. Journal of Information Technology in Construction, 27.

[23] Speer, B. (2011). First Known Use of QECBs will Save Yolo County at Least $8.7 Million Over the Next 25 Years, Energy Analysis (Revised)(Brochure) (No. NREL/BR-6A20-49450). National Renewable Energy Lab.(NREL), Golden, CO (United States).

[24] Morse, K., Kolegraff, S., & Kline, A. (2022). Initial perceptions of remote virtual inspections in the residential construction industry sector. EPiC Series in Built Environment, 3(1), 624-614.

[25] Kim, D., Kong, J., Lim, J., & Sho, B. (2020). A study on data collection and object detection using faster R-CNN for application to construction site safety. Journal of the Korean Society of Hazard Mitigation, 20(1), 119-126.

[26] Li, J., Zhou, G., Li, D., Zhang, M., & Zhao, X. (2023). Recognizing workers' construction activities on a reinforcement processing area through the position relationship of objects detected by faster R-CNN. Engineering, Construction and Architectural Management, 30(4), 1657-1678.

[27] Zhang, L., Zhang, Y., Zhang, Z., Shen, J., & Wang, H. (2019). Real-time water surface object detection based on improved faster R-CNN. Sensors, 19(16), 3523.

[28] Shamsollahi, D., Moselhi, O., & Khorasani, K. (2021). A timely object recognition method for construction using the mask R-CNN architecture. In ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction (Vol. 38, pp. 372-378). IAARC Publications.

[29] Tang, H., & Peng, L. (2022). Influence of Building Recognition of High-point Monitoring Image by the Optimized Faster R-CNN on Urban Planning. International Journal on Artificial Intelligence Tools, 31(02), 2250013.

[30] Liu, C., ME Sepasgozar, S., Shirowzhan, S., & Mohammadi, G. (2022). Applications of object detection in modular construction based on a comparative evaluation of deep learning algorithms. Construction Innovation, 22(1), 141-159.

[31] Lissmatz Van De Laak, M., & Ahmad, E. (2022). Change detection in drone-captured image data for the construction sector: Exploring the possibilities and obstacles of implementing automatic progress monitoring in a dynamic industry.

[32] Mostafa, K., & Hegazy, T. (2021). Review of image-based analysis and applications in construction. Automation in Construction, 122, 103516.

[33] Shamsollahi, D., Moselhi, O., & Khorasani, K. (2022). Construction Progress Monitoring and Reporting using Computer Vision Techniques–A Review. In ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction (Vol. 39, pp. 467-474). IAARC Publications.

[34] Liu, C. (2019). Implementation of Artificial Intelligence for Detecting Modular Objects in Construction (Doctoral dissertation, UNSW Sydney).

[35] Ducut, J. D., Alipio, M., Go, P. J., Concepcion II, R., Vicerra, R. R., Bandala, A., & Dadios, E. (2022). A review of electrical resistivity tomography applications in underground imaging and object detection. Displays, 73, 102208.

[36] Nain, M., Sharma, S., & Chaurasia, S. (2021, March). Safety and compliance management system using computer vision and deep learning. In IOP Conference Series: Materials Science and Engineering (Vol. 1099, No. 1, p. 012013). IOP Publishing.

[37] Shrigandhi, M. N., & Gengaje, S. R. (2022, February). Systematic Literature Review on Object Detection Methods at Construction Sites. In International Conference on Expert Clouds and Applications (pp. 709-724). Singapore: Springer Nature Singapore.

[38] Li, R. Y. M., Chau, K. W., & Ho, D. C. W. (2022). AI Object Detection, Holographic Hybrid Reality and Haemodynamic Response to Construction Site Safety Risks. In Current State of Art in Artificial Intelligence and Ubiquitous Cities (pp. 117-134). Singapore: Springer Nature Singapore.

[39] Seo, J., Han, S., Lee, S., & Kim, H. (2015). Computer vision techniques for construction safety and health monitoring. Advanced Engineering Informatics, 29(2), 239-251.

[40] Rane, N. L., Achari, A., Choudhary, S. P., Mallick, S. K., Pande, C. B., Srivastava, A., & Moharir, K. (2023). A decision framework for potential dam site selection using GIS, MIF and TOPSIS in Ulhas river basin, India. Journal of Cleaner Production, 138890. https://doi.org/10.1016/j.jclepro.2023.138890

[41] Rane, N. L., Achari, A., Saha, A., Poddar, I., Rane, J., Pande, C. B., & Roy, R. (2023). An integrated GIS, MIF, and TOPSIS approach for appraising electric vehicle charging station suitability zones in Mumbai, India. Sustainable Cities and Society, 104717. https://doi.org/10.1016/j.scs.2023.104717

[42] Gautam, V. K., Pande, C. B., Moharir, K. N., Varade, A. M., Rane, N. L., Egbueri, J. C., & Alshehri, F. (2023). Prediction of Sodium Hazard of Irrigation Purpose using Artificial Neural Network Modelling. Sustainability, 15(9), 7593. https://doi.org/10.3390/su15097593

[43] Rane, N. L., Anand, A., Deepak K., (2023). Evaluating the Selection Criteria of Formwork System (FS) for RCC Building Construction. International Journal of Engineering Trends and Technology, vol. 71, no. 3, pp. 197-205. Crossref, https://doi.org/10.14445/22315381/IJETT-V71I3P220

[44] Rane, N. L., Achari, A., Hashemizadeh, A., Phalak, S., Pande, C. B., Giduturi, M., Khan M. Y., Tolche A, D., Tamam, N., Abbas, M,, & Yadav, K. K. (2023). Identification of sustainable urban settlement sites using interrelationship based multi-influencing factor technique and GIS. Geocarto International, 1-27. https://doi.org/10.1080/10106049.2023.2272670

[45] Rane, N., & Jayaraj, G. K. (2021). Stratigraphic modeling and hydraulic characterization of a typical basaltic aquifer system in the Kadva river basin, Nashik, India. Modeling Earth Systems and Environment, 7, 293-306. https://doi.org/10.1007/s40808-020-01008-0

[46] Manavazhi, M. R., & Adhikari, D. K. (2002). Material and equipment procurement delays in highway projects in Nepal. International Journal of Project Management, 20(8), 627-632.

[47] Gomez Cabrera, A., Granados-Castillo, M. A., & Pérez-Cendales, I. K. (2015). Improving construction material and equipment logistics via simulation. Ingeniería y competitividad, 17(1), 85-94.

[48] Palomino-Valles, A., Tokumori-Wong, M., Castro-Rangel, P., Raymundo-Ibañez, C., & Dominguez, F. (2020, March). TPM maintenance management model focused on reliability that enables the increase of the availability of heavy equipment in the construction sector. In IOP Conference Series: Materials Science and Engineering (Vol. 796, No. 1, p. 012008). IOP Publishing.

[49] Horvath, A. (2004). Construction materials and the environment. Annu. Rev. Environ. Resour., 29, 181-204.

[50] Ive, G., & Gruneberg, S. (2000). The economics of the modern construction sector. Springer.

[51] Durdyev, S., Ismail, S., & Kandymov, N. (2018). Structural equation model of the factors affecting construction labor productivity. Journal of Construction Engineering and Management, 144(4), 04018007.

[52] Famiyeh, S., Amoatey, C. T., Adaku, E., & Agbenohevi, C. S. (2017). Major causes of construction time and cost overruns: A case of selected educational sector projects in Ghana. Journal of Engineering, Design and Technology, 15(2), 181-198.

[53] Chen, H., & Samarasinghe, D. A. S. (2020, February). The factors constraining the adoption of prefabrication in the New Zealand residential construction sector: Contractors' perspective. In Proc., New Zealand Built Environment Research Symp.

[54] Hautala, K., Järvenpää, M. E., & Pulkkinen, P. (2017). Digitalization transforms the construction sector throughout asset's life-cycle from design to operation and maintenance. Stahlbau, 86(4), 340-345.

[55] Palomino-Valles, A., Tokumori-Wong, M., Castro-Rangel, P., Raymundo-Ibañez, C., & Dominguez, F. (2020, March). TPM maintenance management model focused on reliability that enables the increase of the availability of heavy equipment in the construction sector. In IOP Conference Series: Materials Science and Engineering (Vol. 796, No. 1, p. 012008). IOP Publishing.

[56] Fregonara, E., & Ferrando, D. G. (2020). The stochastic annuity method for supporting maintenance costs planning and durability in the construction sector: A simulation on a building component. Sustainability, 12(7), 2909.

[57] Leong, T. K., Zakuan, N., Mat Saman, M. Z., Ariff, M., Md, S., & Tan, C. S. (2014). Using project performance to measure effectiveness of quality management system maintenance and practices in construction industry. The scientific world journal, 2014.

[58] Davila Delgado, J. M., Oyedele, L., Beach, T., & Demian, P. (2020). Augmented and virtual reality in construction: drivers and limitations for industry adoption. Journal of construction engineering and management, 146(7), 04020079.

[59] Ahmed, S. (2018). A review on using opportunities of augmented reality and virtual reality in construction project management. Organization, technology & management in construction: an international journal, 10(1), 1839-1852.

[60] Noghabaei, M., Heydarian, A., Balali, V., & Han, K. (2020). Trend analysis on adoption of virtual and augmented reality in the architecture, engineering, and construction industry. Data, 5(1), 26.

[61] Albahbah, M., Kıvrak, S., & Arslan, G. (2021). Application areas of augmented reality and virtual reality in construction project management: A scoping review. J. Constr. Eng, 14, 151-172.

[62] Safikhani, S., Keller, S., Schweiger, G., & Pirker, J. (2022). Immersive virtual reality for extending the potential of building information modeling in architecture, engineering, and construction sector: Systematic review. International Journal of Digital Earth, 15(1), 503-526.

[63] Situ, Z., Teng, S., Feng, W., Zhong, Q., Chen, G., Su, J., & Zhou, Q. (2023). A transfer learning-based YOLO network for sewer defect detection in comparison to classic object detection methods. Developments in the Built Environment, 15, 100191.

[64] Zuo, Y., Wang, J., & Song, J. (2021, July). Application of YOLO object detection network in weld surface defect detection. In 2021 IEEE 11th Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER) (pp. 704-710). IEEE.

[65] Qiu, Z., Wang, S., Zeng, Z., & Yu, D. (2019). Automatic visual defects inspection of wind turbine blades via YOLO-based small object detection approach. Journal of electronic imaging, 28(4), 043023-043023.

[66] Kou, X., Liu, S., Cheng, K., & Qian, Y. (2021). Development of a YOLO-V3-based model for detecting defects on steel strip surface. Measurement, 182, 109454.

[67] Zhou, Z., Lu, Q., Wang, Z., & Huang, H. (2019). Detection of micro-defects on irregular reflective surfaces based on improved faster R-CNN. Sensors, 19(22), 5000.

[68] Wang, M., Kumar, S. S., & Cheng, J. C. (2021). Automated sewer pipe defect tracking in CCTV videos based on defect detection and metric learning. Automation in Construction, 121, 103438.

[69] De Donato, L., Flammini, F., Marrone, S., Mazzariello, C., Nardone, R., Sansone, C., & Vittorini, V. (2022). A survey on audio-video based defect detection through deep learning in railway maintenance. IEEE Access.

[70] Carrera, D., Manganini, F., Boracchi, G., & Lanzarone, E. (2016). Defect detection in SEM images of nanofibrous materials. IEEE Transactions on Industrial Informatics, 13(2), 551-561.

[71] Garfo, S., Muktadir, M. A., & Yi, S. (2020). Defect detection on 3D print products and in concrete structures using image processing and convolution neural network. J. mechatron. robot, 4, 74-84.

[72] Kruachottikul, P., Cooharojananone, N., Phanomchoeng, G., Chavarnakul, T., Kovitanggoon, K., & Trakulwaranont, D. (2021). Deep learning-based visual defect-inspection system for reinforced concrete bridge substructure: a case of Thailand's department of highways. Journal of Civil Structural Health Monitoring, 11(4), 949-965.

[73] Meola, C., Di Maio, R., Roberti, N., & Carlomagno, G. M. (2005). Application of infrared thermography and geophysical methods for defect detection in architectural structures. Engineering Failure Analysis, 12(6), 875-892.

[74] Rane, N. L., & Jayaraj, G. K. (2022). Comparison of multi-influence factor, weight of evidence and frequency ratio techniques to evaluate groundwater potential zones of basaltic aquifer systems. Environment, Development and Sustainability, 24(2), 2315-2344. https://doi.org/10.1007/s10668-021-01535-5

[75] Rane, N., & Jayaraj, G. K. (2021). Evaluation of multiwell pumping aquifer tests in unconfined aquifer system by Neuman (1975) method with numerical modeling. In Groundwater resources development and planning in the semi-arid region (pp. 93-106). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-68124-1_5

[76] Moharir, K. N., Pande, C. B., Gautam, V. K., Singh, S. K., & Rane, N. L. (2023). Integration of hydrogeological data, GIS and AHP techniques applied to delineate groundwater potential zones in sandstone, limestone and shales rocks of the Damoh district, (MP) central India. Environmental Research, 115832. https://doi.org/10.1016/j.envres.2023.115832

[77] Rane, Nitin (2023) ChatGPT and Similar Generative Artificial Intelligence (AI) for Smart Industry: Role, Challenges and Opportunities for Industry 4.0, Industry 5.0 and Society 5.0. Available at SSRN: https://ssrn.com/abstract=4603234 or http://dx.doi.org/10.2139/ssrn.4603234

[78] Rane, Nitin (2023) Contribution and Challenges of ChatGPT and Similar Generative Artificial Intelligence in Biochemistry, Genetics and Molecular Biology. Available at SSRN: https://ssrn.com/abstract=4603219 or http://dx.doi.org/10.2139/ssrn.4603219

[79] Rane, N. L., Achari, A., & Choudhary, S. P. (2023) enhancing customer loyalty through quality of service: effective strategies to improve customer satisfaction, experience, relationship, and engagement. International Research Journal of Modernization in Engineering Technology and Science, 5(5), 427-452. https://www.doi.org/10.56726/IRJMETS38104

[80] Xu, W., Zhang, W., Xing, L., Lu, H., Li, D., & Du, Y. (2022, April). Deep learning-based safety behavior identification of operations and maintenance personnel on a substation. In NDE 4.0, Predictive Maintenance, and Communication and Energy Systems in a Globally Networked World (Vol. 12049, pp. 156-162). SPIE.

[81] Pham, D. L., & Chang, T. W. (2023). A YOLO-based real-time packaging defect detection system. Procedia Computer Science, 217, 886-894.

[82] Ashwathan, R., Asnath, V. P. Y., Geetha, S., & Kalaivani, K. (2022). Object Detection in IoT-Based Smart Refrigerators Using CNN. The Industrial Internet of Things (IIoT) Intelligent Analytics for Predictive Maintenance, 281-300.

[83] Chen, Z. H., & Juang, J. C. (2021). Attention-based YOLOv4 algorithm in non-destructive radiographic testing for civic aviation maintenance.

[84] Martínez, D. P., López-Batista, V. F., de Paz Santana, J. F., Moreno-García, M. N., & García, F. (2022, July). Object Detection Through Computer Vision. In International Conference on Disruptive Technologies, Tech Ethics and Artificial Intelligence (pp. 122-130). Cham: Springer International Publishing.

[85] Harichandana, B. S. S., Agarwal, V., Ghosh, S., Ramena, G., Kumar, S., & Raja, B. R. K. (2022, January). PrivPAS: A real time Privacy-Preserving AI System and applied ethics. In 2022 IEEE 16th International Conference on Semantic Computing (ICSC) (pp. 9-16). IEEE.

[86] Prabhu, B. B., Lakshmi, R., Ankitha, R., Prateeksha, M. S., & Priya, N. C. (2022). RescueNet: YOLO-based object detection model for detection and counting of flood survivors. Modeling Earth Systems and Environment, 8(4), 4509-4516.

[87] Diwan, T., Anirudh, G., & Tembhurne, J. V. (2023). Object detection using YOLO: Challenges, architectural successors, datasets and applications. multimedia Tools and Applications, 82(6), 9243-9275.

[88] Lee, J., & Hwang, K. I. (2022). YOLO with adaptive frame control for real-time object detection applications. Multimedia Tools and Applications, 81(25), 36375-36396.

[89] Lee, J., & Hwang, K. I. (2022). YOLO with adaptive frame control for real-time object detection applications. Multimedia Tools and Applications, 81(25), 36375-36396.

[90] Ferreira, M. V., Almeida, A., Canario, J. P., Souza, M., Nogueira, T., & Rios, R. (2021). Ethics of AI: Do the Face Detection Models Act with Prejudice?. In Intelligent Systems: 10th Brazilian Conference, BRACIS 2021, Virtual Event, November 29–December 3, 2021, Proceedings, Part II 10 (pp. 89-103). Springer International Publishing.

[91] Rane, N. L., Choudhary, S. P., Tawde, A., & Rane, J. (2023) ChatGPT is not capable of serving as an author: ethical concerns and challenges of large language models in education. International Research Journal of Modernization in Engineering Technology and Science, 5(10), 851-874. https://www.doi.org/10.56726/IRJMETS45212

[92] Rane, N. L., Tawde, A., Choudhary, S. P., & Rane, J. (2023) Contribution and performance of ChatGPT and other Large Language Models (LLM) for scientific and research advancements: a double-edged sword. International Research Journal of Modernization in Engineering Technology and Science, 5(10), 875-899. https://www.doi.org/10.56726/IRJMETS45312

[93] Achari, A., Rane, N. L., Gangar B., (2023). Framework Towards Achieving Sustainable Strategies for Water Usage and Wastage in Building Construction. International Journal of Engineering Trends and Technology, vol. 71, no. 3, pp. 385-394. Crossref, https://doi.org/10.14445/22315381/IJETT-V71I3P241

[94] Rane, Nitin (2023) Enhancing Mathematical Capabilities through ChatGPT and Similar Generative Artificial Intelligence: Roles and Challenges in Solving Mathematical Problems. Available at SSRN: https://ssrn.com/abstract=4603237 or http://dx.doi.org/10.2139/ssrn.4603237

[95] Rane, Nitin (2023) Transforming Structural Engineering through ChatGPT and Similar Generative Artificial Intelligence: Roles, Challenges, and Opportunities. Available at SSRN: https://ssrn.com/abstract=4603242 or http://dx.doi.org/10.2139/ssrn.4603242

[96] Er, M. J., Chen, J., Zhang, Y., & Gao, W. (2023). Research challenges, recent advances, and popular datasets in deep learning-based underwater marine object detection: A review. Sensors, 23(4), 1990.

[97] Er, M. J., Jie, C., Zhang, Y., & Gao, W. (2023). Research Challenges, Recent Advances and Benchmark Datasets in Deep-Learning-Based Underwater Marine Object Detection: A Review.

[98] Katkade, S. N., Bagal, V. C., Manza, R. R., & Yannawar, P. L. (2023, March). Advances in Real-Time Object Detection and Information Retrieval: A Review. In Artificial Intelligence and Applications (Vol. 1, No. 3, pp. 139-144).

[99] Zhou, Z., Wu, Z., Boutteau, R., Yang, F., Demonceaux, C., & Ginhac, D. (2023, May). Rgb-event fusion for moving object detection in autonomous driving. In 2023 IEEE International Conference on Robotics and Automation (ICRA) (pp. 7808-7815). IEEE.

[100] Cheng, G., Yuan, X., Yao, X., Yan, K., Zeng, Q., Xie, X., & Han, J. (2023). Towards large-scale small object detection: Survey and benchmarks. IEEE Transactions on Pattern Analysis and Machine Intelligence.

[101] Chirgaiya, S., & Rajavat, A. (2023). Tiny object detection model based on competitive multi-layer neural network (TOD-CMLNN). Intelligent Systems with Applications, 18, 200217.

[102] Liu, T., Zhang, L., Wang, Y., Guan, J., Fu, Y., Zhao, J., & Zhou, S. (2023). Recent Few-Shot Object Detection Algorithms: A Survey with Performance Comparison. ACM Transactions on Intelligent Systems and Technology, 14(4), 1-36.

[103] Zhang, D., Liang, D., Zou, Z., Li, J., Ye, X., Liu, Z., ... & Bai, X. (2023). A Simple Vision Transformer for Weakly Semi-supervised 3D Object Detection. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 8373-8383).

[104] Mao, J., Shi, S., Wang, X., & Li, H. (2023). 3D object detection for autonomous driving: A comprehensive survey. International Journal of Computer Vision, 1-55.

[105] Chowdhury, P. N., Bhunia, A. K., Sain, A., Koley, S., Xiang, T., & Song, Y. Z. (2023). What Can Human Sketches Do for Object Detection?. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 15083-15094).

[106] Liu, G., Zhang, J., Chan, A. B., & Hsiao, J. (2023). Human attention-guided explainable AI for object detection. In Proceedings of the Annual Meeting of the Cognitive Science Society (Vol. 45, No. 45).

[107] Tang, Y., Wang, B., He, W., & Qian, F. (2023). PointDet++: an object detection framework based on human local features with transformer encoder. Neural Computing and Applications, 35(14), 10097-10108.

[108] Chen, J., & Yanai, K. (2023, July). Qahoi: Query-based anchors for human-object interaction detection. In 2023 18th International Conference on Machine Vision and Applications (MVA) (pp. 1-5). IEEE.

[109] Wibowo, S., & Sugiarto, I. (2023). Hand Symbol Classification for Human-Computer Interaction Using the Fifth Version of YOLO Object Detection. CommIT (Communication and Information Technology) Journal, 17(1), 43-50.

[110] Rane, Nitin (2023) Enhancing the Quality of Teaching and Learning through ChatGPT and Similar Large Language Models: Challenges, Future Prospects, and Ethical Considerations in Education. Available at SSRN: https://ssrn.com/abstract=4599104 or http://dx.doi.org/10.2139/ssrn.4599104

[111] Rane, Nitin (2023) Role and Challenges of ChatGPT and Similar Generative Artificial Intelligence in Finance and Accounting. Available at SSRN: https://ssrn.com/abstract=4603206 or http://dx.doi.org/10.2139/ssrn.4603206

[112] Patil, D. R., Rane, N. L., (2023) Customer experience and satisfaction: importance of customer reviews and customer value on buying preference, International Research Journal of Modernization in Engineering Technology and Science, 5(3), 3437- 3447. https://www.doi.org/10.56726/IRJMETS36460

[113] Rane, Nitin (2023) Transformers in Material Science: Roles, Challenges, and Future Scope. Available at SSRN: https://ssrn.com/abstract=4609920 or http://dx.doi.org/10.2139/ssrn.4609920

[114] Rane, Nitin (2023) Contribution of ChatGPT and Other Generative Artificial Intelligence (AI) in Renewable and Sustainable Energy. Available at SSRN: https://ssrn.com/abstract=4597674 or http://dx.doi.org/10.2139/ssrn.4597674

[115] Pan, X., Xia, Z., Song, S., Li, L. E., & Huang, G. (2021). 3d object detection with pointformer. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 7463-7472).

[116] Wang, Y., & Ye, J. (2020). An overview of 3d object detection. arXiv preprint arXiv:2010.15614.

[117] Zhou, Y., & Tuzel, O. (2018). Voxelnet: End-to-end learning for point cloud based 3d object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4490-4499).

[118] Yin, T., Zhou, X., & Krahenbuhl, P. (2021). Center-based 3d object detection and tracking. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 11784-11793).

[119] Song, S., & Xiao, J. (2014). Sliding shapes for 3d object detection in depth images. In Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part VI 13 (pp. 634-651). Springer International Publishing.

[120] Mao, J., Shi, S., Wang, X., & Li, H. (2022). 3d object detection for autonomous driving: A review and new outlooks. arXiv preprint arXiv:2206.09474.

[121] Fidler, S., Dickinson, S., & Urtasun, R. (2012). 3d object detection and viewpoint estimation with a deformable 3d cuboid model. Advances in neural information processing systems, 25.

[122] Alahi, M. E. E., Sukkuea, A., Tina, F. W., Nag, A., Kurdthongmee, W., Suwannarat, K., & Mukhopadhyay, S. C. (2023). Integration of IoT-Enabled Technologies and Artificial Intelligence (AI) for Smart City Scenario: Recent Advancements and Future Trends. Sensors, 23(11), 5206.

[123] Knickerbocker, J. U., Budd, R., Dang, B., Chen, Q., Colgan, E., Hung, L. W., ... & Wen, B. (2018, May). Heterogeneous integration technology demonstrations for future healthcare, IoT, and AI computing solutions. In 2018 IEEE 68th electronic components and technology conference (ECTC) (pp. 1519-1528). IEEE.

[124] Katare, G., Padihar, G., & Qureshi, Z. (2018). Challenges in the integration of artificial intelligence and internet of things. International Journal of System and Software Engineering, 6(2), 10-15.

[125] Bibri, S. E., Alexandre, A., Sharifi, A., & Krogstie, J. (2023). Environmentally sustainable smart cities and their converging AI, IoT, and big data technologies and solutions: an integrated approach to an extensive literature review. Energy Informatics, 6(1), 9.

[126] Chavhan, S., Gupta, D., Gochhayat, S. P., N, C. B., Khanna, A., Shankar, K., & Rodrigues, J. J. (2022). Edge Computing AI-IoT Integrated Energy-efficient Intelligent Transportation System for Smart Cities. ACM Transactions on Internet Technology, 22(4), 1-18.

[127] Guergov, S., & Radwan, N. (2021). Blockchain convergence: Analysis of issues affecting IoT, AI and blockchain. International Journal of Computations, Information and Manufacturing (IJCIM), 1(1).
[128] Valanarasu, M. R. (2019). Smart and secure IoT and AI integration framework for hospital environment. Journal of IoT in Social, Mobile, Analytics, and Cloud, 1(3), 172-179.
[129] Bedi, P., Goyal, S. B., Rajawat, A. S., Shaw, R. N., & Ghosh, A. (2022). Application of AI/IoT for smart renewable energy management in smart cities. AI and IoT for Smart City Applications, 115-138.
[130] Esenogho, E., Djouani, K., & Kurien, A. M. (2022). Integrating artificial intelligence Internet of Things and 5G for next-generation smartgrid: A survey of trends challenges and prospect. IEEE Access, 10, 4794-4831.

Declarations

Funding: No funding was received.

Conflicts of interest/Competing interests: No conflict of interest.

Availability of data and material: Not applicable.

Code availability: Not applicable.

Acknowledgements: Not Applicable.