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TOPICAL REVIEW

Overview of Emerging Technologies for Improving the Performance of Heavy-Duty Construction Machines

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ABSTRACT Construction equipment is one of the most significant resources in large construction projects, accounting for a considerable portion of the project budget. Improving the performance of heavy machinery can increase efficiency and reduce costs. However, research on boosting the machine efficiency is limited. This study adopts a mixed review methodology (systematic review and bibliometric analysis) and evaluates emerging technologies such as digital twin, cyber physical systems, geographic information systems, global navigation satellite systems, onboard instrumentation systems, radio frequency identification, internet of things, telematics, machine learning, deep learning, and computer vision for machine productivity, and provides insights into how they can be used to improve the performance of construction equipment. This study defined three major equipment operating areas—monitoring and control, tracking and navigation, and data-driven performance optimization—classified technologies and explored how they can increase machine productivity. Other circumstantial issues affecting machine operation and loopholes in the existing innovative tools used in machine processes have also been highlighted. This study contributes to the goal of deploying digital tools and outlines future directions for the development of automated machines to optimize project efficiency.

INDEX TERMS Digital models, earthmoving, equipment productivity, mobile equipment, emerging, technologies, tracking, sensing.

I. INTRODUCTION

In recent years, practitioners and researchers have focused on improving the performance of the construction sector, which has a reputation for poor productivity, with only a 1% increase over the previous two decades [1]. Even though construction is one of the largest sectors in the world, accounting for 13% of global GDP, it continues to underperform, although the industry has not been in recession [2]. Construction efficiency gains of 50%–60% or more are expected to add \$1.6 trillion to the industry's value and increase global GDP [3]. Construction equipment is a company's greatest asset during a time crunch because it streamlines and provides the most assistance. As the global construction equipment industry is expected to develop at a compound annual growth rate (CAGR) of 3.9 percent from 2022 to 2030, the sector has enormous potential to add value to construction [4]. This is because the global increase in construction activity is projected to stimulate the demand for machines. Mega projects, such as roads, mines, dams, and open-pit mining, mostly rely on earth moving operations [2]. The performance of heavy machinery, such as excavators, loaders, and dump trucks, has a significant impact on the overall project efficiency. The growing popularity of electric construction equipment is projected to provide new income streams for original equipment manufacturers (OEMs) in the coming years [4]. Increasing heavy machinery utilization is crucial not only for productivity but also for cost management. Therefore, it is important to evaluate and improve the performance of construction machines to increase the productivity of the construction operations.

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Autonomous machine-working systems, which are used to replace workers to enhance productivity, have been employed in several fields. However, in comparison to them, the construction industry is still in the early stages of adopting such breakthroughs [5]. The traditional procedures used by construction projects to manage heavy-duty machinery operations may be one of the causes of poor efficiency in the industry [1]. The lack of skilled workers in utilizing innovative solutions is a challenge. Companies and workers are also reluctant to adopt innovative solutions, as they believe that they can complicate existing procedures by acquiring changes and disrupting existing workflows [6]. In addition, the high cost of critical gears, such as advanced excavators, cranes, and trucks, makes the industry more traditional [7]. In contrast, digital technologies such as artificial intelligence, big data, machine learning, and the Internet of Things (IoT) can improve the productivity of heavy-duty machinery operations owing to data-driven methodologies [8]. The urge to improve productivity and safety is driving the adoption of IoT in construction. IoTs allow real-time connectivity between a computer platform and actual construction sites [5], which can provide not only real-time monitoring and identification of heavy machinery for integrated fleet management and resource allocation, which is essential [10]; they also measure performance, analyze workflow, and reduce equipment-related injuries [8]. Further, the market for IoT in construction was valued at USD 7.8 billion in 2019 and is expected to grow at a CAGR of 16.5 percent to USD 16.8 billion by 2024 [9].

Several papers and extensive reviews have addressed new automated data acquisition, processing, and visualization methods for digital and real-time progress monitoring. Most studies have focused on heavy machinery management with an emphasis on equipment monitoring and localization (Table 1). Some studies have employed computer vision or sensor-based technologies to calculate earthmoving equipment productivity, while others have examined variables that influence efficiency. Although analyzing equipment productivity is crucial, and several authors have proposed solutions, research on assessing heavy machinery productivity using modern technology is minimal. This is because construction machine research, such as data collection and analysis, is still in its early phase. Another factor is that technologies are still under development and constantly evolving. Therefore, a complete literature review is required to evaluate equipment productivity and investigate new technologies. This paper provides an overview of emerging technologies for machine productivity and insight into how they can contribute to optimizing the performance of heavy-duty machines.

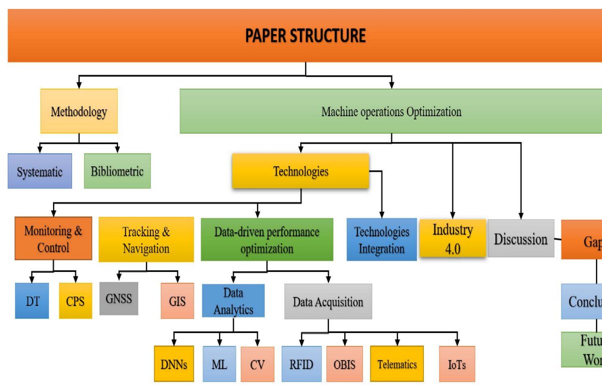
The authors collected literature from 2002 to 2022 using a composite review technique (bibliometric analysis and systematic review), studied the trends in this subject, and categorized the papers into main areas that are important to heavy-duty machinery. This study focuses on technologies that have been classified and examined in terms of their potential contribution to improving the machine performance. While monitoring the equipment, the authors discovered that various technologies can be combined to attain a specific target. Moreover, the authors discovered that, in addition to heavy machinery, personnel, materials, and even the activity itself are monitored for improved output. Our literature review aims to answer the following research question (RQ):

- RQ1: How can emerging technologies improve the performance of the heavy-duty construction machinery used in major construction projects?

To answer our main research question, we identified three research tasks (RT):

- RT1: To identify the areas of machine operation in which emerging technologies can potentially contribute to adding value?
- RT2: Which technology can be used for which specific area of machine operation?
- RT3: What are the existing challenges, and how can they be addressed using new technologies?

The remainder of this paper is structured as follows: The review technique and process are presented in Section 2 "*Review Method*." In Section 3, "*Emerging technologies*" for machine operation optimization (RT_1, RT_2) are discussed. Section 4, "*Technological Integration*," Section 5, "*Industry 4.0,*" Section 6, "*Discussion*" (RT_3), Section 7, "*Identified Gaps*," Section 8, "*Conclusion*". Finally, Section 9, gives "*Future Work*". Fig 1 illustrates the structure of the document.



DT: digital twin; **CPS:** cyber physical system; **RFID:** radio frequency identification; **CV:** computer vision; **GIS:** geographic information system; **ML:** machine learning; **OBIS:** onboard instrumentation system; **GNNS:** global navigation satellite system; and **DNNs:** deep neural networks

FIGURE 1. Article structure.

II. METHODOLOGY

Firstly, a systematic search of the literature was conducted using PRISMA protocol guidelines and bibliometric analysis. This was done by arranging the collected papers based on their keywords, document types, language, and so on. Second, bibliometric analysis was performed to improve the quality of the research and find research trends via quantitative analysis. Fig 2 illustrates the major phases of the review process.

TABLE 1. Related review papers and their contributions.

Focus area	Review article	Contributions
Automatic Equipment monitoring	Azar et al. [10]	Studied techniques for automated equipment monitoring. The equipment monitoring articles were classified into four categories: tracking, safety management, pose estimate, and remote control and autonomous operation. Outlined the future research perspective.
	Naskoudakis et al.[11]	Papers on equipment management were divided into seven categories: maintenance, productivity, operator competency, automation, innovation, environment, optimization.
	Zankoul et al. [12]	Reviewed publications related to Internet of Things (IoTs) applications in construction machinery.
Activity recognition (workers and equipment)	Sherafat et al. [13]	Analyzed worker and equipment activity recognition techniques using most up-to-date literature. Assessed the benefits and drawbacks of multiple activity detection systems. Classified approaches as audio-based, vision-based and kinematic-based.
Earthmoving equipment productivity monitoring	Chen, C. et al.[14]	Presented new automated construction equipment productivity monitoring technologies. Performed comparative analysis of multiple parameters for monitoring and control. Estimated earthmoving productivity Highlighted future solutions for equipment productivity monitoring
Equipment monitoring for project management	Nakanishi, Y. et al. [15]	Reviewed different papers on how to use construction equipment and monitor project management. Categorized studies by technology, purpose, and subject matter. Investigated how project management can be improved using construction equipment such as cranes.
Productivity monitoring	Wesam et al . [16]	Review articles for productivity monitoring (tools and techniques) and their implementation in construction projects. Analyzed methods based on photogrammetry, vision and audio.
Monitoring technologies	Ying et al. [17]	Evaluated sensor-based monitoring technologies for construction machines. Monitoring of oil pollution and leakage, vibration, emission, and entire system. Discussion on motion and IoT technology.
Equipment operations	This study	Identified three important facets of construction equipment's for performance improvement. Evaluated emerging tools and solutions by machine areas like tracking, navigation, control, and data acquisition. Limitations of existing tools and directions for further improvements.

A. SYSTEMATIC ANALYSIS

1) DATA ACQUISITION

A protocol for collecting articles was designed by reviewing studies that used various methodologies and technologies to measure the productivity of the construction equipment. The scope was set to articles in English published between 2002 and 2020 that dealt with heavy machinery productivity and technology in various construction projects.

2) DATABASE AND KEYWORDS

Five databases, Web of Science (WoS), Scopus, Science Direct, ACM, and IEEE Explorer, were chosen to compile the literature on innovative solutions for construction machinery. Google Scholar was used to obtain the citation counts of the collected articles.

The keywords were split into two categories: those connected to technology and those related to construction. Construction-related words are *autonomous, construction, equipment, operation, excavator, monitoring, management, building, project, efficiency, productivity, earthmoving, tracking,* and *optimization. Data visualization, information, modeling, mobile, machinery, digital, models, sensing, and analytics* are words used for technologies.

3) SEARCH STRATEGY

Table 2 lists the keywords used to perform these queries. Each keyword within a group was paired using the OR operator, whereas the groups were paired using the AND operator (Table 2). The last row of Table 2 shows how keywords from different groups are linked to create a query that was run in all five bibliographic databases. The query was used on the article title, article abstract, and article keywords to locate relevant articles from the five selected bibliographic databases published in English from 2002 to 2022.

TABLE 2. Selected keywords in different groups.

Group 1: Construction	Autonomous OR construction, equipment OR operation OR excavator OR monitoring OR management OR building OR project OR efficiency OR productivity OR earthmoving OR tracking OR optimization
Group 2: Technologies	Data OR visualization OR information OR modelling OR mobile OR machinery OR digital models OR sensing OR analytics
Search Query	(Group 1) AND (Group 2)

Using the established technique, a total of 1,980 papers published between 2002 and 2022 were collected. The maximum number of articles was published in the last five years, indicating that the subject is active in academia, and the publishing trend is growing (Fig 3). Maximum data collection was obtained from the Web of Science (WoS) and Scopus databases.

4) DATA FILTRATION

This stage was divided into four steps, as shown in Fig 4: identification, screening, article eligibility, and inclusion. The first step was to determine the number of publications in each database. The second step was screening, where the publications were screened for duplication, title, and abstract. Duplication was based on articles with the same titles that were re-selected by alternative keyword combinations from

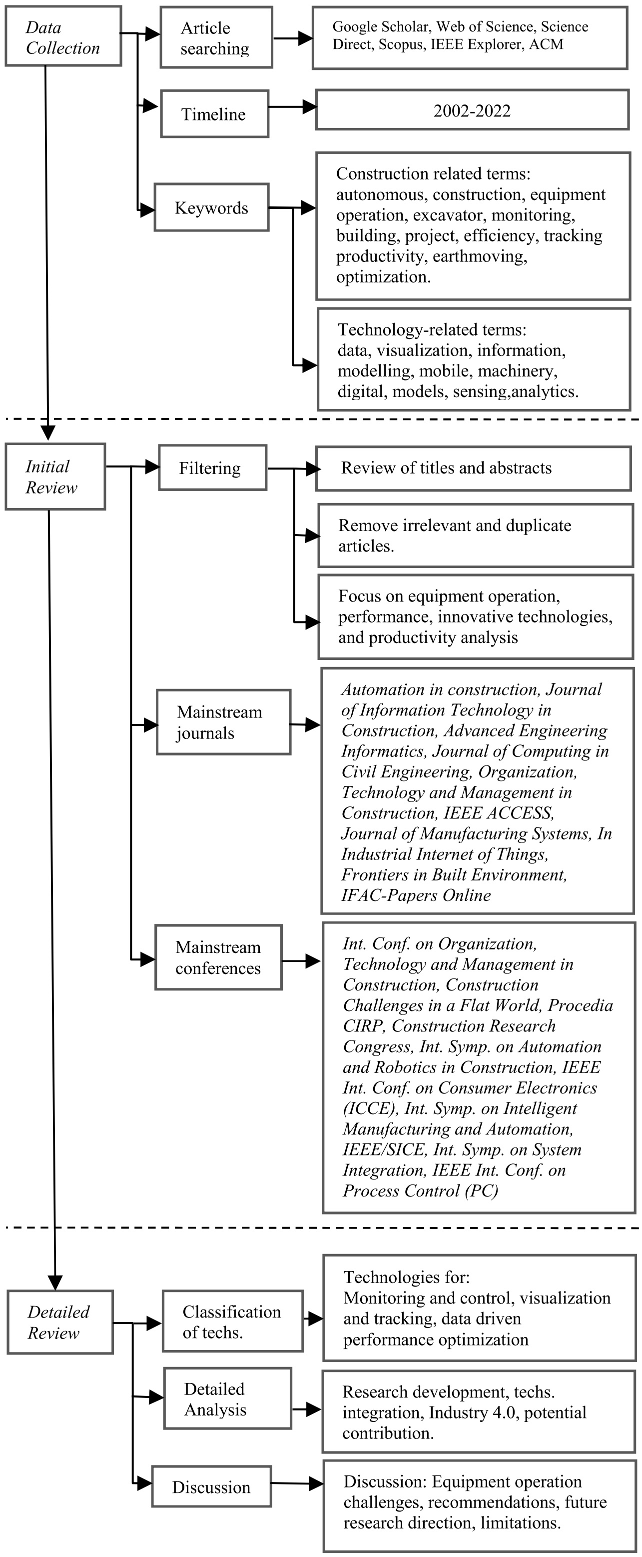


FIGURE 2. **Methodology review.**

the same database or other databases, and 855 publications were removed. Screening of titles and abstracts was used to filter out irrelevant articles. After evaluating the title of each article, screening was performed, and irrelevant studies were removed. In total, 510 irrelevant publications

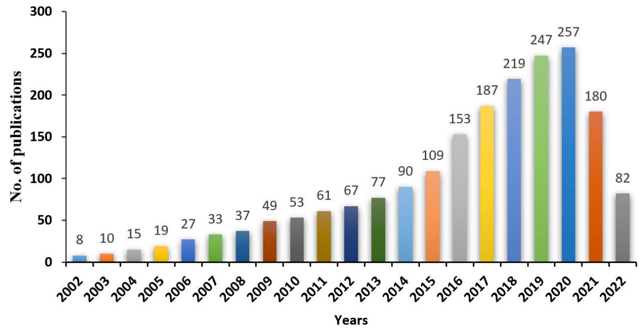


FIGURE 3. **Distribution of collected data (articles) published across the years.**

were eliminated. Subsequently, 440 irrelevant articles were eliminated by reviewing the abstract of each paper.

In the third phase, the full text eligibility for each article was carefully examined considering the tools and methodology used, resulting in a total of 88 articles being included and 87 publications being removed. Following the filtering procedures stated above, the number of publications included in each database yielded the following synopsis: Fig 4 displays 31 studies from WoS, 25 from Scopus, 11 from IEEE, 2 from ACM, and 19 from ScienceDirect.

B. BIBILIOGRAPHIC ANALYSIS

The articles from the selected publications were analyzed based on the keywords, sources of articles, and technological tools used for experimentation. The map of the selected publications was then evaluated based on the title and abstract to establish the correlation between words and the most frequent terms.

1) PUBLICATIONS DISTRIBUTION BY YEAR

Fig 5 illustrates the pattern of publications growing over time for the chosen period from 2002 to 2022, with a higher number of publications published between 2017 and 2022. This pattern indicates that innovation in this area is growing. The number of publications increased in 2018 with 17 articles showing an upward trend, indicating a growing volume of research on this topic.

2) PUBLICATIONS DISTRIBUTION BY JOURNAL/CONFERENCE

Collected publications were also analyzed for their sources to determine the distribution by journal/conference, as shown in Fig 6 and 7, respectively. Only 15 of the 88 papers were chosen from conferences, and the remaining 73 publications were found in journals. In addition, it was found that "Automation in Construction" had the highest number of articles among the selected journals and conferences with 18 records, followed by "Information Technology in Construction", "Journal of Computing in Civil Engineering", and "Advanced Engineering Informatics", with seven, five, and five records, respectively. In the conference category Construction Research Congress, IEEE, and ASCE

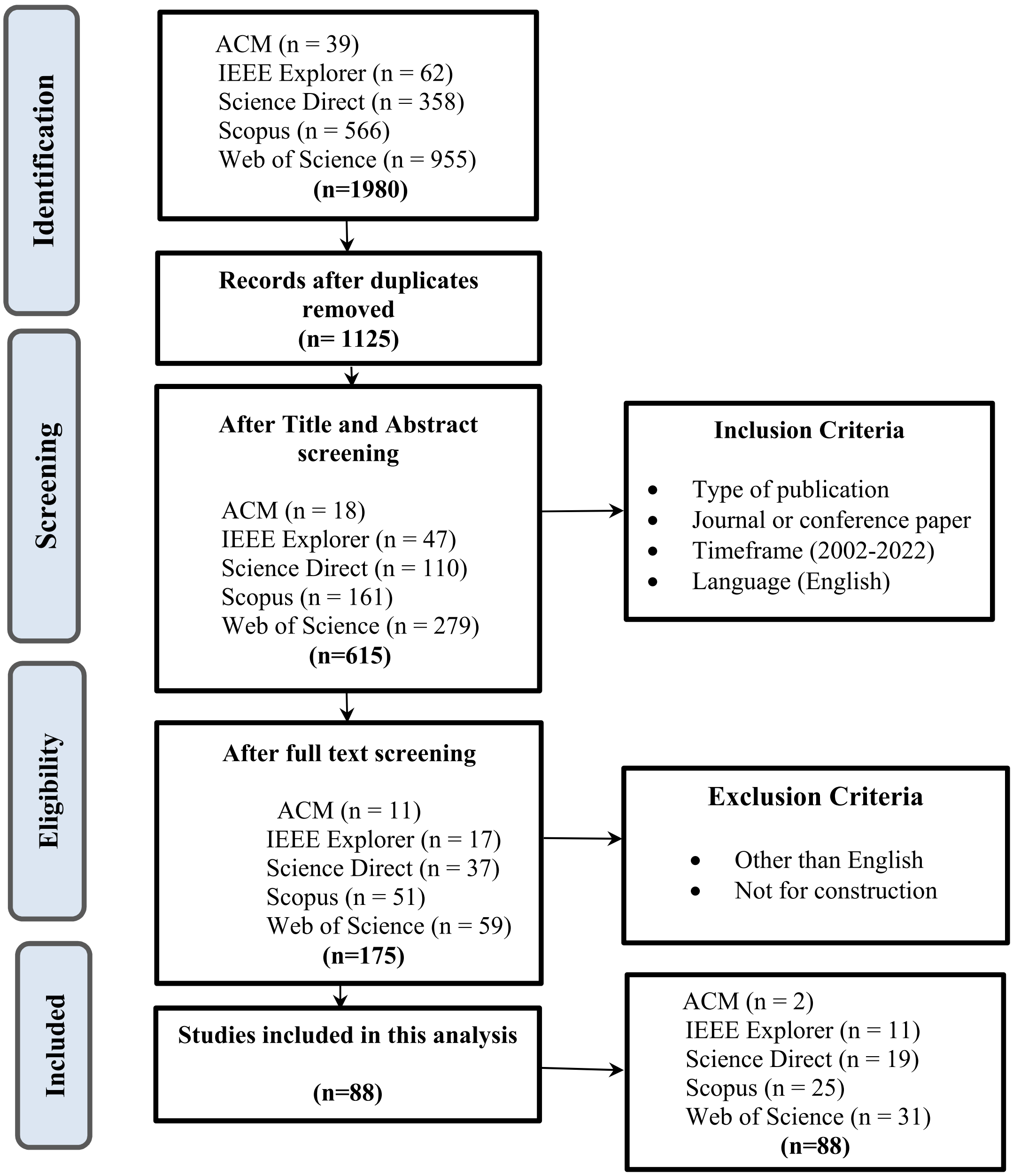


FIGURE 4. PRISMA search methodology.

have five, four, and four records, respectively, as shown in Fig 7.

3) PUBLICATION BY AREAS

The bibliographical network analysis of this manuscript led to the development of six subgroups. Based on data collection technology, there were 11 papers related to productivity measurement and evaluation, 13 papers focused on productivity monitoring, 8 papers related to performance enhancement, 10 papers on operation management, 9 papers on safety execution of operation, and 37 papers related to technologies and innovation. Fig 8 shows the percentage distributions of these districts. Various technologies such as digital twins, cyber-physical systems, telematics, machine learning, deep learning, IoTs, and building information modeling (BIM) have been studied to address the main RQ.

III. EMERGING TECHNOLOGIES

The use of information and communication technology (ICT) in construction projects has the potential to improve project efficiency [3]. Automation and robotics have recently been introduced in the construction industry. These approaches use a combination of computers, machine components, and software to systematically run the equipment [7]. These technologies are used to improve the work environment, health and safety, scheduling, product quality, and reduce on-site

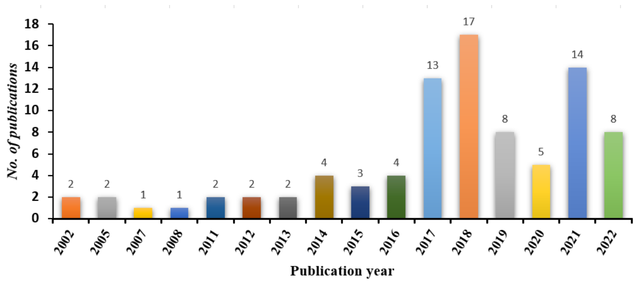
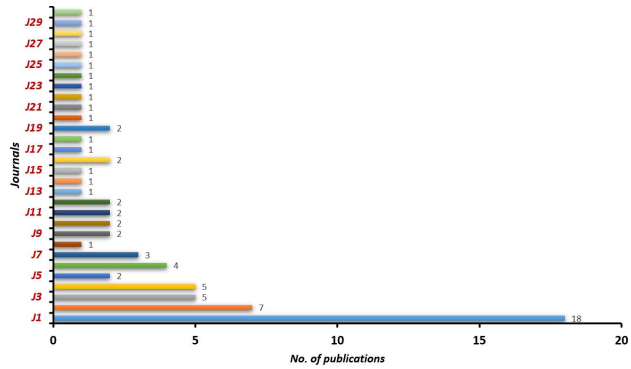
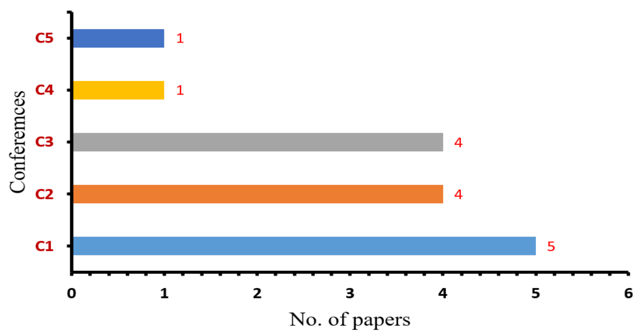


FIGURE 5. Distribution of collected publications over different years.



J1: Automation in Construction J2: Journal of Information Technology in Construction, J3: Advanced Engineering Informatics, J4: Journal of Computing in Civil Engineering, J5: Organization, Technology and Management in Construction, J6: Journal of Building Engineering, J7: Procedia Manufacturing, J8: Information (Switzerland), J9: Tunnelling and Underground Space Technology, J10: IEEE ACCESS, J11: Buildings, J12: Journal of Manufacturing Systems, J13: Information systems and e-business management, J14: Journal of Ambient Intelligence and Humanized Computing, J15: IFAC-Papers Online, J16: The International Journal of Advanced Manufacturing Technology, J17: Manufacturing Letters, J18: In Industrial Internet of Things, J19: Frontiers in Built Environment, J20: Sustainability 14, J21: Applied Sciences (Switzerland), J22: Journal of open innovations, J23: Visualization in Engineering, J24: Canadian Journal of Civil Engineering, J25: Journal of Construction Engineering and Project Management, J26: International Journal of Computer Science and Mobile Computing, J27: Journal of Civil Engineering and Management, J28: Sensors, J29: Rock and Soil Mechanics, J30: Expert Systems with Applications

FIGURE 6. Journals-based distribution of collected articles.



C1: Construction Research Congress; C2: IEEE/SICE; C3: American Society of Civil Engineers (ASCE); C4: DAAAM; C5: IOP

FIGURE 7. Conferences-based distribution of collected articles.

labor costs [7]. Workers can be replaced by machines that are significantly faster and more consistent when robotics and automation are used. Human exhaustion reduces project production, allowing machines to perform more work per day.

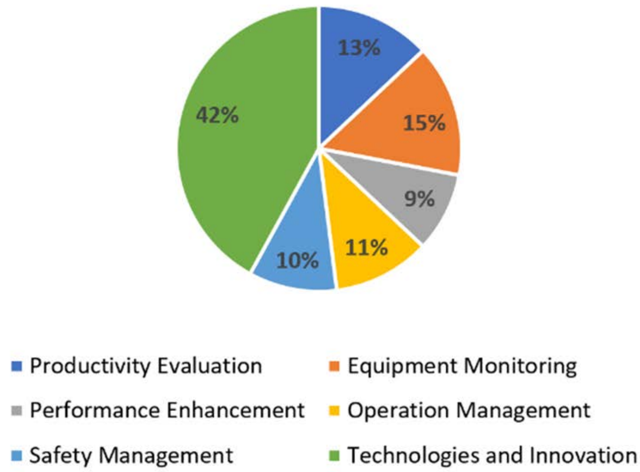


FIGURE 8. Area-wise distribution of collected data.

However, it is important to determine which technologies are used, how often they are used, and the environment in which they are used because on-site job circumstances vary in construction projects (RT_2). We have studied several technologies used in construction machinery to improve productivity. Fig 9 depicts the classification of technologies based on their potential for improving machine performance, which is covered in detail in the following subsections (RT_1 and RT_2).

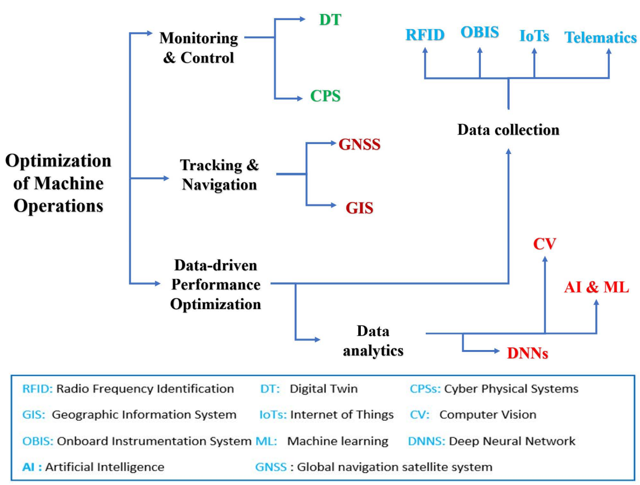


FIGURE 9. Distribution of technologies for optimizing construction equipment based on their characteristics.

A. MONITORING AND CONTROL

In comparison to construction, the manufacturing sector is more advanced in utilizing digital solutions, and research shows that most digitization processes in construction share challenges like those of manufacturing. The construction equipment industry has a well-established distribution network that employs comparable production methods [7]. Although researchers and practitioners are working on launching digitally equipped machinery, they have not succeeded in developing fully automated machines.

New cutting-edge technologies have the potential to significantly improve existing hardware [3].

1) DIGITAL TWIN (DT)

DT is the cyber-physical integration of systems, processes, or assets for virtual simulations, benchmarking, and testing [18]. The cyber-physical system (CPS) is an Industry 4.0 paradigm that can be used to build a DT [19]. DT serves as a link between the physical and virtual worlds, allowing for the collection of real-time entity data. DT aids companies in product creation, testing, budgeting, and process optimization, allowing them to increase the performance of their final products [18]. DT technology, particularly in smart construction, can play a vital role in Industry 4.0. Compared to traditional modeling techniques, this technology is more attractive owing to its distinct features, such as bidirectional communication, real-time self-management, and optimization. Table 3 summarizes the strengths, contributions, challenges, and potential services of DT for designing DT-based machinery. Although the ideas of DT and building information Modeling (BIM) seem to be similar to those of some academics, building professionals have pointed out distinctions. According to [20], they differ in various phases, including goals, capabilities, users, and development. BIM applications primarily focus on a corpus of construction knowledge and target construction clients. Several studies have been conducted to enhance the safety of construction equipment. These projects use technologies such as autonomous crane lifting route development, 3D operator information, operator warnings, and simulations to identify threats [21]. For prefabricated components (PCs) hoisting control, [22] developed a digital twin model (DTm) employing Dijkstra's algorithm to calculate hoisting routes using BIM data in the model. The lifting path was created after the worker obtained the material ID. Similarly, using 4D BIM models, cloud computing, database platforms, and real-time field data acquired by sensors and analyzed by artificial intelligence algorithms, [23] created a digital twin system to increase real-time safety monitoring. A complete database and an integrated 4D crane simulation and onsite operation management system for numerous contemporaneous mobile crane operations were designed in [24]. Similarly, [25] developed a BIM-based solution for the site layout and equipment monitoring. One approach for monitoring construction progress is to model the gap between projected and actual productivity on the ground in BIM [15]. For instance, [26] used a web-based operational mechanism to monitor precast work progress in real time and color-coded the status of the precast throughout production, material handling, on-site arrival, and installation using a BIM model. Moreover, it is possible to verify and explain delays in precast production and delivery by viewing domestic and field progress in real-time. This type of performance monitoring improves communication and cooperation between managers and field personnel [21].

DT can also be useful for tracking, regulating, and examining the equipment [18]. A digital entity has geometric dimensions, shapes, and other features that correspond to the real objects. DT has the potential to map the logic and rules used by physical entities and determine the past, present, and future of a physical entity (assets or processes) [27]. Moreover, in extreme circumstances during project execution or remote operations, where manual monitoring is challenging, DT can be anticipated to gain self-awareness and self-optimization as it offers two-way data exchange and control [18]. Thus, contractors can meet their daily objectives on dangerous or crowded building sites with the support of digital versions of machinery [27]. In addition to improving robustness, DT can assist practitioners and managers to save energy and other resources.

Although DT is a new technology, it is continually evolving and has not yet been developed in the construction industry. However, the literature reveals that researchers have suggested several DT designs to utilize this technology in automating machine operations in the manufacturing industry. Table 4 provides a summary of the scholarly research on DT in manufacturing management systems. Research on DT is still in its early stages, and numerous challenges and shortcomings must be resolved before DT can be broadly used in the construction sector. Modeling every unit of a real-world system requires significant computing power, data storage, and continuous data transmission and processing [28]. The infrastructure required to achieve a high degree of performance has not yet been achieved. Precision, accuracy, data collection, and synchronization are important for reliable simulations [29]. Therefore, real-time communication, sophistication, precision, connectivity, and architectural foundations are challenges that must be overcome before DTs can be used in practice [28]. The use of a secure, reliable, and rapid connection to transmit data in real-time is a well-known requirement. In addition, the technical components, protocols, and tools needed to build a DT or describe it as an all-encompassing technology are yet to be agreed upon [30]. Sophisticated technologies, such as wireless sensor networks, industrial artificial intelligence, blockchains, and transfer learning algorithms, can also be integrated to increase the functioning and capabilities of DT in different areas.

2) CYBER PHYSICAL SYSTEMs (CPS)

CPS combines informatics, real-time control subsystems, components, and human operators to affect physical processes through collaboration and a partially automated control mechanism [5]. One of the primary distinctions between DT and CPS is that CPS embeds a system-level thinking approach based on networked products and functions (integrating the connectivity principle), whereas DT is an engineering system that drives new abilities to design, execute, maintain, and develop new services to optimize its worth [30]. CPS includes the coupling of physical systems with their digital replicas via sensors and actuators, whereas DT provides a digital copy of the facility as designed and implemented [34]. Table 5 presents the typical CPS architecture. As automated mobile machinery is more appealing for operation in restricted work zones and is owned by different stakeholders, this technology offers simpler fleet-coordination setups.

TABLE 3. Strengths, contributions, issues, and potential usage of DT for improving machine performance.

Digital Twin in construction industry		
Strengths & contributions	Shortcomings	Machines optimization
Advanced level innovation [19]; Industry 4.0 standards [18]; Supports smart city initiatives [27]; Bidirectional communication [18]; Self-management [20]; Provides real-time optimization [31]; Can be used in extreme circumstances [32]; Like, overpopulated or hazardous construction sites e.g., tunneling [20], mining [30] etc.	Novice technology, under evolution [33]; Lack of understanding in construction especially confused with BIM [20]; Lack of benchmark [33]; Complex implementation [20].	Effective for two ways data exchange [20]; Data codification [19]; Useful for tracking [32]; Regulating self-awareness [30]; Offers self-optimization [30]; Potential integration with Blockchain [34], IoTs [35], fuzzy analysis [34], data mining [20], ML [33], big data [20], robotics [30], DL [33]; Supports high fidelity simulations [27]; Useful for smart manufacturing [18], [19].

ML : Machine Learning, **DL**: Deep Learning

Collectively, these characteristics make mobile equipment situations intriguing for automation, and certain solutions show economic viability. Earthmoving equipment generally uses electrohydraulic automated control systems with position detectors that provide digital outputs when required. Tractors, graders, scrapers, and back hoes, among other construction and agricultural machinery, are now fitted with electronic control systems such as telematics for excavation operations [1], [5]. The primary function of these machines and their systems is to measure the topography, cutting, and filling of high and markedly low areas. To perform these duties, a machine must be able to assess and manage the height and thickness of a material [10]. Table 6 outlines the potential advantages, design problems, and smart machine-based applications using DT technology.

Because on-site crosslinking of single-value processes is becoming more significant in construction projects [35], future construction processes will require rapid adaptation to counter unfavorable situations. The CPS can address these challenges in the development of mobile machines. Future transformation of communication strategies will require the classification of data in mobile machinery into time dependency, data relevance, and the degree of data collection and consumption. Fig 10 shows the key technologies and algorithms for creating CPS-based mobile machinery in the construction sector [33]. Data and algorithms constitute the virtual world. The data represent the storage information. This storage may be on a CPS central server or decentralized server network. The algorithms process information accessible via bidirectional transfer from existing data or a connecting interface, including the HMI from sensors. The CPS is essential for the development of mobile machines. CPS

TABLE 4. Literature review of articles illustrating DT implementation.

authors	objectives	scope	data acquisition		DT services
			dataset	protocol	
Olivotti et al. [31]	Designed installer base management system (IS).	SMP	UML	OPCUA	a. Real-time state monitoring (I) b. Failure analysis & prediction/maintenance (C)
Liu et al. [32]	Designed novel digital twin-based approach for reusing and evaluating process knowledge. (IS).	SMP + P	XML	OPC	a. Real-time state monitoring (I) b. Analysis for optimization (I)
Haag et al. [33]	Designed cyber-physical bending beam test bench (LP).	SMP + P	MQTT	NG	a. Real-time state monitoring (I) b. Failure analysis & prediction/maintenance (I)
Luo et al.[36]	Designed an automated flow-shop manufacturing systems (IS).	PL	NG	OPC	a. Real-time state monitoring (I) b. Analysis for optimization (C)
Avventuroso et al. [37]	Supply chain management support through data monitoring (IS).	SMP + PL	NG	OPC	a. Real-time state monitoring (I) b. Analysis for optimization (I)
Souza et al.[38]	Supply chain management support through data monitoring (LP).	SMP + PL	XML	OPCUA	a. Real-time state monitoring (I) b. Analysis for optimization (I)
Angrish et al.[39]	Designed system architecture for the virtualization of manufacturing machines (VMM) (NG).	EP + P	Mongo DB database	API function	a. Real-time state monitoring (I) b. Failure analysis & prediction/maintenance (C)
Beregi et al.[40]	Integrating multiple dynamic simulations (LP).	SMP + PL	NG	TCP/IP	a. Real-time state monitoring (I) b. Failure analysis & prediction/maintenance (C)
Botkina et al.[41]	Monitoring a machine tool (NG).	EP	NG	ISO13399 for cutting tools-holder	a. Real-time state monitoring (I) b. Failure analysis & prediction/maintenance (C)
Cai et al. [42]	Monitoring a machine tool (LP).	EP	Dataset description	Compiled C++ program	a. Real-time state monitoring (I) b. Failure analysis & prediction/maintenance (C)
Petr Janda. [43]	Developed a DT based virtual model of heavy machine tool in real-time.	SMP + P	NG	Internal connection Profinet	a. Real-time state monitoring (I) b. Analysis for optimization (I)
Vachalek et al.[44]	Continuous optimization of production processes, proactive maintenance, and managing process data (LP).	PL	NG	OPC	a. Real-time state monitoring (I) b. Analysis for optimization (I)
Wei et al. [45]	Designed a data acquisition system for heterogeneous machines using sensor based I/O module (IS).	SMP	MySQL Database	ODBC	a. Energy consumption monitoring(I) b. Analysis for optimization (C)
Guo et al.[46]	Proposed a simulation model for monitoring machine states and their relative energy consumption to perform analysis (IS).	PL+P	NG	Simens vendor protocol	a. Real-time state monitoring (I) b. Analysis for optimization (I)

I: Implemented, C: considered, SMP: station/single machine or process, PL: production line, P: product, EP: equipment piece, IS: Industrial system, LP: laboratory production, NG: not given

upgradation in construction machinery can potentially lower overall construction expenses by 20–30% [34], [35]. The algorithms shown in Fig 10 can reduce fuel costs and heavy machine moving times by 40% and 50%, respectively [35]. Compared to other sectors that have already embraced Industry 4.0, CPS can increase construction productivity by a factor of three [35]. This technology can also promote small farms and businesses, leading to the formation of a new industrial sector.

TABLE 5. Fundamental structural and functional components of a CPS.

	Components	Description
CPS	Networking and communication	Communication between devices and processes; protocols, standards, and data formats enabling end-to-end connectivity [18].
	Computation, processing, and control	Diagnostics and decision making at many levels of hierarchy based on simultaneous summations of current system status [30].
	Physical output peripherals	Low-level system hardware like actuators, and high-level system hardware like machines and robots [19].
	Inputs from sensors and monitoring devices	Localization and positioning systems with integrated and external sensing methods [34].
	Visualization and interaction interfaces	Interactive user interfaces that display current system status on a screen, wearable, or head-mounted display [35].

B. MACHINE TRACKING AND NAVIGATION

Tracking the operational efficiency of construction machinery improves its productivity and sustainability [47]. Automated assessment of construction equipment efficiency offers crucial information for finding ways to boost productivity and reduce environmental impacts [2]. However, conventional project site progress monitoring approaches are inaccurate and time-consuming to collect and evaluate data because they rely heavily on manual procedures. One of the key variables causing project delays and budgets was identified as a flaw in this strategy [49]. Traditional management approaches have raised key concerns such as shorter monitoring periods, inadequate reporting methodologies, and poor quality of manually obtained data [15]. However, in recent years, a variety of new automated data collection, processing, and visualization technologies have been employed to develop approaches for digitized, real-time progress monitoring. Several articles and comprehensive reviews have addressed these initiatives. The authors examined systems based on two prominent navigation technologies from the perspective of construction equipment tracking to monitor productivity.

1) GEOGRAPHIC INFORMTAION SYSTEM (GIS)

Real-time monitoring and positioning of heavy machinery is useful in many construction and mining operations [10]. It enables integrated asset tracking and active distribution of resources in large construction places. Additionally, geospatial data can be utilized to analyze machine activities and, as a result, evaluate the efficiency [50]. New prospects for intelligent administration of earthmoving operations have surfaced with the introduction of smartphones. These devices are integrated with multiple sensors connected to an internet

TABLE 6. Potential properties, design issues and application of CPS.

Cyber Physical Systems (CPS)		
Properties	Design Challenges	Potential applications and machine-based services
1.Host computation, perform data analysis and onboard simulations [44]. 2.Monitoring, control, and communication [20]. 3.Support construction 4.0, like smart building, smart city etc. [18], [19]. 4.Easy integration with IoTs, represents system like machine to machine (M2M) connectivity, smart grid etc. [5], [27]. 5.Allows bidirectional communication [34]. 6. Supports data collection and construction of DT model [41]. 7. Replication of production system in cyber world [27].	1.Vulnerable to cybersecurity [30]. 2.Complex inter-dependency between cyber and physical systems [34]. 3.Lack of benefit quantification [35]. 4.Production outages due to nonavailability of data [20]. 5.Simulation constraints restricted to CPS boundaries (e.g., a single workstation) [44].	1.Urban transportation: Smart vehicles like driverless cars, buses, and trains etc. [5]. 2.Logistics: trucks, boats, and drones etc. [5]. 3.Farming /mining / construction: mobile machinery, fleet coordination [5]. 4.Real-time synchronous simulation of physical equipment e.g., machines [5]. 5.Smart connected objects for earthmoving equipment [44]. 6.Potential contribution in construction by creating digital replicas of real-world processes in real time [33].

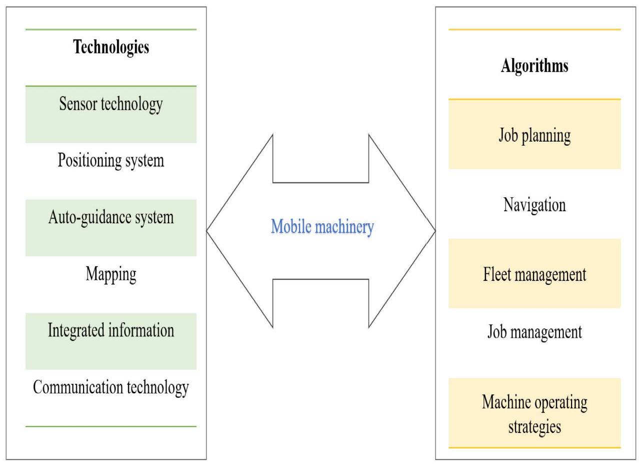


FIGURE 10. Technologies and algorithms for designing CPS-based mobile construction machinery [35].

global positioning system (GPS), accelerometer, three-axis gyroscope, etc., and can function as standalone computers through multiple connectivity options, including wireless, Wi-Fi, and Bluetooth [51]. GPS and GIS integrated solutions increased effective construction equipment operating hours and decreased construction duration and labor costs [50]. GIS can visually analyze spatial information, accurately predict, and analyze schemes, and evaluate geographical data in the real world [52]. Moreover, the integration of GPS and GIS technology has proven to be an effective and easy way to anticipate the time and cost required for transportation asset operations [53]. For example, using GPS and GIS [53], a method for tracking and estimating the performance of a hauling unit was developed. Similarly, [50] created a Wi-Fi-based indoor localization and communication system called the voice communication and locating system (VCLS) and integrated it with BIM and GIS. BIM and GIS were used to monitor the mobile devices and personnel in the planned region. Using GPS/GIS technology to automate site data collection, [54] proposed a technique for probabilistic forecasting of earthmoving productivity using discrete event simulation (DES). Similarly, [51] designed a prototype for construction material and equipment (M&E) management onsite by connecting GIS and GPS to the M&E system based on a wide area network (WAN) to decrease construction waste and improve project efficiency by barcoding an automated data collection tool.

2) GLOBAL NAVIGATION SATELLITE SYSTEM (GNSS)

Deployment of a global navigation satellite system provides accurate and timely positioning. Machines and vehicles can be located in a designated area such as a job site. Most positioning systems for objects are based on measuring the distance [54]. Positioning systems depend on the well-known evaluation of distance signals and translation of data into position information to work correctly [51]. It relies on the distance and type of transmitter and receiver carriers [35]. GNSS is an example of a positioning technology that acts as a carrier by constantly delivering signals [13].

The two most prominent GNNS technologies are the American-based GPS and the Russian-made GLObal'naya NAvigatsionnaya Sputnikovaya Sistema (GLONASS) [52]. GPS has revolutionized navigation. It offers dependable and durable solutions for tracking and monitoring the equipment [10]. However, these methods have certain limitations. Because every piece of equipment must be labelled, this might be troublesome when employing rental equipment or subcontractors, and spatiotemporal data may not be adequate for activity identification, necessitating multimodal sensing [10]. Similarly, for highway construction, GPS was proven to be more reliable and effective for collecting data [53]; however, inconsistencies occurred in GPS data owing to objects that eventually blocked the connection between the GPS receiver and satellites. Compared to the onboard instrumentation system, GPS offers several benefits in terms of poor productivity tracking. For example, GPS can distinguish idle time from activity duration, collect large amounts of data, accurately describe operating situations, and distinguish between truck loading and dumping times [49]. Another difference is that onboard instrumentation can only record the total travel time, whereas GPS data can be used directly to calculate the hauling and return times [54]. Although GPS monitoring offers various advantages, it also requires the collection of large amounts of data, which can make the project manager's work more difficult because of the need to organize, process, and evaluate the collected data [53]. Table 7 summarizes several studies that have used GPS to monitor the productivity and utilization of different types of equipment.

TABLE 7. Methods based on GPS sensors for recognizing equipment operation and analyzing productivity.

Ref.	Objective	Sensors used	Monitoring Units
Vasenev et al.[49]	Developed a framework to process sensor data collected from construction site.	GPS, IMU, temperature	Roller location (track equipment in the field).
Alshibani et al.[53]	Integrated GPS data and a GIS system to monitor and manage earthmoving equipment.	GPS	Truck: load, haul, dump, return.
Pradhananga et al.[54]	Detected work areas, cycle activities, and machine vicinity using low-cost GPS and spatiotemporal analysis.	GPS	Steer loader: haul, return, unload, cycle, Speed.
Teizer et al. [55]	Used machine data and site layout modifications during project to create a cell-based simulation of earthmoving activities.	GPS	Steer loader: haul, return, unload, cycle, Speed.
Vahdatikhaki et al. [56]	Used the RTLS (with GPS and UWB) on a dump truck and an excavator to construct near real-time simulations of their operational states.	GPS, UWB	Excavator: relocation, swing to load, loading, swing to truck, dumping Truck: maneuvering for dumping, returning, maneuvering for loading, hauling.
Han et al. [57]	Proposed an approach for estimating productivity and unit costs utilizing real data collection, creation, simulation, and multiple regression analysis.	GPS	Truck : dump, load, haul, return.
Montaser et al.[58]	Used GPS data and Google Earth to update a near-real-time simulation model, estimate hauling productivity, and find deviations.	GPS	Truck : dump, load, haul, return
Song et al. [59]	Updated the simulation and planned the next operations using location - specific data.	GPS	Truck: load, dump, travel
Moselhi et al.[60]	Updated a near-real-time simulation model and estimated productivity using GPS data and a GIS web-based system.	GPS	Truck: load, travel, dump, return
Song et al. [61]	Discovered and quantified factors that affect the cycle time of an earthmoving dump truck.	GPS	Truck: enter, exit, load, haul, idle time.
Louis et al. [62]	Provided an operational-level decision-making solution using IoT networks and enhancements in modeling and simulation tools.	GPS	Truck: haul, dump, return, wait, cycle Time.
Ahn et al. [63]	Used historical fleet GPS data and support vector regression models to estimate transportation costs.	GPS	Truck: pick up loaded trailer, entering, inside, leaving
Ibrahim et al.[64]	Used sensors to estimate productivity and compared it with simulation results.	GPS, accelerometer, strain gauge, barometric pressure	Loader: hauling volume Truck: load, haul, dump, return
Salem et al.[65]	Proposed a technique for configuration setting of earthmoving operations, and system for onsite automated data collection.	Pressure, moisture, humidity, luminosity, IMU, GPS, weather station	Influence factors of the earthmoving productivity.
Cheng et al. [66]	Tested UWB for monitoring mobile resources in real world construction.	UWB	Truck: dump, load, haul, return.
Mathur et al. [67]	Proposed a solution using smart phone to track construction machines.	Smartphone (IMU)	Excavator: idle, wheel-base motion, cabin rotation, bucket-arm movement.

TABLE 7. ***(Continued.)*** **Methods based on GPS sensors for recognizing equipment operation and analyzing productivity.**

Kim et al. [68]	Calculated cycle times via IMU embedded in smartphone.	Smartphone (IMU)	Excavator: rotating, clockwise, rotating counterclockwise, not rotating, work cycle.
Bae et al. [69]	Developed a system to classify concurrent earthmoving operations.	Electronic joystick and PCI extensions for instrumentations (PXI)	Excavator: digging leveling trenching, lifting, traveling and idling.
Rashid and Louis. [70]	Investigated activity-specific equipment motions instead of construction equipment for performance optimization.	IMU	Excavator: engine off, idle, scooping, dumping, swing loaded, swing empty, moving forward, moving backward, ground levelling.
Slaton et el. [71]	Developed a model for activity recognition of construction equipment.	IMU	Excavator: idle, travel, scoop, drop, rotate, (right, left), various

RTLS: real-time location systems; **UWB:** ultra-wide band; **IMU:** inertial measurement unit. **PCI:** peripheral component interconnect

C. DATA DRIVEN PERFORMANCE OPTIMIZATION

The construction industry is one of the wealthiest industries that produces massive amounts of data [3]. Therefore, there is great potential for using such data to enhance production. In addition, data collection techniques have evolved beyond broadcast and cable transmission to incorporate open communication technologies, such as RFID tags and sensor-based actuator modules [72].

In addition, because of the recent expansion in the construction industry and the usage of information technology, which has provided possibilities such as data collection and analysis, artificial intelligence (AI) algorithms have been used to address complex engineering problems [8]. However, to collect data from jobsites, current productivity evaluation methods require an information system that can analyze and process the collected data [9]. This can be achieved by evaluating the data patterns as inputs and outputs to develop a quantitative evaluation [1]. Models based on such strategies are often data-driven [47]. The data can be used to train a sophisticated prototype model that can understand the complicated links between different input factors and provide relevant outputs to assist engineers in improving their design processes [3]. Here, we investigated the tools and technologies for collecting and analyzing data regarding construction processes.

1) DATA COLLECTION

a: ONBOARD INSTRUMENTATION SYSTEM (OBIS)

OBIS is a powerful asset management application that provides managers and operators with relevant data collected from different job activities. It was designed to collect data to avoid equipment failure or to discover abnormalities to improve safety [15]. The system detects faults in multiple parts of the equipment by placing sensors in the monitored unit [49]. These sensors are used to identify mechanical issues with tracked equipment and measure specific features, such as temperature, pressure, and control lever position, which affect the equipment cycle time and productivity [49]. For example, the OBI of a crane has an encoder sensor and load moment indicator. Encoder sensors, which are used to measure the rotation angle, are either installed between the body of the crane and truck base or between the boom and crane boom. To collect obstacle data, [73] used a mobile crane's boom head and accessible sensors (boom length, rotation angle, and elevation angle). In addition, the crane overturning motion (load multiplied by radius) can be calculated and displayed using the load moment indicator (LMI) [21]. OBI and LMI are well-established technologies. It is currently used as an overload mechanism for large cranes. This technology displays the crane's rated capacity and the percentage of the lifted object's moment to the operator, as well as sounding an alert if the moment exceeds the limit [15].

The OBI offers efficient cost savings and is used for various tasks in a number of earthmoving processes, such as avoiding loader rollovers, regulating scraper wheel slippage and gearbox shifting, and increasing dozer productivity [49]. Caterpillar, a pioneer in the field of operational business intelligence, developed a vital information management system (VIMS) to monitor real productivity and machine conditions [49]. Because OBI is already used as a standard tool for most heavy equipment, no additional installation costs are required. However, systems based on OBI are expensive and cannot anticipate fleet performance, project costs, or completion times in a deterministic or stochastic manner [49]. The use of OBI to track progress has several drawbacks. The information quality is proven to be poor in encoder-based cable length measurements, which are approximated by cable stretch and winch spooling [74]. In addition, data collected through OBI is not useful for tracking productivity [1]. Therefore, to make it more effective, it must be combined with information regarding material quality and site environment, as presented in [48]. It is difficult to avoid accidents involving other cranes and building structures, as well as swaying loads, in terms of workplace safety [21]. In addition to OBI, no additional sensors are available, which is a limitation [73].

b: RADIO FREQUENCY IDENTIFICATION (RFID)

RFID is a wireless-based technology that uses radio frequency (RF) to interact with distinctively traceable tags. RFID systems comprise tags and readers. Tags connected to the equipment were used to collect and transmit digital data to readers via radio waves. These tags are used to track and identify objects [75]. RFID can be used to measure distance, identify targets, and determine proximity [14]. Using triangulation and signal propagation time, the location of tag can be calculated. Event detection begins with a fingerprint pattern [14]. To estimate the tag placement, a biometric is matched to a digital scan. The transmitter density is used to determine the distance. Readers can set a specific voltage rating to set the range distance in which RFID tags can be detected.

Dump truck loading, hauling, and dumping hours can be predicted using RFID tags [49]. Here, RFID tags connected to dump trucks are scanned through fixed readers and mounted on the entry gates of the loading and dumping facilities. Thus, the loading, traveling, and dumping cycle times can be calculated to monitor the time variations [49]. To estimate the machinery placement, tags are placed in various work zones. For instance, [76] placed RFID readers at the loading and dumping gate entrances to determine the loading and dumping timeline. To establish an appropriate work schedule, [75] proposed a mechanism that uses RFID technology to monitor the locations of heavy construction machines. Equipment must be maintained and repaired regularly to ensure dependability and efficiency. Similarly, [75] recommended using RFID to check machinery maintenance. Following their evaluation, all the data were saved in RFID tags and automatically updated via a centralized location. An RFID portable device can also scan a machine's RFID tag to obtain information about all repairs and maintenance performed [52]. In open-pit mines, [77] demonstrated that RFID technology can not only monitor construction machines but also prevent collisions. In the following experiment, the equipment fleet was mounted with RFID tags, and those with blind spots had RFID readers. Thus, RFID technology detects machine movements and avoids dangerous collisions.

RFID, on the other hand, has certain drawbacks. Because fixed RFID readers are only installed at project entry points, this technology cannot pinpoint the source of poor performance because the data provided are insufficient to determine how much soil was excavated or when trucks were completely loaded [49]. Such positioning sensors simply gather location and time data, making it difficult to distinguish between the productive and idle states of the machinery [14]. Furthermore, RFID has significant flaws that must be addressed, such as the fact that it has a higher failure rate when used with metals [14]. With the ongoing digitalization of the fast rate of technical innovation in the construction sector, the term Construction-IT was coined [3]. Therefore, potential RFID-based solutions will reduce costs, enhance device storage, extend the transmission range and power transfer of radio waves, and increase data processing [52].

c: INTERNET OF THINGS (IoTs)

IoT sensors can detect thermal, mechanical, optical, electrical, acoustic, and displacement signals, offering relevant data for processing, transmission, analysis, and feedback, and enabling managers to perform preventative maintenance to maximize performance and avoid accidents [17]. For instance, sensors can monitor significant vibrations or thermal expansion to detect whether a machine's engine or air filter must be serviced or replaced. The IoT system can generate an alarm on managers' digital devices, so they can fix the issue before it is exacerbated. UWB is a wireless-based technology that offers high-speed communication over small distances. It can be used to track the locations of multiple pieces of equipment and to obtain information about them. It can also locate and identify multiple dynamic pieces of equipment on a job site. Like, [62] used a UWB positioning system to collect job data from a worksite. By periodically attaching a tag to the deployed component, workers and supervisors can trace operations. Similarly, [78] developed a system that uses UWB to help operators find equipment and assess hazards. Wearable gadgets and connected IoT devices were developed in [79], which can alert a worker to potentially harmful areas. [80] developed a method for compiling site equipment and creating management analytics. To do this, they proposed "Smart Connected Objects," which include machinery, tools, materials, and even buildings with sensing, processing, and communication capabilities. This edge computing method provides machines with autonomy and awareness to make better decisions. A closed-loop lifecycle management system framework based on the IoT was developed by [81]. To improve the efficiency and safety of mining equipment, [82] used coal mine safety monitoring and maintenance to construct an IoT-based predictive maintenance system. Using IoT and RFID, [83] developed a warning system to inform employees of the possible dangers. An IoT-based system was also employed on-site in [84] to enable data collection, supervision, and analytics. To ensure the safety of each tower crane during operation, [85] utilized the IoT to capture the status information on the crane arms and designed an anti-collision algorithm. The issue and intricacy of tracking job status and productivity assessment can also be resolved by integrating multiple wireless technologies [42]. Vision-based wireless technology can assist in precisely tracking the progress of earthmoving operations and evaluating the machine usage. Adding electronic sensors to target items and/or their parts, capturing consistent point positions of the sensors, and assessing the motion of machinery, such as acceleration, velocity, and rotation, are examples of IoT-based methodologies [62].

d: TELEMATICS

Telematics refers to the use of wireless technology to connect equipment-monitoring systems. Telematics includes wireless communications, vehicle monitoring systems, and positioning sensors that provide real-time location and operation data [79]. The sensors used in these devices capture and transmit data through cellular and GPS networks [42]. This specific data depends on the machine type and telematics unit.

Today's equipment rental companies depend on telematics to collect real-time machine data [1]. Telematics can be used to improve the efficiency of the work locations. Implementing telematics in an equipment footprint can enhance productivity, reduce expenses, and provide data-driven patterns [86]. Working hours, location, fuel consumption, and productivity are significant features of heavy-equipment efficiency [2]. Compared to RFID, telematics has a reduced transmission frequency by default, which restricts its use for precise operation tracking. However, it is possible to increase this frequency, but doing so would require a robust data storage system to support a high volume of information [1], [79]. A detailed description of the RFID, IoT, and telematics is provided in Table 8.

TABLE 8. RFID, IoTs, and Telematics.

Technologies	Details
RFID	Comprises of a tag, a reader, and a computing unit that houses a database and application-specific software [1], [52]. Tags can be active or passive, active ones have own power source with several hundred meters radio wave transfer and contact distance [52]. Used on worksites in highly severe circumstances, good for real-time detection, tracking, and monitoring [1], [52]. Can be used to predict dump truck loading, hauling, and dumping hours [67]. Can be used to track the location of construction machinery on big construction sites to maintain a proper workflow [62], monitor the mechanical state of machinery [75]. Can track the movement of construction machinery and avoid collision among them in open-pit mines [77], also track earthmoving activities at a relatively low cost [76].
IoTs	Provide viable approach for sophisticated emission levels monitoring, create real-time communication between the computing platform and actual field sites [85]. Popular IoT protocols are CoAP, AMQP, MQTT [13]. Provides automated monitoring to identify and store machine actions and gather sequential information relevant to machine operations [35]. Quality of work can be tracked, and productivity can be evaluated using wireless technology [79]. Highly adaptable and customizable to meet the specific needs of stakeholders [35]. MQTT, lightweight in terms of deployment footprint and connectivity, more effective in slow and unstable networks with multiple devices, like embedded applications, microcontrollers, robotics, and traditional desktop PCs [30].
Telematics	A reliable way of collecting machine data in real time [86]. Can transmit location and time, equipment performance and maintenance data like fuel usage, engine hours and oil pressure [1]. Do not require a specific infrastructure of receivers like RFID as it transmits data over ordinary wireless networks or through satellite communication [42]. Is more comprehensive and cost-effective way to observe large equipment fleets [86].

MQTT: Message Queuing Telemetry Transport, **AMQP:** Advanced Message Queuing Protocol, **CoAP:** Constrained Application Protocol

2) DATA ANALYTICS

a: MACHINE LEARNING (ML)

The use of machine learning to solve problems in the construction sector has increased. ML is used to assess and forecast project delays, improve asset design, manage safe operation, assist offsite construction, and categorize and locate facility management components [1]. This process uses more digital data for design, construction, and operation.

Algorithms based on ML make substantial contributions to a variety of heavy machinery-related sectors, such as machine utilization, administration, maintenance, service schemes, acquisition, and monitoring. However, deep excavations in residential areas are challenging, and defining risk levels requires a thorough assessment of the excavation hazards [3]. Here, the key challenge is the complex and variable relationship between components and risk profiles. The complexity of such profiles can be decrypted using machine-learning algorithms [89]. Fuzzy set theory [87], as well as machine learning models such as artificial neural networks (ANNs) [88], [89], random forests (RF) [90], support vector machines (SVM) [91], and Bayesian networks (BN) [92], [93], [94], have been proposed recently to forecast and evaluate the risks of deep excavation. ML methods can also be used in challenging situations, such as construction accidents, and assist management in making better choices [47]. In general, machine learning algorithms based on data collected from fieldwork are often more effective in predicting hazards in excavations [91], [92], [94]. However, each method has its own set of advantages and disadvantages, making it difficult to determine which one is the most appropriate and effective, but it mostly depends on the quality and integrity of the data collected on the field side [3]. Fig 11 shows how machine learning algorithms have been used recently to address issues regarding equipment management and earthmoving operations.

b: DEEP LEARNING (DL)

Deep learning is a subfield of machine learning that deals with algorithms inspired by the structure and function of the brain and is known as artificial neural networks (ANN). It is an extension of ANN for issues requiring more than one hidden layer in active learning [1], [66]. The term "deep" in deep learning refers to the depth of the network, whereas an ANN can be very short. With the assistance of hierarchical structures, high-level abstraction was discovered in the data. Recent vision-based algorithms, such as deep learning-based computer vision solutions, have attracted the interest of researchers in various civil and infrastructure engineering projects [89]. Although academics have used neural networks for decades, deep learning has made substantial advances owing to the availability of inexpensive computer power such as graphical processing units (GPUs) and massive datasets to train deep models [91]. Although DL algorithms are used in a range of applications, the equipment used has not yet been upgraded to integrate deep-learning-based automated systems.

c: COMPUTER VISION (CV)

CV-based methods have the potential to become new data collection and analytics technologies for earthmoving machine optimization; however, there is still a long way to go before a reliable and automated system can be employed in construction projects. Although some researchers have suggested methods for extracting cycle time from video, which is used as an input for process simulation tools, the number of articles that combined construction-process simulation and vision-based monitoring to analyze the existing earthwork productivity and suggest an optimal resource allocation plan were found minimal [95]. Table 9 summarizes the deep learning and computer vision algorithms proposed by various authors for construction machines.

IV. TECHNOLOGICAL INTEGARATION

The integration of information and communication technology (ICT) has a positive influence on the progression

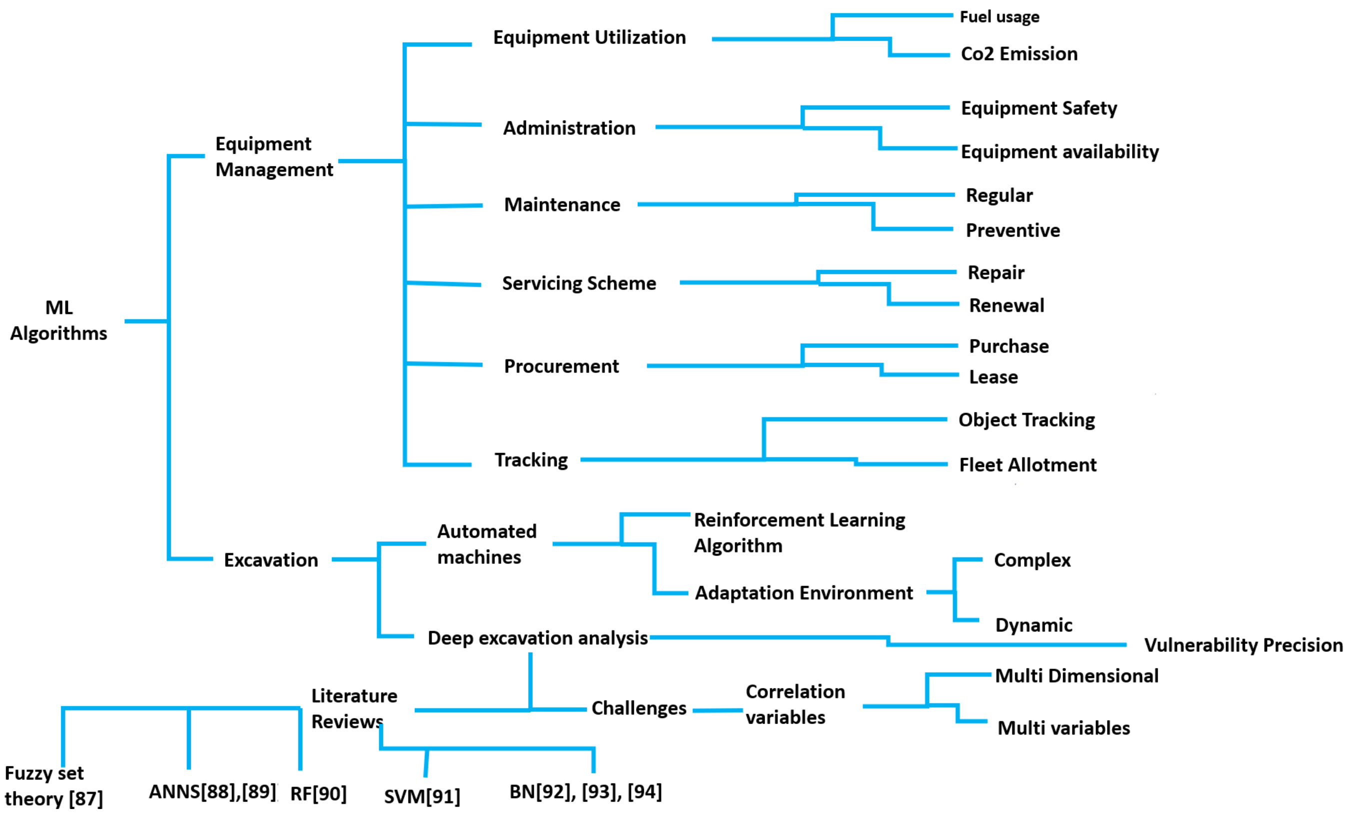


FIGURE 11. **ML contribution to construction machinery and excavation.**

of development in the construction sector. Web-based technologies, cloud computing, BIM, and tracking technologies have been progressively employed at construction sites to improve project communication, cooperation, scheduling, and supervision [14]. Such unique solutions are frequently used in various technology combinations to optimize construction monitoring and model comparisons. The quantity of data collected increases as technology advances. Therefore, by integrating BIM, GIS, and GPS, researchers are actively analyzing these tools to improve the productivity of construction projects. For example, for productivity analysis, [108] studied the relevance of unmanned aerial vehicle (UAV) technology and BIM and [109] integrated 3D BIM models with geotechnical data to increase earthwork efficiency. Similarly, by integrating GPS, telematics, and web applications to improve the operational performance of site equipment, [110] determined the productivity of site equipment and estimated its impact on sustainability using an accelerometer. An IoT-ML-based framework was developed in [47] to determine the emission levels of an excavator. To calculate the cycle times, a machine learning approach was used by [111] to simulate the loading process by classifying raw data collected through GPS, gyroscope, and accelerometer sensors and incorporating them into a smart system placed in front of the loader. Similarly, [47] designed and deployed a methodology for estimating heavy equipment emissions based on on-site acceleration data collected from excavators. [112] created a system that uses accelerometers to monitor equipment efficiency and environmental performance. They used vibration signal analysis as their primary technique to identify and track equipment operations. Supervised learning algorithms were used to classify the accelerometer data into equipment activities (working, idling, and engine-off). Table 10 provides a detailed breakdown of these studies. Although researchers have integrated multiple machine learning techniques, such as ANN and support vector machine (SVM), with BIM to automate construction productivity tracking, these existing techniques are applied on a very limited scale to different construction areas, such as workers, processes, and machinery, and do not cover large-scale job sites [103]. Furthermore, the number of surveillance tools (such as tags and cameras) are limited [48]. Although many AI-related construction activities are still in the development stage, they are anticipated to allow the seamless integration of automated equipment in a 5D BIM planning environment [113].

V. INDUSTRY 4.0

The surge of technology in recent years has been underlined by Industry 4.0 (I_4) and projects in the smart city, engineering, and construction (SCEC) sectors, such as building 4.0, real estate 4.0, construction 4.0, mining 4.0, education 4.0, and manufacturing 4.0 [27]. Connecting physical environments

TABLE 9. Deep learning and computer vision algorithms for construction machines.

Authors	Objectives	Framework	Details
Kim et al.[96]	Proposed a mechanism for categorizing different kinds of equipment operations based on vision.	Can solve Complex problems e.g., audio processing, image recognition, etc,	-Two-dimensional image analysis for excavators and dump trucks -Post-processing and post-tracking are presented in a framework. -Interaction study of heavy equipment improves performance.
Fang et al.[97]	Developed a deep learning system to identify non-hardhat usage.	Parallel computing to reduce overheads.	-Diverse, annotated, and reusable training dataset -Testing image frames dataset, characterized by different visual conditions. -Highly improved precision, recall rate, speed, and robustness. -Facilitate safety inspection and supervision.
Luo et al.[98]	Designed a CNN-based automatic construction site detection technique.	Models can train large data.	-Faster R-CNN technique for multi-scale object identification. -Outperforms similar descriptor techniques to identify building items on pictures. -Resilience and generalization of CNN using a large construction object database.
Schabowicz, K. et al.[99]	Employed artificial neural networks to evaluate productivity for earthmoving machinery system made of excavators and haulers.	Model gets better with more data.	Mass service System (MSS) productivity estimation for a set of construction machines.
Tam et al.[100]	Designed a quantitative model for predicting the productivity of excavators using ANN.	High-Quality Predictions	Explored the non-linear connection between excavation and excavator performance. -A viable choice for calculating excavator productivity.
Cao et al. [101]	Created a classifier for multiple excavation equipment	-Acoustic signal based excavation equipment recognition. -Enhanced acoustic feature extraction algorithm	-A benchmark acoustic wave database collecting from a real construction site -ANN using hot extream learning machine (ELM)
Ham et al.[95]	Integrated vision-based monitoring and modeling to identify possible problems of wind-induced damage at worksites.	Works well-unstructured data e.g., video clips, documents, sensor data, webcam data, etc.	Integrated simulation and visual monitoring approach -Report creation using CCTV footage. -Cheap resource allocation strategy.
Ting K. et al.[102]	Used computer vision and long short-term memory (LSTM) to proactively anticipate hazardous behavior in videos.	Faster and simpler process e.g. carry out repetitive and monotonous tasks at a faster rate i.e simplifies the work for humans	-Tracking workers using a SiamMask -Forecasting their trajectory with an enhanced Social-LSTM -Predicting hazardous behavior with Franklin's point inclusion polygon (PNPoly) method.
Yang J et al.[103]	Prototype for excavator productivity monitoring using CV.	Better products and services i.e faster delivery of high-quality products and services Cost-reduction	-CV and sensor based productivity analysis of earthmoving machines. -End-to-end CV-based approach for detecting several excavators' operations. -Excavator productivity estimation using activity recognition.
Kim and Chi [104]	Calculated productivity and cycle time of earthmoving equipment	Faster recursive CNN (RNN) and TLD	-Novel action recognition framework using sequential visual features and operation cycles. -Learning excavator's sequential working patterns
Roberts and Golparvar Fard [105]	Predicted hauling activities production cycles	HMM, atomic action recognition, deep learning-based detection, and tracking	-2D spatiotemporal features. -A benchmark dataset for detection, tracking and frame-level action recognition of earthmoving operations. -Video analytic for detecting excavators and dump trucks
Bügler et al. [106]	Measured production cycles of loading activities	GMM background subtraction and kernel covariance tracking	-2D motion characteristics and 2D threshold for proximity - Real project
Kim et al. [107]	Proximity monitoring between mobile equipment	CNN based localization YOLO-V3	-Distance measurement in rectified images. -Robust object localization -Provision of advanced detection of struck-by hazards around workers.

CNN: convolutional neural network, **RNN**: recurrent neural network, **TLD:** tracking-learning-detection, **HMM:** hidden Markov model, **GMM:** Gaussian mixture model.

TABLE 10. Illustration of studies based on integration.

Ref.	Objectives	Methodology/Algorithm/Tool used	Data collection
Shahnavaz et al.[47]	Developed and implemented a framework to predict heavy equipment emissions.	Machine learning, Random Forest, IoTs	Acceleration data from real-world operation of excavators using IoTs, accelerometers, gyroscope sensors
J.Sanchez. [108]	Analyzed productivity of construction project.	Qualitative analysis	BIM integration with drones
M. S. K. et al. [109]	Visualized hierarchical geotechnical models for better productivity.	Qualitative analysis	Combined 3D BIM models for earthwork with geotechnical data
Aslan et al.[110]	Measured the operational efficiency of construction equipment.	Logical Regression, decision trees, k-Nearest Neighbor, and Naïve Bayes	Raw accelerometer data
Akhavian et al. [111]	Identified various construction equipment activities.	ML classifiers	Raw data; collected through GPS, gyroscope, and accelerometer integrated in a smart system.
Bhargav D. et al. [114]	Developed a platform to view information about energy usage,	OTANIEMI3D	BIM integration with IoT
	occupancy, and user comfort.		
Akhavian et al. [115]	Designed methodology for multimodal-process data collection, fusion and mining	UWB, ZigBee, AHRS	Integrated field data into simulation model
Sherafat et al. [116]	Hybrid approach to detect various activities of machine.	SVM, mobile, microphone sensors	Audio and kinematic signals
Rashid and Louis. [117]	Recognized equipment activities using time series data augmentation	3-axis accelerometer, and 3-axis gyroscope (80 Hz)	Synthetic data generation using time series

with digital ecosystems is a crucial element of the industry 4.0 paradigm. Autonomous operations tend to develop through the seamless integration of various digital tools, technologies, and programming languages [119]. These include cloud-based storage, fuzzy systems theory, steel work design and construction, and efficient product assembly setup. The synergistic connection can be visualized using computer systems that can autonomously optimize logistics-related manufacturing operations [118]. The transition of industrial processes enables the collection and analysis of real-time data, resulting in more efficient, adaptable, and timely operations [120]. Such developments result from direct machine-to-machine communication. This creates a cyber-physical environment by enabling machines to interact and communicate directly with one another (M2M) without human interaction, leading to an agile production line with efficient communication and optimal decision-making capabilities [121]. Fig 12 shows the leading technologies used in Industry 4.0.

Currently, most construction firms recognize how critical it is to use I_4 applications and practices to increase their economic value [120]. Advanced automation, robotics, M2M communications, and human-to-machine or human–computer–machine communications are required [27]. Through a variety of self-operative functions, DT supports the connections necessary for such advances. It can be used to leverage construction data [23]. However, DT has not been distinguished from the existing computations, virtual models, and simulations [32]. I_4 technologies have been used for static data/model visualization in construction, but effective frameworks for IoT developments have not been widely used [122]. However, focusing on the smart interaction between industrial components and IoT devices, construction lags in technology deployment compared to automobile manufacturing and maintenance. This is because of high acquisition costs, lack of training resources, and unwillingness to alter long-established systems and processes [119]. Construction equipment operations in project management are still milestone-based, that is, progress monitoring is performed through nD BIM completion phases [122]. The real-time smart operation and monitoring of construction machines will improve project timelines and cost management. It adds another layer to sensor-based safety management by tracking how personnel and machinery move and are utilized [122].

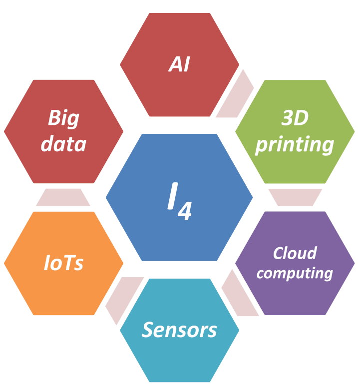


FIGURE 12. Industry 4.0 main technologies.

VI. DISCUSSION

As construction operations grow on a large scale, the complexity also increases. To achieve the accuracy requirements, the techniques and technologies must be employed to execute them also be upgraded. Because too many machines are simultaneously used on the worksite to complete the job, the connectivity of single value-adding processes is important [10]. In terms of architectural needs, timing, and commitment to project completion, each stage must be carefully planned and scheduled in the initial phases to avoid divergence from the expected outcomes that can affect all subsequent processes. Ideally, the goal is to optimize the workflow rather than the individual phases. Because work is being done simultaneously, better synchronizations are required to avoid serious deadlocks if the activity outputs diverge. There must be a constant flow of information to the equipment that is performing other jobs and to the supervisory system, preferably in parallel. Parameters such as time, fuel usage, and the quantity of equipment and personnel are also involved in determining the optimum performance [53]. Hence, a multicriteria performance assessment tailored to the specific conditions of the entire construction process is required to achieve the desired results. In other words, smarter machines require better methods to measure their performance. Digital transformation is the first step toward implementing a production model, and digitalization of the operation is the most important step [64]. Once the process is digitized, all essential data can be accessed and collected for the application of sophisticated technologies. One of the initial phases of digitization in certain industrial upgrades is data harvesting and transfer [74]. Subsequently, the acquired data can be used to optimize machine performance, streamline operations, control defects, and make smart decisions to build a digital infrastructure. Hence, a solid platform for data collection and exchange is required [3].

Power, transmission, and control systems, as well as primary support technologies for construction machines, have all seen significant technical advancements [17]. However, complex structures, difficult construction site environments, and substantial load fluctuations for construction machines cause technical problems. Therefore, detailed construction site data collection, more automated solutions, and effective condition-monitoring systems are essential. One of the most desirable pieces of information from heavy equipment is the downtime. Telematics can be used to record the engine status during idle time, depending on the configuration setting of the machine [86]. Minimizing the idle time of a machine can reduce the emissions and fuel usage. Two major challenges with automated productivity data collection are the potential overflow of low-level data or information that might burden project managers [79], and the lack of direction in evaluating workflow in construction operations [48]. Because increased data access and communication between sensors, devices, machinery, monitoring, and control systems are required to optimize the entire operation, a digital twin and a cyber-physical system can be useful solutions, as physical objects (equipment, actuators, and tools) can link with cyber entities that provide data storage, processing, and analysis. Moreover, the availability of wireless technologies that allow the Internet of Things (IoT) has increased dramatically, and this is expected to be a major advancement in the future integration of online services [72]. Images, videos, and audio books were among the collected data, leading to the creation of large metropolitan datasets. Documentation from machines, maintenance, and subscriptions has previously been overlooked, but it has now been brought to light, like a gold mine, providing for the extraction of previously unknown data, invisibility, and other important details to improve prediction and productivity [84]. Rather than spending time on data to be produced, continuous data techniques must be devised to collect, retain, filter, and analyze large amounts of data to maximize their utility [42]. This is especially important given that data harvesting and development goals, such as Auto-ID, laser scanners, and sensor networks, as well as basic data operating costs, have become more affordable [54]. The lack of qualified and skilled laborers and managers to use sophisticated tools and software discourages the promotion of emerging technologies [6].

Modern technology offers solutions to major challenges, enabling industrialized production to fully achieve its potential. The latest technological integration, for example, IoT, optimization algorithms, and sensing technologies, can significantly improve management techniques in construction projects [121], [6]. Moreover, soft computing methodologies have improved predictive capabilities compared with traditional methods in modeling the complicated dynamics of most geotechnical engineering systems. The use of emerging artificial intelligence tools can assist in understanding the complicated behavior of subsurface construction [8]. It is possible to operate earthmoving equipment using information models that provide the information required for machine control systems to function properly [14]. The construction sector has the potential to be transformed through digital technology, which can address and offer solutions to some of its issues. The production management system support (PMSS) can be designed by creating a DT-based installer base management system (IBMS) that aids in data structure and machine management [18]. Construction projects are characterized by several overlapping and concurrent tasks and processes, which can increase the likelihood of error as well as the cost of time and potential losses [29]. Real-time sensor data is therefore highly beneficial for virtual solutions [118]. With the use of a digital twin, enhanced simulation results are required for better decision-making and monitoring of data coming from sensors [28]. It is also feasible to support the lifecycle of a machine process such as material recovery by establishing an IBMS [43]. Likewise, advances in construction technology, upgrading existing components, adding new parts, intelligently processing existing data, and developing new sensors that offer information that is not currently available will contribute to increased heavy-duty machine productivity [52]. Techniques regarding autonomous excavation, where the machine is placed next to its working area and digging can be performed via sensors and control, have been growing [113]. In 2015, Komatsu, a well-known producer of equipment that specializes in data-driven and machine-learning-enhanced analysis, introduced its smart construction system. Automated systems enhance the analytical efficiency, accuracy, and quality [13]. INSITE is currently working on a system that combines computer vision, deep learning, and aerospace algorithms to make a machine smarter by predicting its location and visual perceptions [113]. Such solutions will make machine operation more reliable, productive, and efficient. Further digitization will improve the equipment performance and provide more opportunities to achieve the overall aim of process optimization.

VII. IDENTIFIED GAPS

In this section, we discuss major gaps in the applications of new technologies employed in construction projects to evaluate the performance of the equipment.

1) Computer-vision-based solutions are proposed in integration with other tools, like BIM, to evaluate the productivity of construction activities, such as crane cycles and excavation operations. However, the challenging environment of construction sites limits the accuracy of these procedures despite improvements over conventional methods. Congestion, background clutter, obstructions, and varying lighting at construction sites influence the accuracy of these techniques [102], [105].
2) Several studies have integrated audio signals, Bluetooth, and smartphone sensors with machine-learning algorithms, such as ANN and SVM, to monitor machine productivity and excavation operations [85], [42]. Adopting these techniques with machine learning algorithms has improved their ability to monitor construction productivity and performance; however, anomalies, monitoring range, and tagged device privacy problems still need to be addressed.
3) Recently, sensor technology has been used in construction machines. However, owing to the complex mechanical structure, power and transmission systems, and operational environment of construction machines, sensor-based applications experience tougher requirements [17]. Therefore, sensor technologies cannot be instantly applied to construction machines, and extensive testing and optimization are required to ensure their suitability for construction machinery.
4) Radio-based technologies, notably GPS, offer reliable and robust solutions for equipment tracking and monitoring. However, these solutions have certain limitations. First, every piece of equipment must be tagged, which might be a problem for rental equipment or subcontractors. Second, spatiotemporal data cannot be sufficient for activity recognition, necessitating a multimodal sensing system [10].
5) Telematics is a cost-effective method to manage large machinery deployments. However, the reduced data

transmission frequency restricts the use of telematics for extensive performance observations [123]. Its frequency can be enhanced, but it requires additional data storage capacity to manage higher projected data volumes.

6) RFID tags can communicate up to 100 m, which is beneficial for large-scale construction. They also worked without lines of sight. However, this requires an algorithm to identify the tagged construction equipment [62]. Moreover, when signals from multiple readers overlap, an RFID reader collapses. Several other Wi-Fi networks can interfere with or distort the signals used by the RFID tags.

VIII. CONCLUSION

Heavy-duty machinery, which is a significant contributor to all construction projects, will lead the market in the coming years. Owing to an increase in worldwide infrastructure projects, the demand for such equipment will also increase. In addition, the size and complexity of construction projects have increased, necessitating innovative solutions. This study evaluated the potential of advanced technologies to improve the performance of construction equipment. As construction machine research using innovative tools is still under development, the authors presented significant insights into CPS, DT, GPS, OBIS, RFID, IoTs, ML, DL, and CV. The review found that DT and CPS self-operative functions for advanced automation, machine-to-machine communications, human-to-machine or human computer-machine communications, RFID for equipment in open-pit mines and collision prevention, ML in anticipating challenging environments, and GPS and GIS integration to increase equipment operating hours and reduce idle time, useful. To improve the quality of data collected through OBI for tracking performance, it must be integrated with information regarding the material quality and site environment. Moreover, reluctance to accept modern technologies, unwillingness to interrupt workflow, shortage of trained people, and expansive gearing have been found to be some of the existing factors behind delayed advancements. To increase the overall productivity, the authors also considered all important players, such as people, equipment, and bottlenecks. There are still several possible research trajectories for the use of new technology in construction equipment. This evaluation is expected to serve as an important source of information for scholars in this area.

The technologies discussed in this article only cover off-road construction machinery. The equipment performance on energy consumption and emission issues was not included in this study. Additionally, the data collected for this study are worldwide and do not cover any machine-operating zone.

IX. FUTURE WORK

Most ongoing research is still in the proof-of-concept phase and makes little or no use of ground truth data. These studies have employed small datasets and partially covered complex construction sites. The number of sensors that can collect data is limited. Vision-based technologies require a reliable data-storage platform, which limits their usage. Larger-scale experiments with multiple machines operating simultaneously would assist in understanding the added value of these technologies. Existing commercial accident warning systems use radio-based sensors to identify hazards; however, this requires tagging every worker. This would be beneficial to research passive technologies, such as laser scanning and vision systems. Real-time accident warnings are a promising area of investigation. This method prioritizes strategic accident avoidance over reactive intervention. Commercial machine control systems have increased productivity. However, these systems depend on expensive real-time locating systems (RTLs), which limits their industrial usage. There is great potential in this area to develop low-cost alternatives based on smart technology. Remote control and autonomous operation are complex and comprehensive areas because both require synchronized modules to operate the process. Existing research has focused on navigation, 3D environment modeling, motion planning, and optimum end-effector trajectory, providing substantial improvements in the area. Future teleoperated and autonomous operations will require systems such as situational awareness of the operator, operator response, communication performance, obstacle avoidance, machine-to-machine communication, and simultaneous localization and mapping. Heavy machinery generates significant emissions during construction. Optimizing such processes using digital solutions can reduce the environmental impact. The use of DT as a key tool is required for Industry 4.0, deployment in the development of sustainable construction.

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