Machine Learning in the road construction sector: A review

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Abstract

Changes in contracting schemes with lengthy guarantee periods have created a strong momentum for road construction contractors to improve quality and performance to surpass other competitors. Previous studies have demonstrated the effectiveness and efficiency of the application of Machine Learning techniques in tackling the challenges in various fields in the AEC industry. Yet, the current status of the research and application of Machine Learning in the road construction sector has not been fully explored. Also, it is unclear what should be focused on in the future to ensure the sector benefits from Machine Learning in the long run, given the road construction sector is notorious for its reluctance to embrace innovative working methods from construction digitalization. On these premises, an integrative literature review was conducted, where the study firstly collected existing studies concerning the applications of Machine Learning within the road construction lifecycle and critically analyzed the results from three dimensions, namely the application domains, utilized Machine Learning algorithms, and source of the dataset. Subsequently, discussions were made to logically synthesize the findings from the critical analysis to specify the direction for future research. The most fruitful application fields of Machine Learning techniques are pavement distress classification and detection, preventive maintenance, and asphalt mixture property and performance testing, which mainly cover pre-construction and post-construction phases. However, it is essential to have a lifecycle thinking approach for a future research direction, given that phases within the road construction lifecycle are interrelated. In addition, emerging Machine Learning algorithms has been shown to be the "game changer" to the sector. Cutting-edge Machine Learning methods such as Reinforcement Learning may have the potential to further benefit the sector. Lastly, analysis shows that, although using self-generated data can enable the researchers to acquire a large volume of the dataset without bias in the data distribution, it can greatly reduce the generalizability of the developed Machine Learning models. One possible solution for a future research direction could be using a new data acquisition scheme based on an ontology covering the entire road construction lifecycle, with a data management scheme applied to structure the data.

Keywords: Road construction, Machine Learning, pavement distress classification and detection, preventive maintenance

1. Introduction

Compared to other industries, the AEC industry has been suffering from a slow pace for digitization and adoption of emerging digital technologies [1,2]. Within the AEC industry, the road construction sector plays a vital role in meeting the constantly growing needs from mobility to socio-economic development. Over the past few years, changes in the contracting schemes have led to fierce competition among the companies in the road construction sector, due to the lengthy guarantee periods and the increasing awareness of the clients in improving and assuring the overall road construction quality [3,4]. As a direct result, a strong momentum has been created in the road construction sector where companies are forced to improve the quality and performance to surpass other competitors. Given that the adoptions of innovative digital technologies have been proved to significantly increase the productivity and performance and efficiency in tackling persistent challenges in various fields in the AEC industry [5–13], it is reasonable to recognize this momentum as an initiative to the road construction sector to realize the switch to digitization.

Among all the emerging digital technologies, Machine Learning has shown enormous problem-solving capabilities in the AEC industry [14–22], by mimicking the reasoning process of the human brain [23]. The concept of Machine Learning is not appearing apparent in recent years. On the contrary, pioneering research on the topic of Machine Learning can date back to the 1950s, focusing on allowing computers to perform tasks that normally require human intelligence and to behave like human beings in terms of thinking and learning [24]. In this era of Internet technology, networks are ubiquitous, which results in dramatic changes in the information environment for the development of Machine Learning techniques due to the rise of the information community, where the information can be exchanged and integrated conveniently [25]. Remarkable breakthroughs have been made in maturing the development of Machine Learning techniques and corresponding applications. Among them, one of the most notable achievements in the algorithm development could be the emergence of Conventional Neural Networks (CNN) in 2012, which successfully solved the large-scale visual recognition problems [26]. When it comes to the applications of Machine Learning in the public domain, the most famous case is AlphaGo, which is developed by DeepMind using the concept of reinforcement learning and defeated a series of well-known professional go players.

Although the research and applications of Machine Learning have gained considerable recognition, it is not deniable that the AEC industry may hold its concerns in terms of the steep learning curve when shifting from traditional working methods to innovative yet unfamiliar digitalized and algorithm-based working methods [27]. This would be more recognizable in the road construction sector, which is notorious to be stubborn in the experience-based working methods, and highly rely on “craftsmanship” and intuitions. Besides, another major concern could be the lack of data to support the applications of Machine Learning techniques. Although attempts have been made to establish a data-driven environment through the road construction lifecycle, which creates a constant flow of extensive information and data, issues including the lack of generic ontology covering its lifecycle and the lack of effective data sharing schemes have hindered the further development and adoption of Machine Learning techniques in the field of road construction. Consequently, what is the current status regarding the recognition of Machine Learning within the road construction sector should be thoroughly examined to provide insights in advocating for further explorations of applying Machine Learning techniques as a “game-changer”.

On these premises, this study will start with a literature review to briefly introduce a few of the most notable Machine Learning techniques or algorithms, as well as a discussion among existing implementations of Machine Learning techniques in the road construction sector. Subsequently, future innovations and potential associated challenges in the Machine Learning adoption in the road construction sector will also be addressed. The following contents are organized as follows. In section 2, the methodology used for conducting this review is demonstrated. A brief introduction of Machine Learning techniques and algorithms is given in section 3, and section 4 analyzes the Machine Learning applications in different dimensions. Several future directions of research are given in section 5; followed by conclusions in section 6.

2. *Research methodology*

Given the purpose of the literature review in this research is to collect and critically analyze the current status of the applications of Machine Learning techniques in the road construction, thus enabling the researcher to specify a future research direction, an integrative review will be conducted [28]. Therefore, three stages will be included in the integrative literature review process, namely literature collection, critical analysis, and synthesis.

In the first stage, the literature collection will mainly use Scopus and ScienceDirect as the major querying databases to ensure the accessibility of existing literature. Besides, the selection range will be from 2012 to 2022. This is because most of the notable breakthroughs of the Machine Learning techniques emerged during this period after CNN has achieved prominent performance in image recognition, which is believed to greatly influence future studies [7]. The literature collection will be mainly conducted using keywords, such as “machine learning”, “machine learning in road construction”, “deep learning”, “artificial neural network”, “recurrent neural network”, “conventional neural network”, “random forest”, “support vector machine”, etc. Furthermore, the searching of the existing literature was only confined to the English journals related to construction and civil engineering.

After the collection process, the collected literature will be critically analyzed by assessing the primary messages that the studies attempts to convey, by deconstructing the collected literature into basic units according to the researcher’s focus [28]. In this study, three major dimensions will be applied in the critical analysis, namely specific applications in road construction, utilized Machine Learning algorithms, and source of the dataset. The first dimension will focus on the particular application fields where the Machine Learning techniques are utilized, which is essentially related to the corresponding challenges of the road construction sector. Meanwhile, the dimension regarding the Machine Learning algorithms is mainly focusing on the technical perspective of how certain algorithms solve specific problem contexts, thus providing insights into the relationships between the application of particular algorithms and road construction challenges. Last but not least, the data sources of the collected literature will be examined. Given that the data for the Machine Learning development is one of the most important prerequisites, while the sources of the dataset, whether it is assessed from the public databases or generated by the researchers, can reveal the mainstream in the corresponding studies of the data acquisition and availability, thus enabling the researcher to investigate how the different data acquisition approaches influence the final performance and what are the associated problems, and to which extent the sector can provide sufficient data to support the utilization of Machine Learning techniques.

The last stage will be synthesizing the new knowledge on the topic. After analyzing the current research status regarding the topic, a research agenda will be formed based on the critical analysis of the collected literature. Specifically, the directions of the future studies will be given, based on the critical analysis on the three formulated dimensions.

3. Machine Learning overview and algorithms

Machine Learning can be roughly explained as an intelligent system that can learn and improve its performance based on historical data to make inferences [29]. As mentioned previously, Machine Learning mimics the human learning process, where humans learn from the past or experiences through induction, summarization, and internalization. Therefore, when new situations take place in the future, humans can deal with them by utilizing their knowledge gained from the past through the learning process. As for Machine Learning, the learning process will mainly rely on the input data and inner algorithms. Based on the problem domains, the typical Machine Learning problems can be divided into regression problems, classifications problems, and clustering. Besides, as shown in Figure 1, based on the differences in the given datasets, Machine Learning can also be divided into supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, etc. [30].

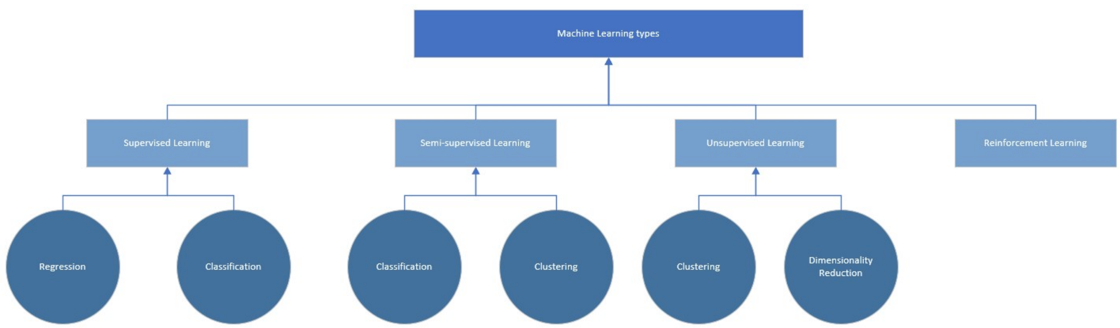

Figure 1: Typical Machine Learning types

When it comes to the Machine Learning algorithms, [31] provided a series of most widely used algorithms, which can be briefly classified as gradient descent algorithms, linear regression algorithms, multivariate regression analysis, logistic regression, decision tree, support vector machine, Bayesian learning, Naïve Bayes, K-nearest neighbor, K-means clustering, and back-propagation algorithms. In addition, as the problems that traditional Machine Learning algorithms try to solve become more complex, the concept of deep learning was widely used to build "deeper" layers of abstractions from the rather simple and "shallow" Machine Learning architectures [1]. Topics related to civil engineering and construction that can be covered by the utilization of deep learning techniques include feature extractions from building complexities, image detection and classification, image captioning, activity recognition, object detection and tracking, data augmentation [1,32–34].

4. Existing Machine Learning applications to road-construction-specific challenges

In this section, the literature search results will be represented to discuss the current status regarding the application of Machine Learning in the road construction sector, where Table 1 represents the summary of the results.

In total, 33 papers were reviewed and were published in journals such as Automation in Construction, Construction and Building Materials, Advanced Engineering Informatics, International Journal of Pavement Engineering, Engineering with computers, etc.

As mentioned in section 2, three major dimensions were chosen for the result interpretation, including the focused applications, utilized Machine Learning algorithms in corresponding applications from the collected literature, and the source of the dataset used for the Machine Learning training and testing. The source of the dataset was mainly divided into three categories, namely the public dataset, self-generated dataset, and hybrid source. The public dataset refers to the dataset that is open-source and is extracted from previous studies or organizations owning the data by the researchers, while the self-generated dataset refers to the dataset generated or created by the researchers through field inspections or laboratory tests. As for the hybrid source, this category includes studies that utilized datasets combining both the public and self-collected datasets. In Table 1, the results regarding the dataset source will be represented as the percentages of collected literature that fall into corresponding categories.

Table 1: Summary of existing Machine Learning applications in the road construction sector

Road-construction-specific applications	Machine Learning algorithms	Source of dataset			References
		Public dataset (%)	Self-generated dataset (%)	Hybrid source (%)	
Pavement distress classification and detection	Convolution Neural Network Artificial Neural Network Encoder-Decoder Networks Self-Correcting Neural Network Least Squares Support Vector Machine Stochastic Gradient Descent Logistic Regression	10.0%	80.0%	10.0%	[35–44]
Preventive Maintenance	Artificial Neural Network Random Forest Decision Trees Gated Recurrent Unit Neural Network YOLO + U-net model	62.5%	37.5%	0	[45–51]
Asphalt mixture property and performance test	Artificial Neural Network Generative Adversarial Network Gene Expression Programming Decision-Tree-based Ensemble Method Support Vector Regression Convolution Neural Network Bagged Trees Ensemble Method eXtreme Gradient Boosting Model U-NET++	27.3%	63.6%	9.1%	[52–62]
Cost estimation	Instance-based Learning Support Vector Machine Stacking Ensemble Methods	100%	0	0	[63,64]
Road construction environmental impact prediction	Support Vector Regression Random Forest	100%	0	0	[65,66]
Pavement segregation detection	Naive Bayesian Classifier	0	100%	0	[67]

Machine Learning applications in the road construction sector

The results in Table 1 show that 6 application areas were identified from the collected literature, where one of the most fruitful application domains is focusing on realizing the classification and automatic detection of the pavement distress images using Machine Learning algorithms that have the capability of analyzing and processing the visual images. The practical significance of the application and research in this field is it can greatly streamline the visual inspection process of the pavement conditions without rendering the accuracy. Given that the traditional visual-based inspection methods for the pavement distresses, such as cracks, potholes, rutting, raveling, blurs, and repairs, are conducted manually, which may be subjective and requires extensive effort to capture and annotate the pavement conditions [68]. However, it is worth noting the root difference between the distress classification and distress detection, where the former refers to assigning labels to the given images and the latter is concerned with identifying and localizing the target objects from the given images. For instance, for the distress classification, [35] developed a Stochastic Gradient Descent Logistic Regression model to achieve consistent and accurate classification of pavement raveling from given images considering two labels, namely raveling and non-raveling. When it comes to distress detection, [40] proposed and developed a deep CNN to firstly classify pavement cracks from given images considering the noise of surface variations and other non-crack patterns. For this research, the sliding window technique was used to re-organize the images into several small patches for the classification, each patch also contains the information regarding the relative location of the identified crack, thus showing the complete crack location on the original image. Also, for distress detection, apart from localizing the target pavement distress, the application of Machine Learning methods can also determine the severity of the identified distress. For example, in [42], the authors implemented a pavement imaging system to create three-dimensional stereo visions, which enables the localization of distresses, as well as the identification of the distress severity based on the distress depth and width.

While the applications in the distress classification and detection mainly focus on streamlining the pavement inspection process, another application area of Machine Learning named Preventive Maintenance, is concerned with the prediction of the potential distress given a series of input variables. Therefore, corresponding research adopted Machine Learning methods to solve regression problems, where the outputs are indicators that can reflect the severity of certain distress or the overall conditions of the pavement. For instance, in [45], the outputs include pavement quality index (PQI), pavement condition index (PCI), riding quality index (RQI), rutting depth index (RPI), and skid resistance index (SRI), where a Hybrid Neural Network was developed to predict the listed five performance indicators using traffic intensity, ambient conditions, and maintenance history as inputs. For this type of application, the predictions on the pavement conditions in the long run under the influence of a series of factors can potentially guide the decision-making process regarding the road pavement maintenance, before actual distress emerges, thus enabling early preventive maintenance and enhancing the maintenance quality.

When it comes to the pavement material properties and performance tests, Machine Learning techniques were also widely applied in studies for predicting mixture properties or performance indicators, including air void content [52], viscoelastic behavior [55], dynamic modulus [59–62], rutting depth [56,57], and indirect tensile strength (ITS) [57]. When the laboratory tests regarding the properties of pavement mixtures are not applicable, Machine Learning approaches can provide the potential to obtain efficient yet reliable predictions. One innovative research within this category of applications is [53], where the authors applied the concept of generative design and Generative Adversarial Networks (GANs) to automatically establish a digital asphalt aggregate image database, with desirable quality in terms of the angularity distributions.

In contrast, applications regarding road construction project cost estimation and environmental impacts received less attention. In essence, the utilization of Machine Learning techniques in these two application fields still focuses on the regression problems by investigating the hidden correlations between the inputs and outputs. Similar to the application of Machine Learning in the pavement mixture properties and performance, the predictions on project costs and environmental impacts using Machine Learning methods show promising results given lengthy traditional cost estimation or environmental impact calculation methods can be avoided. Furthermore, the applications of Machine Learning in these fields also enable the possibility for further extension of the application scenarios to the optimization of the corresponding planning, given that Machine-Learning-based prediction approaches can significantly shorten the computational time required for the estimation, especially when the process can be parametric, thus facilitating the iteration and evolution of the planning solutions.

Lastly, while the other identified applications focus on either the pre-construction phase of the road construction projects or the post-construction phase concerning the pavement maintenance and operation, [67] proposed the application of Machine Learning methods in the construction phase of the pavement. A Naïve-Bayesian-classifier-based framework was proposed to classify the paved section into several segregation levels of aggregates and asphalt binders from the surface texture images collected during the construction. Nonetheless, it is worth noting that the objective of this research is still about aligning the characteristics measured during the construction phase to the certain pavement failure related to the distribution of aggregates and asphalt binders after the construction.

Machine Learning algorithms utilized in the road construction research

According to Table 1, the deep learning architectures are the most frequently adopted algorithms, especially CNN, which have been proved to be effective in image processing applications. Next to CNN is the Artificial Neural Network (ANN). However, in some of the studies, the architectures of developed ANNs were with rather deeper depth (more than 2 hidden layers) to improve the capability of the models to deal with non-linear complexities [45,55,59]. Unlike CNNs, ANNs were more widely applied for regression problems according to the collected research. Nonetheless, these deep learning methods may be more time-consuming in terms of the training and could be more "greedy" to the volume of the training dataset [1]. Therefore, when it comes to regression problems, it is highly recommended to adopt multiple Machine Learning methods to conduct a comprehensive comparison using multiple performance metrics. No current Machine Learning algorithm can fit all the problems without considering the specific problem contexts and dataset based on which it will be trained.

In order to further improve the performance of the utilized Machine Learning algorithms and developed models, techniques such as data augmentation and meta-heuristic-based hyperparameter optimization methods were used in various studies. For instance, in [40], considering the high diversity of the collected image datasets, the authors increased the number of samples with cracks by rotating images with random angles or moving images with random directions and distances in pixels, while in [49], Particle Swarm Optimization (PSO) algorithm was used for the optimization of hyperparameters of the developed ANN, which significantly enhance the ultimate performance compared to the traditional ANN.

Source of dataset

According to Table 1, most of the research related to pavement distress classification and detection and mixture properties, used self-generated data for the Machine Learning model training, while most of the studies regarding preventive maintenance, cost estimation, and environmental impact prediction utilized public data, or partly used self-generated data for the supplement. A possible reason for the preference of the self-generated data for the image-based classification and detection or predictions of properties that can be measured in laboratories is that the researchers can avoid problems such as data bias or imbalanced datasets. Furthermore, considering the challenge related to the data availability, using self-generated data can tackle issues such as the lack of required data for training Machine Learning models or data confidentiality concerns, especially when data exchange and sharing is required to build a dataset with a considerable volume.

However, an inherent issue with using a self-generated dataset is that for Machine Learning models trained on one specific dataset, it is impossible to compare the performance with other Machine Learning models developed from different datasets in other studies. When it comes to the studies regarding Preventive Maintenance, cost estimation, and environmental impact prediction, considering the difficulty in collecting data, such as PCIs, cost elements, and environmental indexes, it is more reasonable to turn to public data source, especially most of the data in the interest of the aforementioned application areas are measured and owned by public organizations such as the government.

5. Synthesis from the literature review

While the critical analysis conducted in the previous stage of this study has examined the current status regarding research on the selected topic, as an essential part of the integrative literature review, it is necessary to direct the research focus in the future based on the knowledge extracted from the existing literature. Therefore, in this section, several future directions of the applications of Machine Learning techniques in the road construction sector are given and discussed, as well as their associated challenges. Since the analysis of the examined literature was conducted based on three dimensions, the formulation of the future research focus will also be done by relating to the findings of each dimension.

Applying Machine Learning in the road construction lifecycle

According to the results of the literature review, all the identified applications of Machine Learning from the collected studies are confined to a single phase within the road construction lifecycle, which is shown in Figure 2. For instance, for the applications of Machine Learning techniques to the pavement preventive maintenance, the input variables, i.e., the factors that are considered to have potential impacts on the pavement long-term performance, only considered factors in the operation phase, such as the traffic intensity, climate, and maintenance history. However, these studies do not consider the potential significance of the construction process quality with different on-site operational strategies, quality of pavement mixture, and quality of raw materials of the mixture to the quality of the construction product. Therefore, by introducing indicators from all the phases within the road construction lifecycle, a comprehensive pavement quality prediction model can be expected, which can benefit various stakeholders, including mixture manufacturers, contractors, asset managers, and public clients.

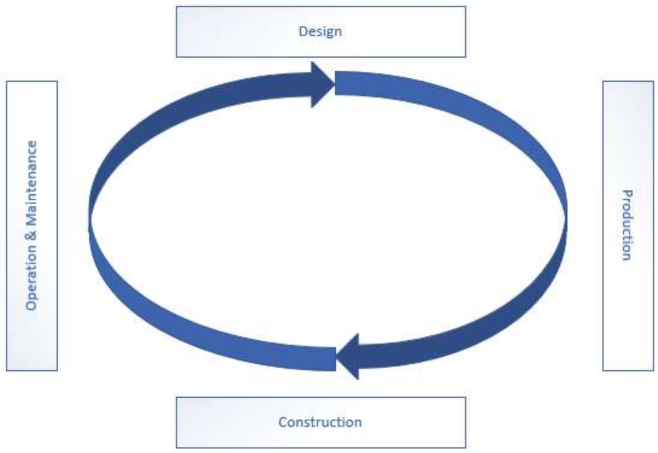

Figure 2: The road construction lifecycle

Introducing cutting-edge Machine Learning algorithms

One important finding from analyzing the utilized Machine Learning algorithms from the collected literature is the research regarding Machine Learning applications for the road construction sector, has been heavily boosted by the emergence of state-of-art Machine Learning algorithms, particularly the utilization of CNN. Therefore, it is reasonable to believe that by introducing emerging Machine Learning algorithms in this sector, can greatly improve the efficiency and effectiveness of solving the challenges that the sector is currently facing, considering the performance, scalability, and robustness.

Ever since the success of AlphaGo, the concept of reinforcement learning has been spotlighted in recent years reflecting the impressive advances of Machine Learning techniques. As a branch of Machine Learning, reinforcement learning receives delayed feedback, while considering the state transitions in the environment, and reward mechanisms from the actions taken in and to the environment [69,70]. One possible application scenario of reinforcement learning is the automatic control of the construction machinery on the construction site. In this scenario, the environment will be the physical construction site and all the ambient conditions, while the actions will be the operations of the machine operators, i.e., the agents or controllers. Furthermore, the reward function for this scenario could be to achieve the best construction process quality with the minimum variability in terms of the compaction consistency and temperature homogenous. In the realistic construction environment, the controllers receive limited or nearly unknown information regarding the behaviour of the environment, which in return, limits their decision-making process to seek the optimal strategies to achieve the goals. However, using reinforcement learning, the concept of value will be introduced to accumulate immediate rewards and approach to the ultimate success step by step [69].

Nonetheless, the development of such a reinforcement learning framework will demand a large volume of data, however, unlike supervised learning, reinforcement learning data comes from various interactions between the agent and the environment. For the problem of data balance, supervised learning can achieve data balance by labeling various complementary data. But this is difficult to solve for reinforcement learning, because the data collection is done by the reward functions, whereas the understanding of the task stimulus signal is imperfect, thus collecting useless and repetitive data most of the time. In addition to the uncontrollable data collection process, reinforcement learning will require a heavy computational cost. However, this may significantly hinder the developing process.

New data acquisition and management schemes

As analyzed from the last dimension in the previous section, most of the previous studies tended to build Machine Learning models using self-generated data. On one hand it can avoid the issues such as the imbalance within the dataset and the shortage of required training and testing data. On the other hand, it reveals a hidden challenge regarding the data availability, which significantly hinders the further development or deployment of Machine-Learning-based technologies in road construciton sector.

In general, the data availability issue refers to the difficulty of collecting balanced data (i.e., no bias in the distribution of data) with a considerably large amount, considering the precision and accuracy, thus ensuring the generalizability of the developed Machine Learning model. This issue can manifest in multiple ways. For instance, the data-driven environment in the road construction sector has been only established in recent years, it may still take a long time until the dataset with considerable size can be generated. In addition, when integrating data from various organizations, it is inevitable that the collected data will have different formats and resolutions, which renders the data processing for the Machine Learning model development a challenging task. Furthermore, because of the sensitive characteristic of the infrastructure projects, confidentiality will become another obstacle to acquire required data for the Machine Learning applications. However, as mentioned in the previous section, although using self-generated data can partly solve the data availability issue, it can also result in a rather low generalizability of the developed Machine Learning model.

Therefore, it is important to have a new data acquisition scheme. It is firstly essential to build an ontology to cover the concepts and relations concerned with the road construction lifecycle, and based on this ontology, the data acquisition methods can thus be unified to collect uniform data formats and precisions, while the corresponding data management schemes should also be developed accordingly to structure the collected data. However, the problem related to the data confidentiality may still persist for a long time. Potential solutions include developing Confidential Machine Learning (CML) approaches to protect the confidential data used for the model training and validating, using cryptographic primitives and various composition strategies, as introduced in a recent research [71].

6. Conclusion

The objective of this paper is examining the research status of Machine Learning techniques in the field of road construction, thus advocating further investigations of how these innovative data-driven techniques improve road construction productivity and tackle challenges that obstacle the sector. Specifically, 33 papers from high-ranking journals were reviewed, focusing on various application areas of Machine Learning techniques in road construction. To interpret the findings, three dimensions were used to group the collected literature, focusing on the specific application domains, utilized Machine Learning algorithms, and source of the dataset. The results show that pavement distress classification and detection and mixture properties prediction are the most fruitful application areas, and deep learning architectures were frequently used for image processing problems and complex regression problems. As for the data source for the model training, most of the research used self-generated datasets considering the convenience of avoiding the potential data bias and imbalanced data. Lastly, potential future innovations were discussed, focusing on the application of Machine Learning on the road construction lifecycle and possible application scenarios of reinforcement learning, with the underlying objective of enhancing the overall quality of the road construction products.

In general, applications of Machine Learning have shown great potential for tackling various challenges in the road construction sector, particularly in pre-construction and post-construction phases. However, a lifecycle approach is required for the future research direction, given that phases within the road construction lifecycle are interrelated. Besides, introducing emerging Machine Learning algorithms has been shown to greatly stimulate the overall development of the Machine Learning techniques in road construction. Regarding the future, cutting-edge Machine Learning methods such as Reinforcement Learning may have the potential to further boost the sector. Lastly, regarding the issues related to data availability, the analysis shows that although using self-generated data can enable the researchers to acquire a large volume of the dataset without bias in the data distribution, it can greatly reduce the generalizability of the developed Machine Learning models. One possible solution for a future research direction could be using a new data acquisition scheme based on an ontology covering the entire road construction lifecycle, with an appropriate data management scheme applied to structure the data.

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