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Review

Application of Machine Learning in Construction Productivity at Activity Level: A Critical Review

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Abstract: There are two crucial resources (i.e., labor and equipment) of productivity in the construction industry. Productivity modeling of these resources would aid stakeholders in project management and improve construction scheduling and monitoring. Hence, this research aims to review machine learning (ML) applications in the process of construction productivity modeling (CPM) for construction labor productivity (CLP) and construction equipment productivity (CEP) from dataset acquisition to data analysis and evaluation, which includes their trends and applicability. An extensive analysis of 131 journals focused on the application of machine learning in construction productivity (ML-CP) from 1990 to 2024 via a mixed review methodology (bibliometric analysis and systematic review) was conducted. It can be concluded that despite the rise in automated dataset collection, the traditional method has its advantages. The review further found that the selection of ML models relies on each particular application, available data, and computational resources. Noticeably, artificial neural networks, convolutional neural networks, support vector machines, and even deep learning demonstrating have been adopted due to their effectiveness in different functionalities and processes in CPM. This study will supplement the insights gained in the review with a comprehensive understanding of how ML applications operate at each stage of CPM, enabling researchers to make future improvements.

Keywords: construction productivity; activity level; machine learning; systematic review

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1. Introduction

The construction sector is extensively acknowledged among the major sectors, which is attributable to its contribution to the GDP serving part of the backbone in the economic development of a country [1,2]. Many efforts have been made for productivity measurement and improvement of the construction industry throughout the decades [3]. Having said that, CPM has been the focus area for numerous scholars, in which multiple models are being formulated. They are generally divided into two vital categories (statistical and artificial intelligence) [4]. Numerous techniques and models (i.e., regression models and ML models) have been developed for productivity estimation [5]. CPM is essential to enable a more precise productivity estimate by bypassing the subjectivity and irrelevance of traditional approaches, such as incorporating an estimator's judgment, disclosed productivity data, and past project data [6]. Productivity variation in construction is explained by models that take into account the influencing factors. Prospective and concurrent construction projects' management (i.e., estimating, planning and scheduling) can leverage these models due to their efficiencies for decision making [3]. Nonetheless, productivity in construction still presents itself with challenges due to the increase in complexity, resources (e.g., labor and equipment), and construction projects themselves being highly dynamic [4,7].

A subfield of artificial intelligence known as ML is the optimization of performance conducted by computers based on experience [8,9]. Lately, scholars have made substantial use of ML for analyzing vast volumes of data, effective productivity management, and progress monitoring [10,11]. ML holds a promising approach not only in CPM but also during dataset acquisition for the measurement of productivity, as well as quantifying influential factors [9]. By leveraging ML, automated data collection methods become possible. In addition, exploiting the data-driven features and potent computing potential of ML aims to improve CPM by promoting increased automation in the measurement of productivity, accurate estimation, and optimization in construction scheduling and monitoring [5,12].

The development and application of ML-based models for various facets of productivity are common. This is so to increase the accuracy in estimation of construction productivity [5]. Apart from productivity estimation, automated measurement of productivity [13,14] and quantification of productivity influential factors [3,15,16] have also been actively explored due to their quick reliable output values. As construction productivity possesses great volume in the construction industry, several reviews, as tabulated in Table 1, have been conducted related to either construction productivity, ML, or both. Some reviews focused solely on the types of productivity monitoring methods [17], while others outlined specifically on vision-based progress monitoring and tracking [18,19]. In addition, active exploration of ML applications in construction productivity led to several studies on deep learning (DL) as well [20]. However, research topics concerning construction productivity are commonly diversified into labor and equipment, and there are limited systematic analyses of ML applications on them. Furthermore, these previous reviews primarily concentrated on productivity monitoring techniques or ML applications separately. In addition, they have fallen short of offering an extensive and methodical understanding of the broader research terrain of ML applications from dataset acquisition to data analysis and evaluation. It is essential to explore dataset acquisition for CLP and CEP separately, as they do have their differences (e.g., data collection techniques and influential factors).

Table 1. Reviews of ML in construction productivity.

Ref	Year	Method	Domain	Aim
[17]	2021	Systematic Review	Productivity monitoring	It reviewed the application of tools and techniques for productivity monitoring in construction projects.
[18]	2021	Systematic Review	Construction safety Progress monitoring Damage evaluation	It reviewed the applications of visual-based techniques in construction.
[19]	2021	Critical Review	Safety management Progress monitoring Productivity tracking Quality control	It reviewed computer vision in construction from a holistic approach and identified the opportunities and challenges.
[20]	2022	Bibliometric Review	Deep learning in construction	It reviewed deep learning applications in construction focusing on neural networks.
[21]	2020	Critical Review	Construction monitoring system	It reviewed automated methods and techniques for recognizing the activities of construction workers and equipment.
[22]	2023	Systematic Review	General domain	It reviewed conversational artificial intelligence in architecture engineering and the construction industry.

Despite these significant efforts by past researchers, previous reviews have not covered a holistic approach to CPM without considering the dataset acquisition, which is the input for CPM. This is rational because CPM relies highly on the input of data, and this goes back to the dataset acquisition stage [23,24]. Moreover, the focus of CPM opting for traditional or automated data acquisition is not present in previous reviews. By reviewing the ML workflow in CPM, the reasoning behind for the adoption and comparison of multiple ML algorithms and models can be identified. There is a scarcity of a thorough overview of the process of application of ML from dataset collection to the development of construction productivity models. To paint a complete picture of the current research area, it is necessary to carry out a comprehensive review, due to the lack of a particular overview. Therefore, a systematic review regarding the application of ML-CP was performed. This review focused on the analyzation of related published papers from dataset acquisition to data analysis and evaluation. The results can assist future scholars in undertaking more in-depth studies and obtaining a clear and thorough grasp of the issues. In particular, this study yields the following offerings to the domain: (1) The examination of traditional and automated dataset acquisition applicability and ML approaches adopted for CLP and CEP. By doing so, the practicality of each method can be gauged while studying the influence of ML in dataset collection and why the various applications of ML algorithms for automated dataset acquisition have been used. (2) The exploration on the application of ML-CP, from model selection, training, and testing to evaluation. This enables further understanding on why many different ML models are utilized by researchers for CPM. Additionally, the preference of traditional or automated data collection for data analysis and evaluation can be yielded. (3) By conducting a thorough review, it aims to gather significant insights and learnings from previous research endeavors. In general, this systematic review provides encouragement towards CPM research, leading to the continuing improvement of CLP and CEP, separately.

2. Research Methodology

The research findings were examined using a mixed-review methodology which incorporated both bibliometric analysis and qualitative (systematic review) techniques. The rationale behind the selected approach is that bibliometric analysis provides a statistical outlook of the relevant previous literature, thus enabling the mapping of the inter-relationships (publications, authors, countries, and research themes) in specific research areas [25]. Meanwhile, a systematic review is commonly utilized to analyze the main outcomes of various studies or to discern patterns in the knowledge framework of the literature [26]. Relevant works of literature related to construction productivity and ML were extracted from the Scopus database since it is among the largest online academic databases and a commonly applied search engine [27,28]. In addition, this review focuses on peer-reviewed journals as the Scopus database has extensive citation records and wider literature coverage in comparison to Web of Science [29]. To achieve a comprehensive review, the timeframe of the papers was determined to be from 1990 to 2024. This is because construction productivity, particularly labor productivity, has been a popular research area for the last couple of decades [30,31]. With the advancement of construction technology and information technology, as well as artificial intelligence, there is a significant increase in research working towards automation in construction productivity measurement, as well as estimation. Subsequently, considering the need to produce an evidence-based outcome, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) process was selected as the literature selection process is transparent, elevating the quality of this review [32].

According to PRISMA guidelines, the extraction of papers from the database is performed using the following categories: identification, screening, eligibility, and included. Figure 1 shows the paper extraction process via the PRISMA sequence diagram.

In step one, an extensive search was carried out within "titles, abstract, keywords" from the Scopus database. The following rule was applied to the chosen keywords: ("construction productivity") AND ("machine learning" OR "neural network" OR "artificial intelligence"). The initial search resulted in 799 papers. In step two, a total of 641 papers were excluded. The filtering of papers by restricting to subject areas ("engineering", "computer science", "business", "management and accounting", "social sciences", "environmental science", "mathematics", "energy", "multidisciplinary", "decision sciences", "arts and humanities", "economics, econometrics and "finance"), reviewed academic publications in English, and review journals was carried out. Subsequently, the title, keywords, and abstracts were thoroughly scrutinized to ensure alignment with the research direction. Twenty-seven publications were eliminated in step three after a full-text review, as the papers were not pertinent to the research topic. By identifying records from reference and citation searches, two additional papers, which are closely related to the research topic but previously not targeted were added. Eventually, 133 papers were deemed relevant for subsequent bibliometric analysis and systematic review.

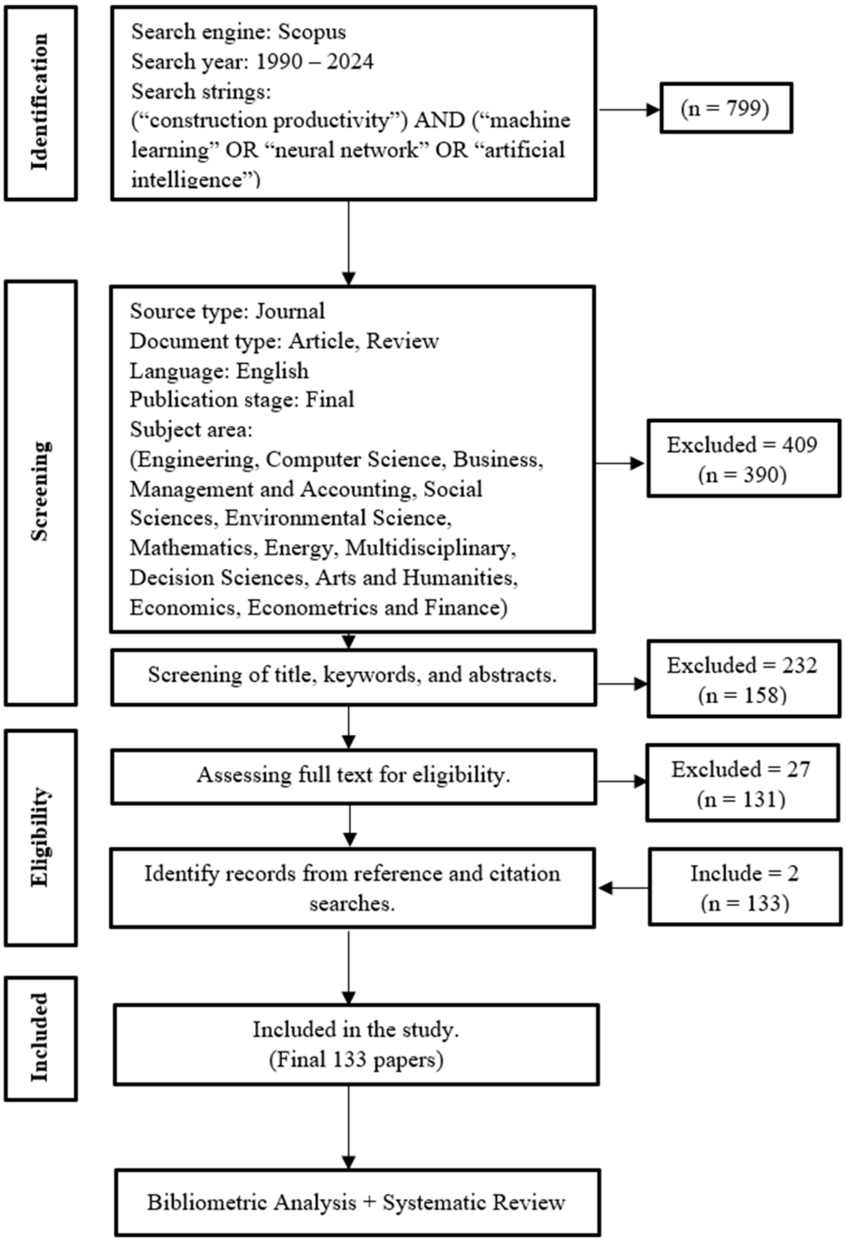

Figure 1. PRISMA sequence diagram for paper extraction.

3. Overview of the Application of Machine Learning in Construction Productivity Publications

The trend of the quinquennial publications from 1990 to 2024 of journal papers related to ML-CP are depicted in Figure 2. It can be discerned that the quantity of papers exhibited a steady ascending trajectory. In addition, the significant boost in papers happened after 2014 when the amount was more than double and closely doubled again after 2019, resulting in a remarkable growth over the last decade. Therefore, this positive trend underscores the incessant importance of research in ML-CP.

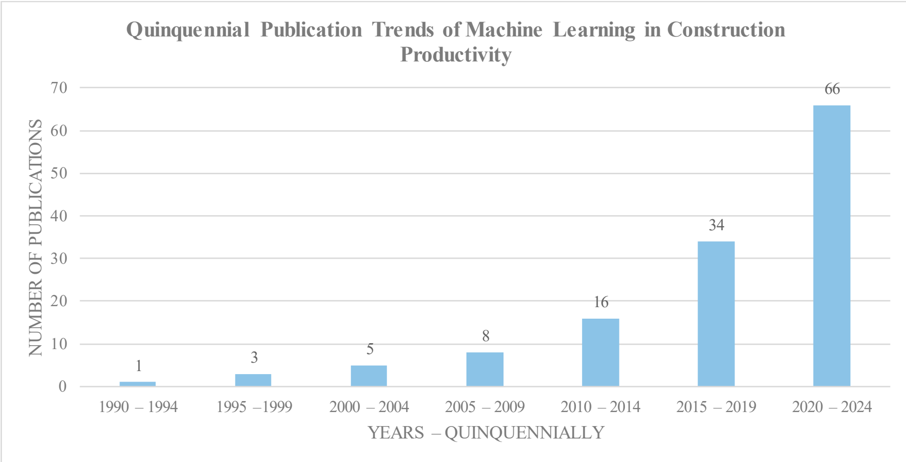

Figure 2. Quinquennial publication trends on ML-CP.

Using VOSviewer version 1.6.20, the mapping of the ML-CP research domain was acquired. The network visualization of the keywords was conducted to illustrate the results of the bibliometric analysis. A total of 55 out of the 1085 keywords met the threshold to be included as a result the after setting the minimum number of occurrences to four. This was carried out through several trials to acquire the optimal clusters. In relation to the publication trends, Figure 3 illustrates the evolution of ML-CP research. Generally, it is noticeable that during the last few decades, "mathematical models", "construction labor productivity", and "estimation" are tending to focus. General keywords such as "construction" and "productivity" are represented in the middle spectrum, which could be due to an emphasis on the topic throughout the whole period. Unsurprisingly, "neural network" has been found since the early timeframe indicating its constant presence in the literature [33–35]. However, the recent gravitation towards "machine learning" and "deep learning" plausibly indicates the shift of focus in construction productivity research from "regression analysis" and "mathematical models". As sensing technologies continue to advance, more data are becoming available. Naturally, the data processing techniques have also steadily progressed. Therefore, the active exploration of ML and DL approaches among researchers in the area of construction productivity is noticeable. For example, the measurement of productivity via vision [36], kinematic [37], and audio [38] adopted ML and DL algorithms for the extraction of productivity data.

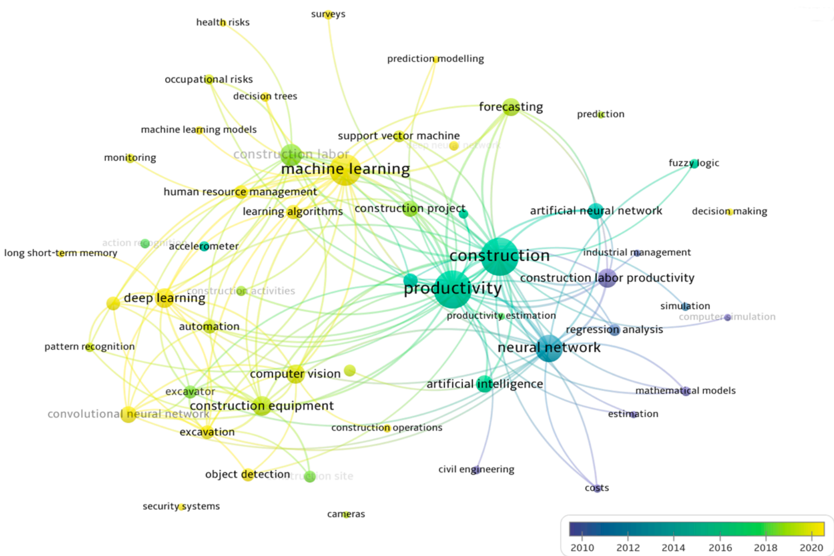

Figure 3. Timeline visualization of keyword relationships associated with ML-CP.

In terms of journal sources, with 133 identified papers, Table 2 outlined the top ten journals with the highest count of relevant publications. Within these journals, "Automation in Construction" (45 papers), "Journal of Construction Engineering and Management" (30 papers), "Journal of Computing in Civil Engineering" (15 papers), and "Advanced Engineering Informatics" (14 papers) demonstrated high publication volumes and are considered the top-ranked construction journals. Nevertheless, future studies can utilize this information as a reference when researchers submit their scholarly works.

Table 2. Top ten ML-CP journals ranked by number of publications.

Name of Journal	Number of Publications
"Automation in Construction"	45
"Journal of Construction Engineering and Management"	30
"Journal of Computing in Civil Engineering"	15
"Advanced Engineering Informatics"	14
"Engineering, Construction, and Architectural Management"	6
"Construction Innovation"	5
"Canadian Journal of Civil Engineering"	4
"Computer-Aided Civil and Infrastructure Engineering"	3
"Construction Management and Economics"	1
"Computing in Civil Engineering"	1

According to statistics, the first authors of the 133 selected works are affiliated with more than 25 different countries/regions. This demonstrated the fact that the area of ML-CP is under the influence of the international academic community, with scholars across the globe contributing knowledge to this domain. Figure 4 illustrates the top ten countries/regions' contributions of papers to the research field. Standing on the peak, the United States of America (USA) lead with 32 papers, followed by Canada with 26 papers. Generally, the high volume of papers produced indicates that the academic community and the construction industry in the USA and Canada are very concerned about increasing construction productivity. In addition, China (ten papers) ranked third, while Hong Kong (eight papers) and Australia (eight papers) came fourth, followed closely by the Republic of Korea and the United Kingdom (UK) at seven papers each. A total of 112 out of 133 publications, or 84.2%, were published by a primary contributor from the leading ten countries/regions. This huge amount highlights the inputs of these authors to the research of ML-CP is substantially greater compared to those authors from other countries/regions, thus indicating how much emphasis is attributed to the improvement of construction productivity by the leading countries/regions.

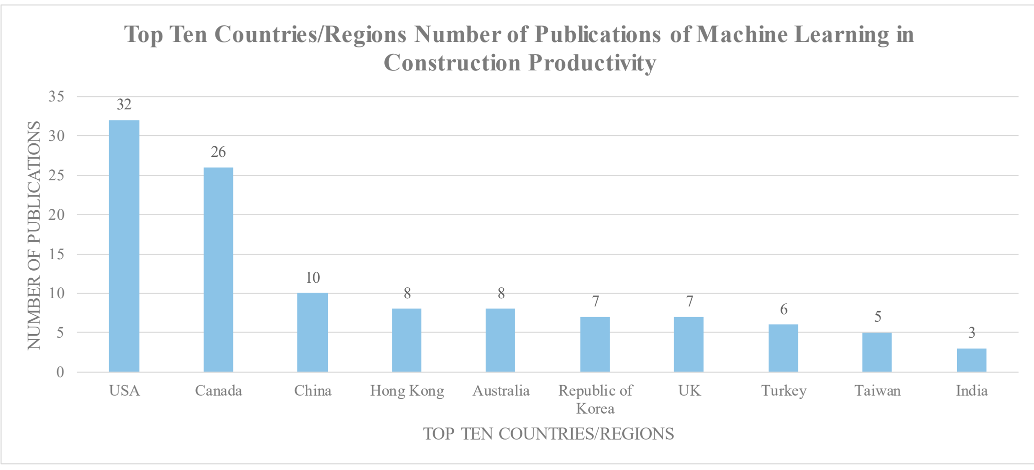

Figure 4. Top ten countries/regions' number of publications related to ML-CP.

Figure 5 highlights the distribution of keywords across various research, as well as the occurrence rates of the keywords with their relationships to each theme in the research area. For the purpose of visualizing their frequency, the recurrent keywords are displayed in circles of larger size. Among these keywords, “construction”, “productivity”, “machine learning”, and “neural network” exhibit the highest associations. The details of the top 20 keywords are shown in Table 3, where the occurrences indicating the frequency count for each keyword were acquired from the available publications. For instance, other than the main keywords “productivity”, “construction”, “machine learning”, and “neural network”, “construction equipment” and “construction labor” appear frequently, indicating the research on CLP and CEP are widely explored separately and in conjunction with “machine learning”, as well as “neural network”, as shown in Figures 6 and 7, respectively. Moreover, the total strength linked to each item is determined by the value of the total link strength. For example, higher values indicate stronger inter-relatedness between the keywords.

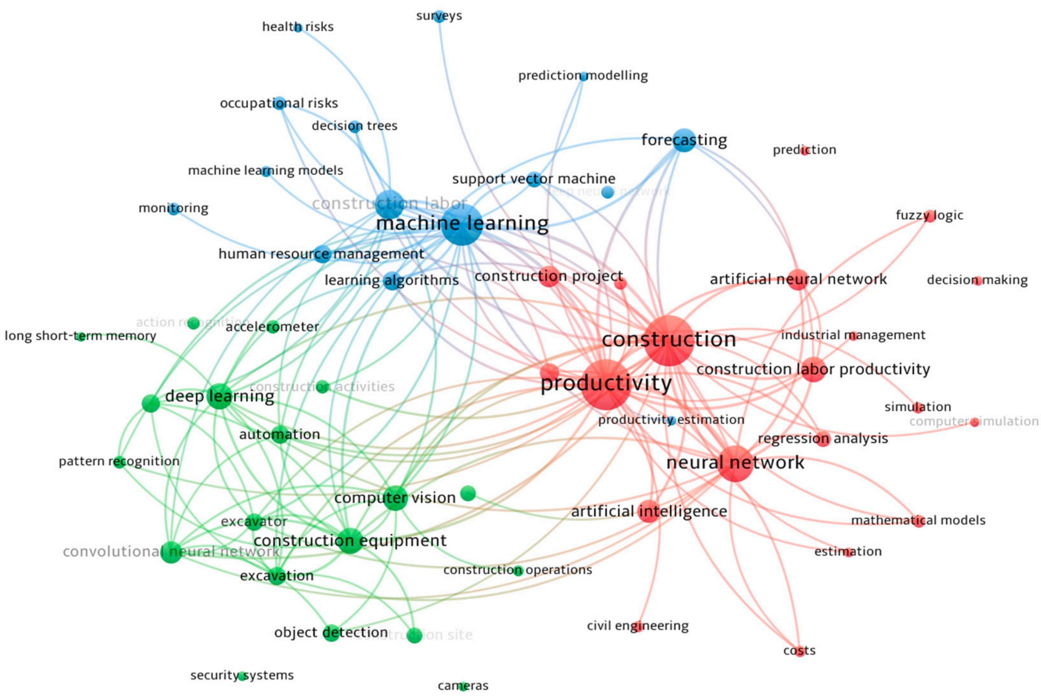

Figure 5. Visualization of keyword relationships associated with ML-CP.

Table 3. Top 20 keywords and their relationship data as related to ML-CP.

Keyword	Occurrences	Total Link Strength
Productivity	60	341
Construction	59	338
Machine learning	44	250
Neural network	35	207
Project management	27	182
Construction labor	24	158
Construction equipment	20	154
Deep learning	20	124
Forecasting	17	103
Excavation	11	98
Convolutional neural network	15	96
Computer vision	19	95
Construction project	14	89
Activity recognition	11	87

Table 3. *Cont.*

Keyword	Occurrences	Total Link Strength
Automation	11	85
Excavator	10	85
Construction labor productivity	19	84
Construction management	12	84
Learning algorithms	12	81
Artificial neural network	14	80

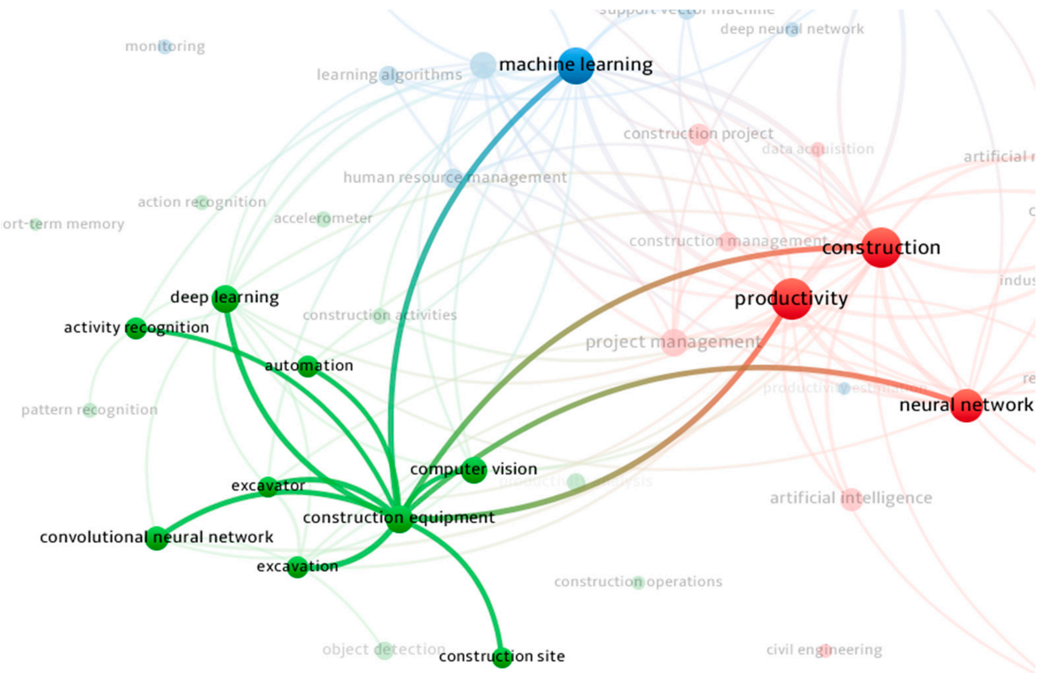

Figure 6. Visualization of relationships for the isolated "construction equipment" node.

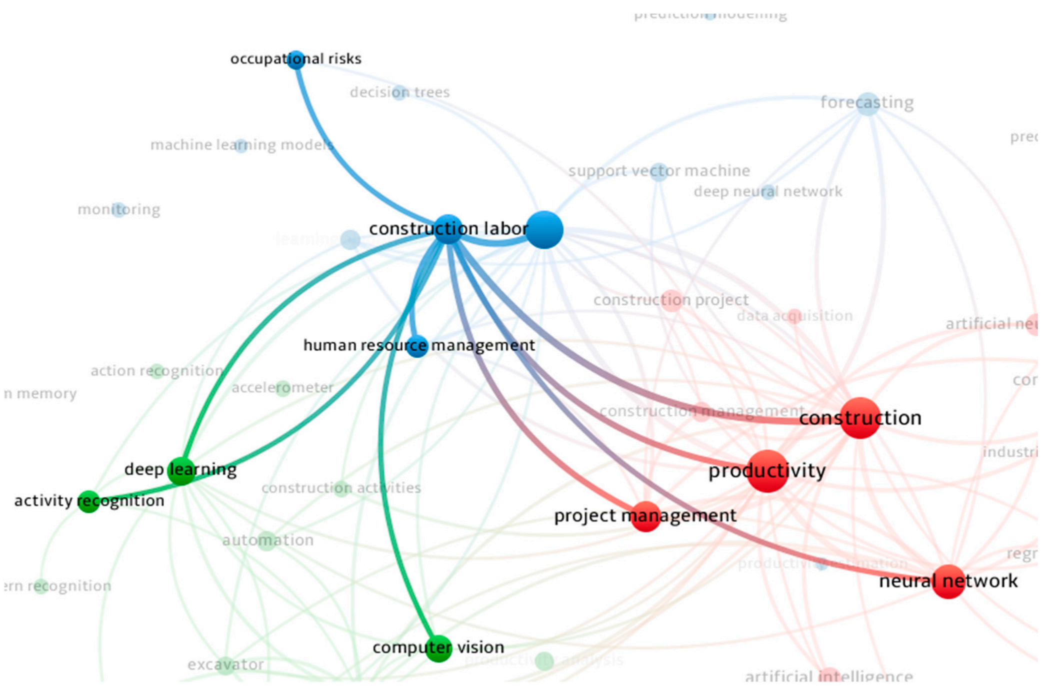

Figure 7. Visualization of relationships for the isolated "construction labor" node.

4. Critical Review of the Application of Machine Learning in Construction Productivity Modeling (ML-CPM)

This review study examines the application of ML-CPM published since the 1990s [30,31,39]. To delve deeper into ML-CPM-related studies, a systematic review was performed right after the bibliometric assessment of the identified publications. It was found that ML-CPM research mainly focused on construction productivity at the activity level in terms of CLP and CEP [6,27,40]. Figure 8 illustrates the framework for the systematic review of ML-CPM. The applications of ML on both CLP and CEP were elaborated on as follows.

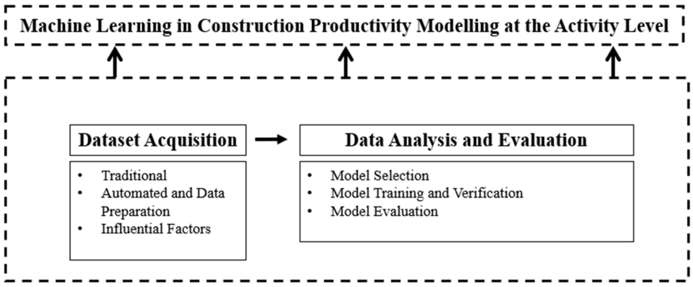

Figure 8. Framework for analyzing ML-CPM at the activity level.

4.1. Dataset Acquisition

Generally, data acquisition is the fundamental step for CPM as comprehensive data, in a considerable amount, are needed for developing (building, training, and testing) a productivity model [6,41]. Moselhi and Khan and Luo et al. [23,42] highlighted the fact that subsequent analyses depended highly on the methods and accuracy of the dataset collected. Data collection typically requires inputs captured or measured traditionally, automatically, or with a combination of both. The traditional approach of data collection is a simple approach that requires the person to record productivity inputs in person manually with the help of the devices illustrated in Figure 9. However, due to technological advancement and the limitations of the traditional approaches presented in Table 4, there has been a shift towards monitoring and tracking for measurement of CP automatically using sensors (e.g., vision-based, kinematic-based, and audio-based).

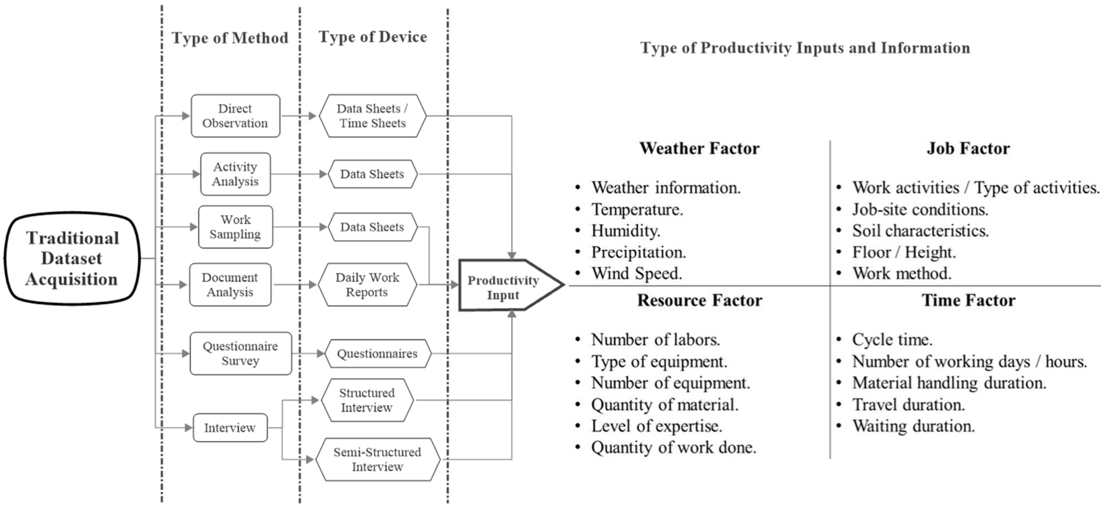

Figure 9. Traditional approaches of dataset acquisition.

4.1.1. The Traditional Approach Measurement of Construction Productivity

A number of studies (e.g., regarding formwork labor productivity [23] and piling works [24,43]) were conducted on monitoring, gauging, and estimating CP using a variety of traditional approaches, as shown in Figure 9.

Direct observation has been widely adopted by researchers as it is a cost-effective approach to measure the work outputs [23,41,44] and the inputs do not require much processing [23,45]. However, the activities in construction are plenty and complex and the surroundings are ever changing. Although, the tools (e.g., data sheets and time sheets) for documenting the productivity inputs are customizable and allow one to cater to the documentation of productivity information [23,46].

The definition of work sampling is “a technique in which a large number of observations are made over a period of time of labor, equipment, or processes to facilitate quantitative analysis of an activity” [47]. Developed in 1927, it was a popular tool for work measurement to control inputs and it is an evolution from direct observation. This is mainly due to the fact that observation can cater to only a handful of workers for each moment [44,48]. Meanwhile, an evolution and extension of work sampling and activity analysis is where both of these methods depend on instantaneous or direct observation [44,47]. However, according to Gouett et al. and Shahtaheri et al. [44,49], work sampling and activity analysis are more towards productivity analysis and improvement tools, rather than productivity measurement methods.

Daily Work Reports (DRWs) are a comprehensive, inexpensive, and reliable source of input and have served as a popular source of past data. DWRs generally contain records of environmental conditions (i.e., rainfalls, job-site conditions, weather, ground conditions, production rates, facilities costs, labor, and equipment work hours) [50,51]. Consequently, data extraction from the report is required to be carried out to obtain the desired productivity inputs in a standardized format, as shown in Figure 10, to be useable for training ML models for productivity estimation. In addition, Sadatnya et al. [52] proposed a two-tier algorithm to optimize data extraction, as manual extraction requires much effort. Despite being a great source of productivity input, DWRs may include unavoidable human errors because observations and documentation are done by humans [52].

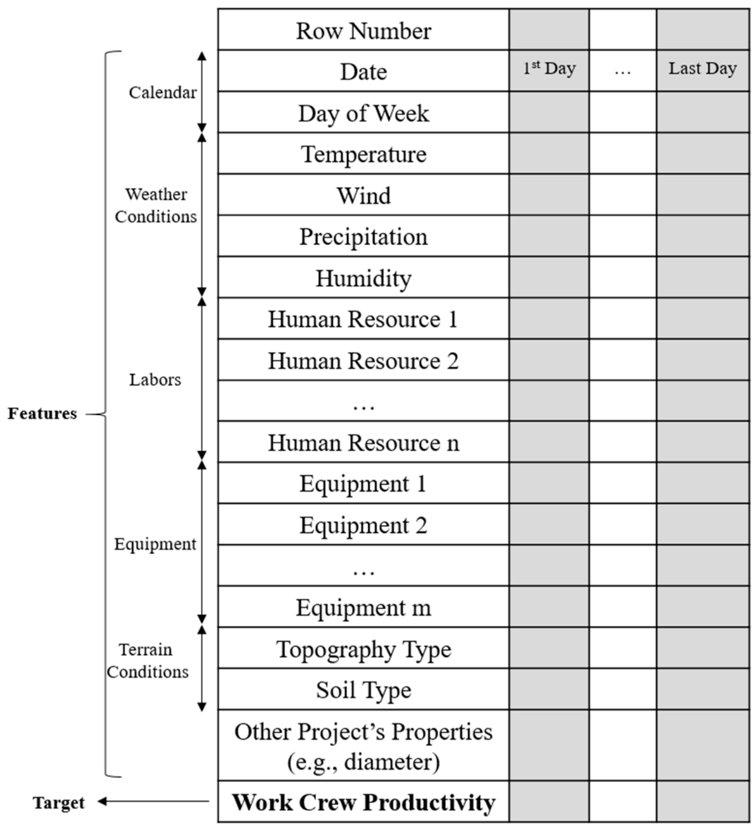

Figure 10. Illustration of the data extraction from DWRs [52].

Furthermore, questionnaire surveys and interviews are used to collect productivity in quantitative form (e.g., cycle time, work hours, and number of resources) and qualitative form (e.g., productivity for certain soil conditions and productivity influential factors), respectively. Interviews are considered direct data collection, where many methods can be used to fill the forms (e.g., site interviews, telephone calls, and site visits to fill the data forms). Meanwhile, questionnaire surveys can be done electronically or physically (e.g., post). Both methods are flexible depending on the researchers' preferences and needs [24]. Generally, researchers have adopted both methods to develop their productivity prediction models for various activities such as prefabricated external insulation wall systems [53], pile construction [24,43], resource allocation [54,55], and reinforcement bar placements [56].

Table 4 summarizes the strengths and limitations of the traditional approach to collecting construction productivity data [46,57,58]. For instance, traditional dataset acquisition is labor intensive, subjective due to the involvement of human judgment, cost sensitive, time consuming, and prone to errors [14,37,59]. However, they do have their strengths as well, as DWRs are an inexpensive source of data and direct observations are straightforward and adaptable. Meanwhile, interviews and questionnaire surveys are able to acquire a large quantitative and qualitative dataset easily. Generally, the dataset acquired traditionally does not require much or any processing to obtain productivity information.

Table 4. Summary of traditional approaches in dataset acquisition.

Type of Study	Types of Traditional Method	Type of Device	Type of Productivity Input	Strengths	Limitations
[41] Equipment Productivity	Direct Observation	Data Sheets	Number of equipment, capacity of equipment, cycle time, type of equipment, and kind of road surface.	Adaptability, straightforward, and reliable	Tedious, time consuming, difficulties in analysis, and prone to error due to human judgment [37,46,60].
[23,45] Labor Productivity	Direct Observation	Data Sheets	Weather factors: humidity, temperature, precipitation, and wind speed. Job Factors: work method, work type, and floor/height. Resource factors: crew size, quantity of material, number of equipment/machinery, and level of expertise.		
[44] Labor Productivity	Activity Analysis via Direct Observation	Data Sheets	Work activities (type, direct, or prep work), temperature, number of laborers, material handling duration, travel duration, and waiting duration.		
[49] Labor Productivity	Activity Analysis via Direct Observation	Data Sheets	Work activities (type, direct, or prep work), temperature, number of laborers, material handling duration, travel duration, and waiting duration.		
[61] Crew Productivity (Labor + Equipment Productivity)	Direct Observation	Time Sheets	Weather Factors: temperature, humidity, precipitation, and wind speed Job Factors: work type, floor/height, and work method. Resource Factors: crew size, quantity of material, and number of equipment/machinery.		
[50] Production Rate	Document Analysis	Daily Work Reports (DWRs)	Job-site conditions, quantities of work, weather conditions, and temperature.	Straightforward, easily available, inexpensive, and multifaceted Information.	Reliability and prone to human error [52]
[51] Labor and Equipment Productivity	Document Analysis	Daily Work Reports (DWRs)	Work activities; weather information; number, types, and hours of equipment used; and number, types, and hours of labor used.		
[52] Crew Productivity (Labor + Equipment Productivity)	Document Analysis	Daily Work Reports (DWRs)	Work activities; weather conditions; number, types, and hours of equipment used; and number, types, and hours of labor used.		

Table 4. *Cont.*

Type of Study	Types of Traditional Method	Type of Device	Type of Productivity Input	Strengths	Limitations
[3] Labor Productivity	Daily Record and Interview	Data Sheets, Structured Interview	Work activities, number of laborers, quantity of work done, and number of hours	Adaptability, standardization, large dataset, straightforward, reducing level of noise of the qualitative data, and providing feedback/verification against collected quantitative data.	Labor intensive, cost sensitive, tedious post processing, and prone to error [46,59].
[24,43] Equipment Productivity	Interview and Questionnaire Survey	Structured Interview and Questionnaires	Cycle time, soil characteristics, and number of equipment.		
[53] Labor Productivity	Interview	Structured Interview	Construction working hours, construction workers, and construction equipment		
[55] Labor Productivity	Interview and Questionnaire Survey	Structured Interview and Questionnaires	Work activities, quantity of work done, number of days, number of laborers per day, and exposure conditions.		

4.1.2. The Automated Approach to the Measurement of Construction Productivity

Compared to the traditional approaches (e.g., direct observations and survey-based methods), developments in data collection automation to monitor resources and measure the progress of activities have shown encouraging potential [14]. Kim and Cho [62] mentioned that given construction tasks naturally consist of repetitive physical activities, automating the identification of workers' movements can aid in measuring productivity. Several efforts have been made to develop automated dataset collection for both labor productivity and equipment productivity, mainly vision-based, kinematic-based, and audio-based approaches [12,13,63–65]. Generally, previous studies adopted automated dataset collection, which was then analyzed by ML algorithms to extract productivity data. This is because the dataset is in the form of pure raw data (images, videos, sounds, accelerations, velocities, orientation data, and location data), which would need to be processed. For instance, each dataset would need to undergo specific data preparation steps (i.e., data segmentation, feature extraction, feature selection, and classification) to acquire the productivity data, unlike the traditional approach, which is much more straightforward, as discussed earlier. Additionally, to enhance the learning capacity and prediction performance of ML algorithms, data preparation is essential, where the acquired data should be sorted and brought to conformance [3,66]. Figure 11 demonstrates the overview of the automated approach, where each type of productivity and sensor will be reviewed further.

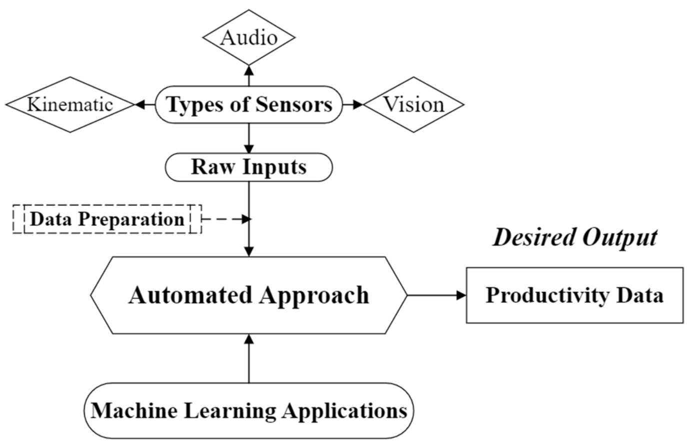

Figure 11. Overview of the automated approach to dataset acquisition.

The Automated Approach to the Measurement of Construction Labor Productivity

During the last few decades, the measurement of the productivity of labor activity has primarily leaned on traditional methods. With the advancement of technologies, recognizing labor activity can be done via three major sensing technologies (i.e., vision-based, audio-based, and kinematic-based). Subsequently, the incorporation of classification algorithms using ML or DL for action recognition have been used for the generation of productivity data.

Kinematic-based

The rapid development of body-worn sensors (e.g., accelerometers and Inertial Measurement Units (IMUs)) and smartphones has enabled the detection of motion associated with workers' activities. Location-based sensing devices (e.g., Radio Frequency Identification (RFID), Ultra-Wideband (UWB), and Global Position System (GPS)) are commonly explored by researchers as well, but they are not suitable for detailed activity monitoring for workers, as the location information is insufficient to distinguish between the different activities carried out by workers in the same position [67,68]. Generally, the execution of any activities will allow humans to initiate certain postures or actions which are defined as motion [62]. The measurement of workers' posture and motions during various construction activities is conducted via the body-worn sensors. They collect data in the form of acceleration, velocity, and orientation. Due to the need for the attachment of sensors to workers' bodies, their working performance might be impacted despite the sensors being low-cost and offering automated data acquisition [2].

Recognition accuracy is dependent on the quantity of the sensors and the placement of the sensors. Multiple sensors or single sensors have been explored to capture labor motions for the dataset. A motion dataset regarding the material handling activities (placing, lifting, carrying,) of laborers was collected via a set of motion tracking devices (17 IMUs), a commercial product named Perception Neuron [62]. In addition, acceleration data was collected via a motion node (GLI Interactive LLC, Seattle) single accelerometer for the study masonry of works [37]. The optimum placement of sensors on laborers for masonry works was explored by Ryu et al. [68] as well. The waist has often been regarded as a promising position [37] due to the placement where the whole-body mass is at the center, and the primary body motion [69] is better represented by the sensor signals from the waist. Still, this would not be the case if the activities are hand- or arm-dominant, as it would be difficult to differentiate the actions. This was proven when the wrist-worn accelerometer achieved higher accuracy [68] compared to the waist-worn sensor [37].

Due to the nature of classifying activities from kinematic-based sensing technologies being considered data mining, the training of data generated via ML algorithms are called classifiers [37]. By identification and classification of the actions, the productive time of the activity can then be identified. Past scholarly works have demonstrated the processing of these extensive datasets is performed via ML algorithms to achieve automated action recognition. The evaluation of five different classification techniques (support vector machine (SVM), decision tree, k-nearest neighbor (k-NN), artificial neural network (ANN), and logistic regression) was conducted, where k-NN was highly superior in terms of accuracy and even computational time [14]. However, in Ryu et al.'s [68] research, SVM produced slightly better performance among k-NN, decision Tree, and ANN techniques. In addition, the utilization of a stratified 10-fold cross-validation for the selection of the right classifier model of the three algorithms (decision trees, multilayer perceptron, and naïve Bayes) was conducted, where multilayer perceptron emerged superior to others for recognizing activities in masonry [37]. Due to the variability of movement among workers, multiple acceleration signal patterns could be produced, including those that are performing the same actions. This would lead to a decrease in classification accuracy [68]. Therefore, a larger volume of data is required to be trained and tested concurrently with multiple algorithms to achieve the best accuracy. Thus, the majority of the researchers adopted multiple algorithms and sample sizes and conducted hyperparameter tuning to gauge their accuracy, enabling them to select the optimum classifier rather than just opting for one.

Despite the promising automated kinematic-based approach in action recognition via the integration of sensing technologies and ML applications, the concerns are as highlighted below:

- How can DL help to minimize the influence of human variability?
- How do kinematic-based approaches perform in other labor-intensive trades apart from masonry trades?

Vision-based

As the deployment of cameras is becoming more common at construction sites, images and videos as sources of information have been made more accessible and trustworthy [59]. In addition, the emergence of computer vision and ML technologies has allowed automated analysis of construction activities. Computer vision algorithms utilize images and videos from one or more cameras to recognize and classify events and have been heavily studied for both the purpose of safety monitoring and construction worker productivity analysis [46,59].

Numerous pieces of research in vision-based areas can be categorized into three levels (i.e., object detection, object tracking, and activity/action recognition) [21,36]. However, recognizing action is crucial for the capturing of spatiotemporal information, which can be used to track progress and calculate quantities of accomplished work [70,71]. The work conducted in the field of computer vision techniques has produced strong recognition models, which have generally resulted in extremely well-performing models. For instance, an improved convolutional neural network (CNN), a three-dimensional (3D) CNN, was developed to accommodate complex activities of workers capturing temporal and spatial information [46]. In addition, an improved version of You Only Watch Once (YOWO), YOWO53, was developed, with at least a 16% improvement of accuracy in activity classification for the computation of the percentage of workers' value-adding and non-value adding activities [36]. The majority and recent researchers adopted and improvised DL algorithms (YOWO, CNN, Faster Region-Proposal Convolutional Neural Network (Faster R-CNN), and You Only Look Once (YOLO)) are proven to be more promising compared to traditional ML algorithms (e.g., SVM and k-NN) in this approach due to the complex and changing conditions (e.g., background of workers, viewpoint changes, illumination variance, and human variability) in the recorded image or videos [36,46,59,72].

The significant advantage of computer-vision algorithms over kinematic-based approaches is that they do not require workers to wear sensors on their bodies. However, computer-vision methods can have certain drawbacks as well. Using cameras is a fixed approach that requires a well-lit environment and the possibly of experiences of occlusions of practically all configurations, especially in situations involving dynamic work. Additionally, because camera files (pictures or videos) require a large storage space, keeping the data required for the supervised ML algorithms could potentially be expensive [21]. Ultimately, similar to all supervised DL-based approaches, a large dataset is needed for this approach to be feasible. Despite the convenience, as compared to the kinematic approach, much processing is needed after the images or videos are gathered, opening this approach to more future developments.

Audio-based

The primary use of audio-based recognition for activity detection of construction workers has been captured through either a single microphone or an array of microphones placed on construction sites [73]. Rashid and Louis [38] were able to sort four activities (table-saw cutting, nailing with a nail gun, drilling, and hammering) in a modular construction factory environment. SVM was primarily used extensively in this method since it was required to train numerous classification models to perform a comparative analysis of various feature sets and window size combinations [38]. However, research in audio-based approaches for measuring or capturing CLP is very limited, as this approach is only feasible when the workers' activities generate distinctive sounds. A combination with other action recognition approaches should be explored for the quantification of productivity data (e.g., cycle time and productive time).

To summarize the measurement of productivity in CLP, several different modalities and methods have been discussed. The majority of the body of knowledge focuses on clearly defined activities that vary among each of the three methods. Despite the convenience of audio-based methods, the applicability is severely limited as they are only applicable to activities with unique sound patterns. This limits the practical implementation in a generalized model. On the other hand, computer vision needs the greatest data storage capacity, and the cameras are generally installed at a stationary position where they need to remain physically non-intrusive. Therefore, to monitor multiple or all the workers of the entire construction site would require extensive camera setups that might lead to high costs. This is deemed necessary in order to replace manual CLP monitoring (e.g., work sampling). Thus, kinematics-based approaches seem to be the optimal option of the three techniques. On the other hand, the limitations of kinematic-based approaches shall not be overlooked as well. This technique of gathering data is the only one of the three that requires physical intrusion, and it is also the most manipulable. Nevertheless, it is observed that most studies were carried out using a limited sample of construction workers and did not address complicated construction working sites.

The Automated Approach of the Measurement of Construction Equipment Productivity

Construction equipment is considered a principal element of construction production as well; therefore, its operation must be measured and examined methodically in order to track project productivity. Generally, given that various construction tasks are repetitive and that the number of cycles in a given amount of time often determines the production rate, CEP measurement of production rates depends heavily on the cycle time. Construction heavy equipment often performs repetitive tasks as cyclical operations; therefore, recognizing those cyclic actions or activities for cycle times is considered vital for scheduling and productivity analysis in construction projects [12]. Similarly, with CLP, automated CEP measurement of productivity relies on three broad categories of sensor modalities (kinematic-based, vision-based, and audio-based) as well.

Kinematic-based

Generally, construction equipment generates distinct kinematic signals when they are in operation. These signals are acceleration, angular velocity, velocity, and orientation data. There are adoptions of location-based sensors (e.g., UWB, GPS, and RFID) and motion-based sensors (e.g., accelerometers and IMUs). However, the ability to provide detailed analysis of production cycles and track stationary activities of construction equipment is not within the capacity of location-based methods [74]. Therefore, researchers tend to focus on utilizing IMUs for activity recognition.

Predominantly, the characteristics and the volume of the data reflects highly on the selection of the learning algorithm [75,76]. There is typically no “single” optimal classifier; therefore, each situation calls for a different assessment of the learning algorithm using cross-validation [77]. Akhavian and Behzadan [76] researched equipment productivity and adopted five learning algorithms (logistic regression, k-NN, decision tree, ANN, and SVM) to enhance the robustness of the results. In their test cases, ANN emerged as having the best relative overall accuracy after training and testing performed through a stratified 10-fold cross-validation. Meanwhile, in Ahn et al. [75], research in measuring the operational efficiency of equipment (excavator) used naïve Bayes, ANN, and decision tree; the accuracy of each classifier differs according to the number of samples. This can be further improved by having a larger sample size to alleviate the effect of external noises.

Two DL techniques for compactor and excavator activity recognition were compared [71]. Only accelerometer data were used in this research. They achieved a lower accuracy of 77.6% in comparison to other research and emphasized the need for a more complete dataset in order to further increase the accuracy. This clearly identifies the importance of the dataset volume for DL applications. However, a novel Fractional Random Forest method with comparable performance to a DL-based method’s (up to 94%) activity recognition model that worked with small datasets was proposed by Langroodi et al. [78]. The importance of fractional feature augmentation was highlighted and was able to elevate the performance of the activity recognition model regardless of the type of ML model.

Vision-based

Mainly, construction equipment for earthmoving activities (e.g., excavators, dozers, dump trucks, and backhoes) have been explored for the purpose of automated measurement of productivity via vision-based techniques. Noticeably, the vision-based dataset acquisition approach is more popular for measuring equipment productivity rather than labor productivity, due to the countless complexities of human movements compared to equipment. Recent work in computer vision and pattern recognition has shown that traditional ML methods, such as nearest neighbor models, SVM, and linear regression, in tasks like object detection, object tracking, and action recognition are inferior to the DL approaches [21,79,80]. This superiority can be attributed to the capabilities of advanced neural networks, including Recurrent Neural Networks (RNNs) and CNNs, which excel at modeling sophisticated connections of input data (i.e., images and videos) and output predictions (e.g., object categories and action categories) [81].

Given the benefits that DL algorithms offer over traditional ML methods, their application for recognizing construction activities has been the focus of recent research. Specifically, Ren et al. [82] developed models incorporating the Faster R-CNN and Double-layer Long Short-Term Memory (DLSTM) layers using data gathered in experimental arrangements. This approach yielded precision rates of 90.9% and recall rates of 89.2%. Kim and Chi [81] conducted a study where excavators engaged in earthmoving tasks were analyzed through vision-based activity recognition. Three models, CNN-LSTM, CNN, and CNN-DLSTM, were analyzed, where the CNN-DLSTM model achieved the highest accuracy.

Despite the advancement of neural networks, as shown in Figure 12, there is no single fit algorithm for every scenario, due to different techniques (object detection, tracking, and action recognition) requiring different algorithms. Thus, hybrid methods and further improvement of architectures are commonly found in vision-based dataset preparation to extract productivity data.

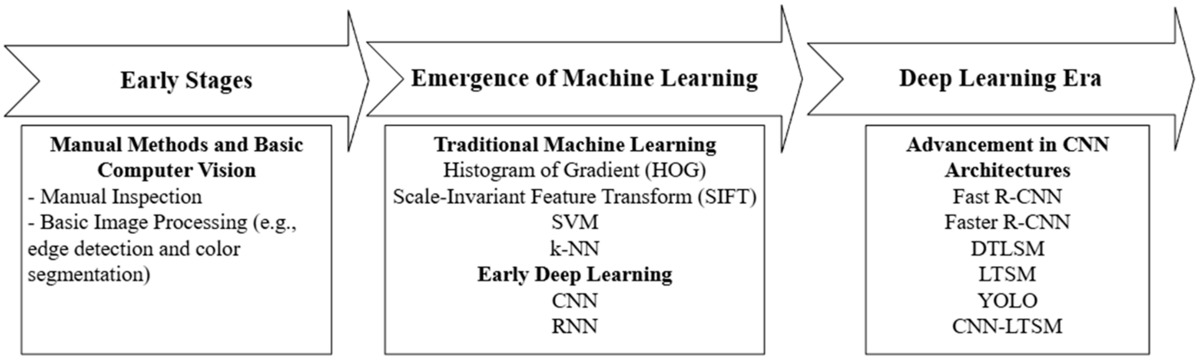

Figure 12. Advancement of techniques for vision-based CEP monitoring.

Audio-based

The development of audio-based methods for recognizing construction equipment activity is relatively new [78]. Because construction heavy equipment frequently produces distinctive audio patterns while carrying out different tasks, these audio signals may serve as valuable sources of information. By analyzing this data, we may be able to extract a significant amount of information about the underlying operations [83]. Signal processing and ML or DL algorithm techniques are used to identify the distinct sound patterns that every activity or piece of equipment produces after the recordings are done via microphones.

An audio-based approach depends on frequency magnitude features as inputs to ML algorithms. SVM has been popular in this area due to its efficiency in handling high dimensional data and the limited number of labeled data points. For instance, Cheng et al. [83] processed the audio signals from equipment by applying SVM to distinguish the activities of each equipment via their sound patterns. The value of detail specificity for productivity measurement can be minimal, despite producing high accuracies. In addition, Bayesian models are supplemented with SVM outputs to produce cycle time estimates of an accuracy exceeding 85% [12]. Evaluation of 17 ML classifiers and three DL approaches were explored to determine the suitable analytics algorithm where Random Forest achieved a high 93.16% accuracy, while DL approaches achieved results between 90% and 94% [84]. Overall, the choice between ML and DL techniques depends on the specific application, available data, and computational resources. Notably, researchers exploring this area held to the perspective of wanting to identify the ML algorithm that could perform best. This explains the fact that numerous researchers adopted and compared multiple algorithms in their case studies continuously in search of improvement.

To summarize, ML-based equipment activity recognition methods have advanced significantly in recent years. In addition, a growing trend in general research toward the adaptation of DL algorithms to increase the accuracy and generalizability of these approaches can be noted. Because construction equipment models vary widely, it would be necessary to gather a substantial amount of data from many versions pertaining to every piece of equipment to ensure the correctness of the activity recognition models.

4.1.3. Construction Productivity Influential Factors

Precisely describing labor productivity in projects and identifying the factors influencing CLP is crucial for improving overall project performance [6]. In recent years, initiatives aimed at improving CLP have gained significant attention within the construction industry [27,66]. According to Moselhi and Khan [45], CLP is influenced by a multitude of parameters, some with long-term effects, others with short-term or temporary impacts, and some with both long-term and ripple effects. Numerous studies have focused on either identifying and/or quantifying the impact of individual parameters as summarized into four main categories, as shown in Figure 13.

Environmental Factor	Job Factor
• Temperature. • Humidity. • Precipitation. • Wind speed. • Soil conditions. • Weather conditions (e.g. rainy).	• Work activities / Type of activities. • Floor / Height. • Work method. • Overtime work. • Sequence / Planning of work. • Total volume of work. • Rest time. • Work interruptions (e.g. design changes).
Human Factor	**Resource Factor**
• Gang / crew size. • Age. • Language. • Education, experience, and skill. • Discipline. • Supervision. • Leadership. • Level of motivation. • Effective communication.	• Incentive programme. • Proper Health, Safety, Environment (HSE) programme. • Suitable site layout. • Sufficient facilities / accommodation. • Availability of materials / tools. • Quality of materials / tools. • Availability of labors.

Figure 13. Summary of CLP influential factors at the activity level.

When designing a productivity study, it is essential to consider not only the effect of parameters on productivity but also the number of parameters included in the model. A comprehensive understanding requires considering the interplay of these factors; hence, this is enabled with the aid of a ML mechanism. El-Gohary et al. [3] presented an engineering framework to simulate and enhance contractor's CLP, encompassing a broad range of influencing factors at the micro-level (activity level at a construction site). The links between CLP and the pertinent influential factors were quantified and mapped using ANN. In addition to ANN, Heravi and Eslamdoost [15] conducted a sensitivity analysis to identify the determinants that have the greatest impact on the predictive capability of neural networks. The analysis revealed that the key influencing factors are worker motivation, suitable site layout, labor competence, poor decision-making, and proper planning.

Addressing and improving these key factors has the potential to significantly enhance labor productivity in future projects. Additionally, Moselhi and Khan [45] ranked the determinants that impact the daily CLP of formwork installation operations on construction job sites, and the element that has the most impact on daily productivity is temperature. This was identified using three different variable selection techniques (Stepwise regression analyses, Neural Networks, and Fuzzy clustering). Despite several studies exploring and quantifying the relationship between CLP and influencing factors using ML algorithms having great results, not all of the above mentioned factors or other new parameters are yet to be explored. The rest of the parameters should be further analyzed to identify the most influential factors in CLP allowing relevant parties to take action accordingly.

In terms of equipment-driven activities, construction equipment is a critical resource to drive productivity. Nevertheless, the analysis and identification of the factors influencing CEP in equipment-driven activities are limited [16,85]. The identified factors influencing the CEP are summarized in Figure 14. As a result, the human factor was regarded as the most influential factor after the researchers conducted interviews with experts and questionnaire surveys. This is because generally, equipment are just tools operated by humans. However, there is clearly a shortage of research on the quantification of the correlation between CEP and their influencing factors.

Environmental / Location Factor

- Weather conditions.
- Soil conditions.
- Underground facilities.
- Groundwater level.
- Spaciousness of working area.
- Site restrictions.

Job Factor

- Planning / Sequence of work.
- Appropriateness of equipment to job.
- Work activities / Type of activities.
- Total volume of work.

Equipment Factor

- Equipment breakdown frequency / downtime.
- Equipment maintenance frequency / downtime.
- Equipment age.
- Equipment availability.
- Equipment warranty.
- Equipment delivery to working area.
- Equipment functional range.
- Equipment ergonomic design.

Human Factor

- Skill of equipment operator.
- Experience of equipment operator.
- Education of equipment operator.
- Coordination between labor and equipment operator.

Figure 14. Summary of CEP influential factors at the activity level.

4.2. Data Analysis and Evaluation

Generally, CPM revolves around three important elements (measurement of productivity, influential factors, and ML applications), as shown in Figure 15. Various research has been reviewed earlier under dataset acquisition. Therefore, moving on to the data analysis and evaluation section, there are several crucial steps to be followed to develop a productivity estimation model. The general ML workflow of CPM is depicted in Figure 16. Data analysis and evaluation can be broken down into several important stages.

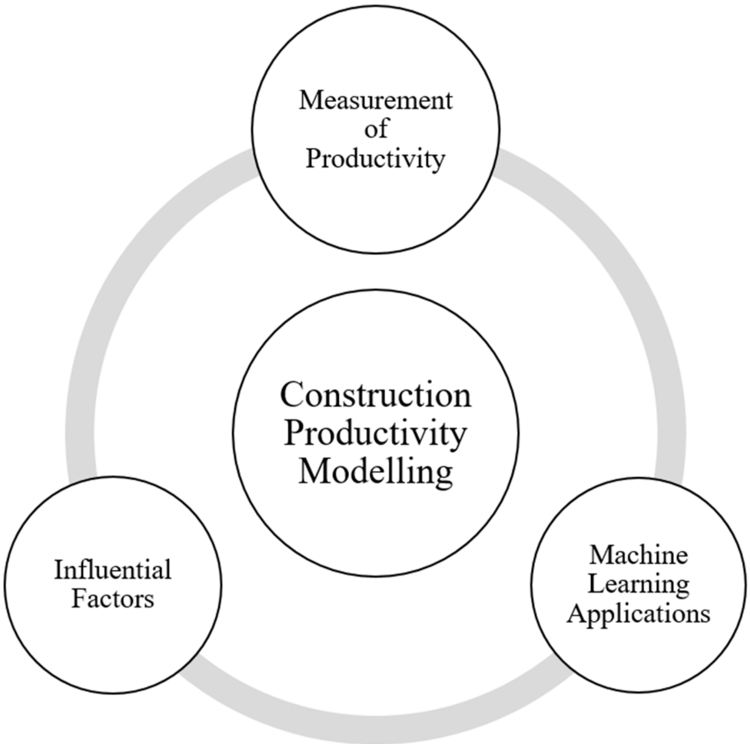

Figure 15. CPM elements.

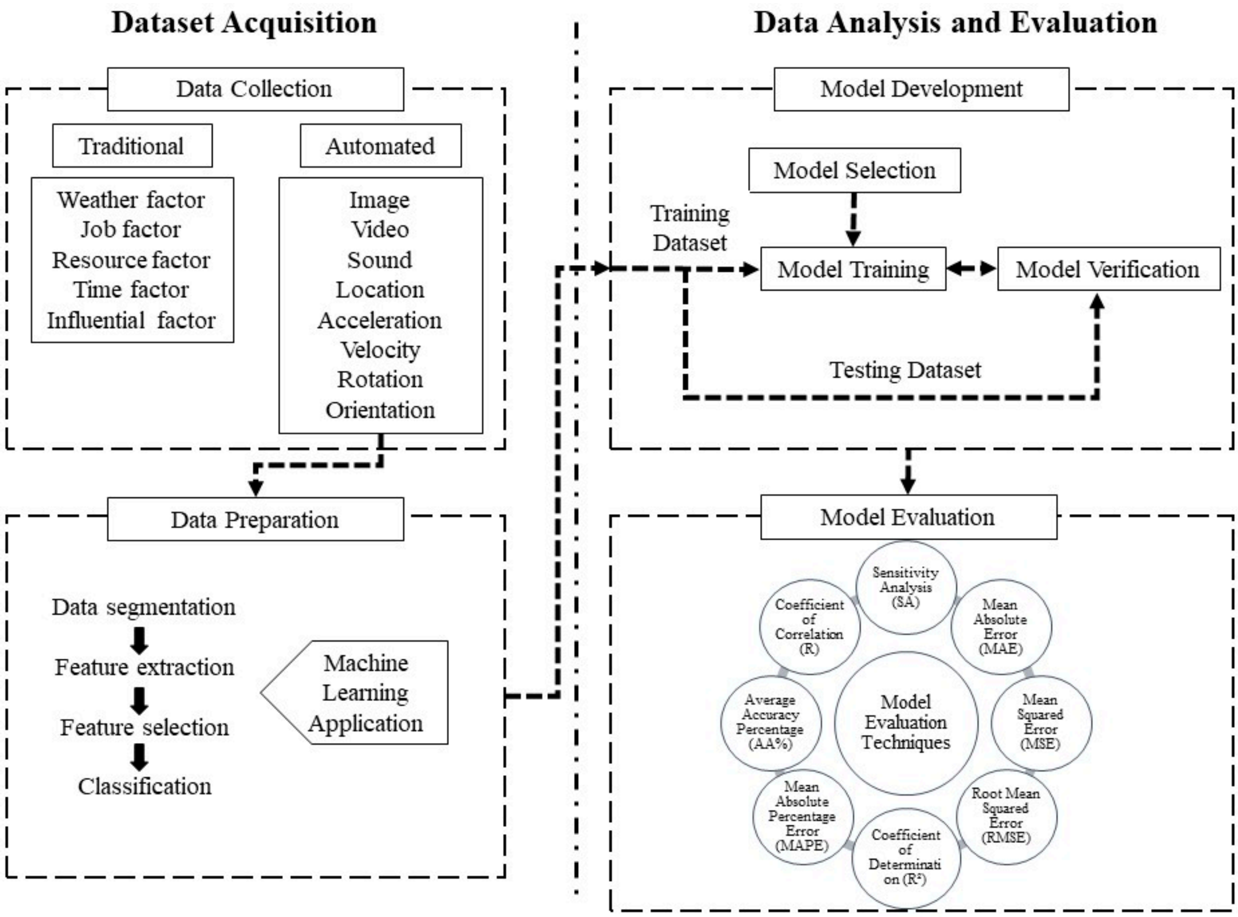

Figure 16. ML Workflow for CPM.

4.2.1. Model Selection

Experts and estimators in the construction sector may assess construction productivity rates under certain circumstances using their mental models. In actuality, estimators assess these variables by mentally modeling the production process in order to get an estimate [6]. However, relying only on one's judgment is constrained by the expertise and experience of the estimator in question and may not always yield accurate and consistent estimates. Therefore, the formalization of this modeling process is needed via an integrated, cohesive, and methodical approach for productivity measurement and analysis. Currently, there are various ML models used to predict construction productivity. Nevertheless, there is no set benchmark for choosing the best algorithm. Consequently, experimenting with multiple algorithms applied to the same dataset to determine the best model for a particular case is one way to deal with this [4,5,66,86].

Upon analyzing the existing literature, as summarized in Table 5, it has become apparent that among the prediction models ANNs have been extensively employed for both labor and equipment since then and now. Despite ANNs showing promising accuracies, Mirahadi and Zayed [87] has suggested a modified neural network-driven fuzzy reasoning framework to improve productivity estimation accuracy even further. Besides, the exploration of meta-ensemble ML models via different variation types was created to demonstrate the innovation of other potential algorithms instead of an ANN [66]. Generally, selecting CPM techniques is mostly based on the amount and characteristics of the influencing factors, the intricacy of the mapping connection, the capacity of a certain modeling method, and the researcher's preferences.

Evidently, references [4,86] adopted the same dataset but in terms of technicality different techniques, such as single point estimate and prediction interval, were adopted. A straightforward approach was carried out by Golnaraghi et al. [4], comparing the results of the four types of ANN models to obtain the most accurate model, which is BNN. However, Nasirzadeh et al. [86] proposed an ANN-based PIs to increase the model robustness and with the inclusion of uncertainty, the predicted variable will fall within the lower and upper range with a defined confidence level. This will result in having a more reliable prediction. Considering both scenarios, ANN-based PIs can be considered a hybrid approach compared to the deterministic model.

Table 5. Summary of CPM ML models selection.

Ref	Year	Type of Productivity	Description	Data Collection Method	Productivity Input	Number of Influencing Factors	ML Model	Accuracy
[1]	2012	Labor	Prediction of labor productivity of marble finishing works.	Traditional (Direct observation)	Work sampling	9	ANN	90.90%
[3]	2017	Labor	Labor productivity prediction of reinforced concrete foundation works.	Traditional (Interview and Historical database)	Total quantities and m^2 completed per total works days spent	29	ANN	94.43%
[4]	2019	Labor	Comparing various ANN labor productivity models for formwork installation.	Traditional (Direct observation)	Square meters of formwork per labor-hour	9	ANN (GRNN, BNN, RBFNN, and ANFIS)	94.9% (BNN)
[5]	2021	Labor	Labor productivity model for formwork installation using SOS-LSSVM-FS.	Traditional (Direct observation)	Square meters of formwork per labor-hour	9	SOS-LSSVM-FS	MAPE 3.67%
[6]	2008	Labor	Steel drafting productivity.	Traditional (Questionnaire)	Labor hours per piece-by-piece basis	19	ANN	90%
[15]	2015	Labor	Concrete foundation labor productivity.	Traditional (Questionnaire and Interview)	Earned work hours per expended work hours	15	ANN + BR and ANN + ES	~95% (ANN + BR)
[41]	2010	Equipment	Determine productivity of selected sets of machines (excavators, trucks, and platform) for earthworks.	Automated (Vision)	Cubic meter per hour	8	BPNN-CGB	Set 3
[43]	2005	Equipment	Pile construction productivity prediction.	Traditional (Questionnaire)	Cycle time	7	ANN	AVP > ~90%
[66]	2022	Labor	Formwork installation labor productivity prediction.	Traditional (Direct observation)	Amount of work done per day (m^2) per number of labor per day x work hour	9	Voting-ensemble and Stacking-ensemble	R^2= 0.7967 (Stacking)
[86]	2020	Labor	Labor productivity model for formwork installation.	Traditional (Direct observation)	Square meters of formwork per labor-hour	9	ANN-based PIs	At 95% CL = 92.5% PICP
[87]	2016	Labor	Improving productivity estimation for construction operations.	Traditional (Direct observation)	Volume of poured concrete in cubic meters per man-hour	9	NNFR	> 75% improvement in MSE
[88]	2006	Equipment	Dozer productivity estimation.	Traditional (Field data)	Loose cubic meter per hour	7	MR and ANN	0.00027 (ANN MSE)
[89]	2004	Equipment	Estimating concreting cyclic operations productivity.	Traditional (Direct observation)	Volume poured per hour	5	CBR	~ 90%

Table 5. *Cont.*

Ref	Year	Type of Productivity	Description	Data Collection Method	Productivity Input	Number of Influencing Factors	ML Model	Accuracy
[90]	2006	Labor	Estimating productivity of concreting activities (formwork, steel fixing, and concrete pouring).	Traditional (Questionnaire)	Formwork (F): man days per cubic meters of concrete Steel fixing (SF): man days per steel quantity Concrete pouring (CP): man days per cubic meter of concrete	14	NN	At 90% accuracy level, F: 91% SF: 97% CP: 38%
[91]	2022	Labor	Predicting masonry task productivity.	Traditional (Direct observation and Interview)	Number of blocks placed per crew every 5 min	6	DNN; k-NN; SVM; and LR	97.5% (k-NN)
[92]	2023	Labor	Comparative analysis of labor productivity modeling using a fuzzy inference system.	Traditional (Questionnaire)	Earned work hours per expended work hours	12	ANN; ANFIS; and FIS	93.14% (ANFIS RSME)

Notes: "BPNN/BNN-CDB = Back propagation neural network with conjugate gradient algorithm; MR = Multiple regression; CBR = Case-based reasoning; NNFR = Neural-network-driven fuzzy reasoning; SOS-LSSVM-FS = Symbiotic organisms search-least square support vector machine-feature selection; ANN = Artificial neural network; BR = Bayesian regularization; ES = Early stopping; PI = Prediction interval; DNN = Deep neural network; k-NN = K-nearest neighbor; SVM = Support vector machine; LR = Logistic regression; GRNN = General regression neural network; RBFNN = Radial base function neural network; ANFIS = Adaptive neuro-fuzzy inference system; Fuzzy inference system = FIS; MSE = Mean square error; MAPE = Mean absolute percentage error; PICP = Prediction interval coverage probability; FCM = Fuzzy C-Means Clustering; GA = Genetic algorithm".

4.2.2. Model Training and Verification

The partitioning of the dataset into training and testing (prediction) subsets is essential. The training subset is utilized for the "learning process" of the ML model, while the testing subset consists of data, which has not been encountered during training. This testing data assesses the ML model's ability to generalize. Although there is no strict guideline regarding the exact percentage distribution between the training and testing sets, it is crucial to ensure that there is an adequate amount of training data for the effective convergence of the ML model [3]. The processes of training and testing are dynamic and ongoing, allowing for additional training and testing as more data becomes available. Table 6 below shows the productivity models' training details.

Table 6. Summary of construction productivity model development details.

Ref	Year	Type of Productivity	ML Model	Accuracy	Training Technique	Data Size	Model Training %	Model Validation %	Model Testing %
[1]	2012	Labor	ANN	90.90%	Back-propagation	150	60	15	25
[3]	2017	Labor	ANN	94.43%	Feed-forward back-propagation	29	75	-	25
[4]	2019	Labor	ANN (GRNN, BNN, RBFNN, and ANFIS)	94.9% (BNN)	BR	221	80	-	20
[5]	2021	Labor	SOS-LSSVM-FS	MAPE 3.67%	LSSVM, SOS, FS, and 10-fold cross validation	220	90	-	10
[6]	2008	Labor	ANN	90%	Back-propagation	111	80	-	20
[15]	2015	Labor	ANN + BR and ANN + ES	~95% (ANN+BR)	Back-propagation (ES and BR)	27	70	15	15
[41]	2010	Equipment	BPNN-CGB	Set 3	Back-propagation and stop criteria	200	85	-	15
[43]	2005	Equipment	ANN	AVP > ~90%	Back-propagation	102	70	30	-
[66]	2022	Labor	Voting-ensemble and Stacking-ensemble	$R^2 = 0.7967$ (Stacking)	10-fold cross validation	221	80	-	20
[86]	2020	Labor	ANN-based PIs	At 95% CL = 92.5% PICP	Cross, validation, and simulated annealing	221	60	20	20
[87]	2016	Labor	NNFR	>75% improvement in MSE	ANN, FCM, GA, and alpha-cut	131	90 70 Training 15 Validation 15 Testing	-	10
[88]	2006	Equipment	MR and ANN	0.00027 (ANN MS error)	Back-propagation	N/A	75	-	25
[89]	2004	Equipment	CBR	~90%	N/A	240	90	-	10
[90]	2006	Labor	NN	At 90% accuracy level, F: 91% SF: 97% CP: 38%	Feed-forward back-propagation	F = 90 SF = 80 CP = 90	90 50	-	10 50
[91]	2022	Labor	DNN; k-NN; SVM; and LR	97.5% (k-NN)	Adam optimizer	3811	~63 (2400)	~18 (700)	~19 (711)
[92]	2023	Labor	ANN; ANFIS; and FIS	93.14% (ANFIS RSME)	Backpropagation; hybrid training; and logical rule	98	80	-	20

Notes: "N/A = Not available".

Typically, researchers randomly divide the dataset into three (training, validation, and testing) or two (training and testing) sets during the development of the model. It is apparent that the ratio of the training dataset shall be higher than the testing and/or validation to obtain a more precise accuracy as tested by Ezeldin and Sharara [90] with 50:50 and 90:10. In addition, to avoid overfitting problems in the model, the adoption of k-fold cross validation [5,66,86] was recommended and commonly used. Furthermore, the further splitting of the training set into three subsets (training, validation, and testing) was performed by Mirahadi and Zayed [87] to mitigate the overfitting issues in the model training procedure. However, due to its proneness of overfitting, researchers implemented several techniques (early stopping, Bayesian regularization, stop criteria, and ensemble method), which significantly improved the prediction accuracies.

4.2.3. Model Evaluation

Numerous performance evaluation metrics have been adopted to gauge the accuracies of the outputs (productivity estimation) of the developed models, as illustrated in Figure 17.

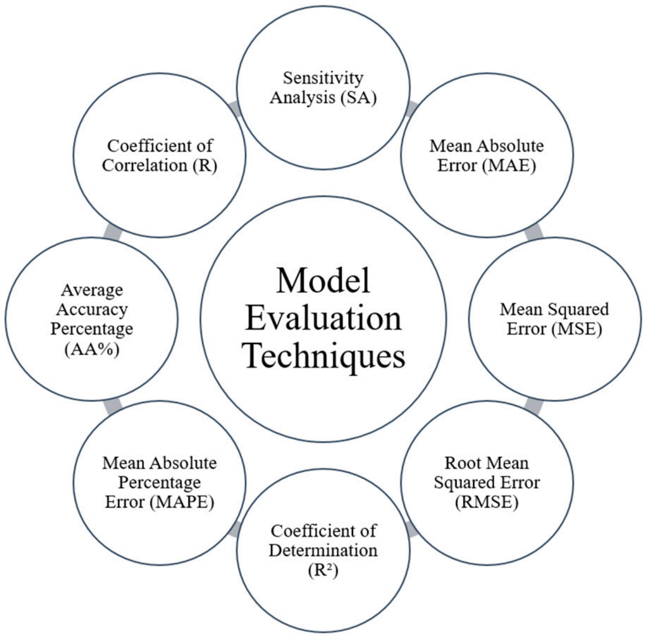

Figure 17. Summary of common model evaluation techniques in CPM.

Generally, the predicted outputs are compared with the actual measured productivity. Depending on the researchers, they are either compared with the original dataset used for training and testing [87], a reserved set of the original dataset [5,6,15,41], or a completely new dataset measured [66]. More than one statistical method is normally utilized to evaluate the results. Notably, a lower value in MAE, MSE, RMSE, and MAPE or a higher value in R, R^2, and AA% are preferable as they reflect the reliability and accuracy of the developed model. SA is widely exploited to check the changing effects of changing neural network model inputs on outputs [43]. This process works well for determining how much each aspect influences the neural networks' ability to anticipate outcomes. The reason behind this is that neural network model findings are difficult to interpret [15].

The wide adoption of ML models in construction productivity and model evaluation techniques to gauge their output accuracies has led the emergence of Explainable AI (XAI) [93]. XAI is present to help users understand how an AI-enabled system results in specific outputs in terms of explainability and interpretability [94]. This is because explainability and interpretability is often associated with trustworthiness [93]. Therefore, a possible research question for future research is listed below:

- How do feature relevance explanation techniques such as Local Interpretable Model-agnostic Explanations (LIME) and Shapley Additive Explanation (SHAP) effect the ML models in CP?

5. Synthesis of Findings

Undeniably, the number of studies conducted on automated dataset acquisition is large. Despite the disadvantages of the traditional method mentioned, the majority of the datasets collected for CPM are obtained traditionally, as shown in Table 5. Therefore, it can be deduced that the straightforwardness, convenience, and reliability of the traditional methods do have an edge and preference among researchers for construction productivity estimation. The application of ML has enabled multiple options (i.e., vision, kinematic, and audio) of automated dataset acquisition depending on the scenario, allowing a wider amount of data to be collected in a shorter amount of time. However, there is no single ML algorithm that fits the whole process of data preparation for each automated dataset acquisition method. Hence, the comparison of multiple ML classifiers were conducted to opt for the one that performs best. Through the application of ML, quantification of the correlation between the influential factors of CLP becomes possible, but there is a lack of attention on the CEP aspect, which can be explored in the future. In terms of the selection of ML models for CPM, continuous improvement to ANNs for CPM can be noticed. The exploration into XAI for CPM can further enlighten and strengthen the confidence of the deliverables of the ML models for construction productivity estimation.

6. Conclusions

This review provides a summary of the applications of ML-CP, and undeniably, throughout the last 30 years, ML-CP has been among the focal points of interest. This study via a mixed-review methodology has provided a comprehensive review of ML-CP related studies, from dataset acquisition to data analysis and evaluation. This review divides the process of CPM and analyses and the application of ML in each stage to enrich the existing field of knowledge. The findings of this review equip researchers with a foundation to gain additional insights about ML-CP. Specifically, this review evaluates CLP and CEP separately, whenever possible, and highlights the applications of ML, and even DL in some cases, in each stage of CPM. For instance, during dataset acquisition (measurement of productivity, quantification, and ranking of influential factors) and data analysis and evaluation (model selection, model training and testing, and model evaluation).

Despite considerable efforts to examine the advancements in measuring and modeling construction productivity, this review is not comprehensive and is confined to the activity level within the construction industry. Future research could investigate labor and equipment productivity across various industries. Additionally, the adoption of deeper learning approaches in the context of construction productivity represents a promising avenue for future exploration, particularly as information technology continues to evolve. It is important to recognize that significant improvements in CLP and CEP cannot be realized without a holistic coordination and collaboration of every stakeholder from the industry, organizational, and project team levels. Future review initiatives could focus on these critical aspects.

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