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Review

Machine Learning Applications in Road Pavement Management: A Review, Challenges and Future Directions

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Abstract: Effective road pavement management is vital for maintaining the functionality and safety of transportation infrastructure. This review examines the integration of Machine Learning (ML) into Pavement Management Systems (PMS), presenting an analysis of state-of-the-art ML techniques, algorithms, and challenges for application in the field. We discuss the limitations of conventional PMS and explore how Artificial Intelligence (AI) algorithms can overcome these shortcomings by improving the accuracy of pavement condition assessments, enhancing performance prediction, and optimizing maintenance and rehabilitation decisions. Our findings indicate that ML significantly advances PMS capabilities by refining data collection processes and improving decision-making, thereby addressing the intricacies of pavement deterioration. Additionally, we identify technical challenges such as ensuring data quality and enhancing model interpretability. This review also proposes directions for future research to overcome these hurdles and to help stakeholders develop more efficient and resilient road networks. The integration of ML not only promises substantial improvements in managing pavements but is also in line with the increasing demands for smarter infrastructure solutions.

Keywords: Machine Learning; road pavement management; state-of-the-art; condition assessment; performance prediction; decision-making

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Citation: Tamagusko, T.; Gomes Correia, M.; Ferreira, A. Machine Learning Applications in Road Pavement Management: A Review, Challenges and Future Directions. *Infrastructures* **2024**, *9*, 213. https://doi.org/10.3390/infrastructures9120213

Academic Editor: Tatiana García-Segura

Received: 9 October 2024
Revised: 17 November 2024
Accepted: 18 November 2024
Published: 21 November 2024

1. Introduction

Road pavement management is vital to maintaining safe efficient sustainable transport infrastructures [1,2]. This process encompasses assessing pavement conditions, predicting performance, allocating resources, and choosing the best Maintenance and Rehabilitation (M&R) strategies. Effective pavement management is essential for extending the lifespan of the road network, minimizing maintenance costs, and ensuring a safe and comfortable driving experience [1–5].

Road pavements experience deterioration over time due to factors like aging, traffic loads, and environmental conditions. This deterioration is exacerbated when defects emerge and corrective actions are delayed. The combination of deferred maintenance, increasing traffic loads, and uncertain climatic conditions can lead to pavements experiencing structural and functional decline before the end of their design lives, significantly escalating maintenance costs [1,6]. Regular and appropriate maintenance, however, can extend pavement life, but budget constraints often impede timely interventions [7].

Amid growing budgetary pressures on road agencies, the need for cost-effective and efficient road infrastructure management has become increasingly vital. At the same time, road users expect higher levels of road quality, comfort, and safety [4,8]. This is particularly true in more developed countries with extensive well-established road networks. As a result, road managers prioritize the transition from the traditional design-and-build approach toward a more sustainable repair-and-maintain mode [1,2]. This paradigm shift requires developing and implementing innovative strategies and technologies, such as Machine Learning (ML), to tackle the challenges of maintaining and enhancing the performance of aging road networks while meeting user demands.

Traditional Pavement Management Systems (PMS), despite being valuable tools for managing road networks, have certain limitations [2,3]. These systems often rely on manual data collection methods, which can be time-consuming, labor-intensive, and error-prone [8–12]. Furthermore, evaluating pavement conditions and performance using conventional techniques can be subjective and might not capture the complex interactions between various factors impacting pavement deterioration [5,13,14]. As a result, there is an increasing need for more advanced and accurate decision-making tools in pavement management.

ML and Artificial Intelligence (AI) present promising solutions to these challenges by delivering data-driven techniques capable of learning patterns from datasets and making predictions based on those patterns [15,16]. Over the past decade, interest has grown in utilizing ML and AI to enhance various aspects of pavement management, from pavement condition assessment to maintenance planning [17].

Existing reviews on ML applications in pavement management tend to focus on specific areas, such as pavement condition assessment [18–21], distress detection [9,20,22–24], crack detection [25,26], performance prediction [27,28], and decision-making [29]. While insightful, these focused reviews often lack a holistic perspective of how ML is transforming pavement management as a whole. Moreover, the rapid evolution of AI in recent years, marked by advancements like foundation models, Large Language Models (LLMs), and generative AI [30–32], requires a reassessment of ML's capabilities and potential impact on the field.

Our study updates the literature by integrating recent AI developments and applications of these technologies within road pavement management frameworks. Building on Justo-Silva et al. [27], who reviewed modeling techniques, our research extends these models to broader management practices. Unlike Peraka and Biligiri [8], who focused on data collection procedures, analytical methods, and decision-making tools, our work also addresses performance prediction and enhances M&R optimization. Additionally, informed by Soni et al. [21] on the challenges of monitoring pavement surfaces, our approach takes a holistic view, advancing the use of ML in PMS and contributing to a complete field view.

This review seeks to bridge this gap by providing a comprehensive analysis of ML applications across all phases of pavement management, with a particular emphasis on advancements over the past five years. Our unique contribution is threefold:

1. Holistic Perspective: We move beyond focusing on individual aspects of pavement management to offer an overview of how ML is being applied across condition assessment, performance prediction, and M&R Decision-Making, demonstrating its multifaceted impact on the field;
2. Integration of Recent Advancements: We incorporate the latest developments in AI, including emerging algorithms like LLMs and generative AI, to assess their potential applications and future directions within pavement management;
3. Critical Analysis of Challenges and Opportunities: We identify and critically analyze both the technical challenges impeding the wider adoption of ML (e.g., data quality, model interpretability, and ethical considerations) and the significant opportunities it presents for creating smarter, more efficient, and sustainable pavement management practices.

This research conducts a literature review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to address the proposed research questions [33]. The methodology for selecting analysis papers involves a detailed identification, screening, and eligibility process, as outlined in Section 3.

The remaining sections of this paper are organized as follows: Section 2 provides an overview of the role of ML in road pavement management, discussing traditional PMS and highlighting its limitations while introducing relevant ML algorithms for pavement management. Section 4 explores the applications of ML in pavement management, focusing on condition assessment, pavement performance prediction, and M&R Decision-Making.

In Section 5, the technical challenges associated with implementing ML, as well as the ethical implications, are examined. The main findings are presented in Section 6, while the study's conclusions are offered in Section 7.

2. Background

2.1. Traditional Road Pavement Management Systems

In many developed countries, road agencies dedicate substantial resources to maintain, rehabilitate, and preserve existing road networks [2]. The growing competition for funding across various sectors has generated a need for enhanced PMS, assisting decision-makers in maintaining cost-effective and durable pavements [4].

Hence, a PMS is a systematic approach offering tools for administrators and engineers to manage road pavements effectively [2,34]. Therefore, the decision-making process integrates information from existing frameworks, engineering experience, budget constraints, scheduling requirements, management priorities, public input, and political considerations.

Generally, PMS implementation occurs at network or project levels [2,35]. At the network level, PMS assists in selecting optimal strategies for designing, constructing, and rehabilitating pavements, aiming to achieve the highest benefit-to-cost ratio for a road network within a given analysis period. At the project level, PMS identifies the most suitable design, construction, or rehabilitation alternative for a specific project. In road pavement management, the decision between maintenance and rehabilitation usually relies on the pavement's surface quality and structural condition [35]. Distinct quality indices and thresholds are used to determine the necessary intervention at a particular point in the pavement's life cycle.

Efficient PMS is critical in assessing road network conditions, predicting performance and directing decision-making processes related to M&R activities [1,2,36,37]. According to Jorge and Ferreira [38], a typical PMS consists of five modules: a road network database; a quality evaluation system; a cost model; pavement performance models; and a decision-aid tool. However, the PMS in the context of this study includes the following modules: database; pavement condition assessment; performance prediction; and optimization of M&R activities (see Figure 1).

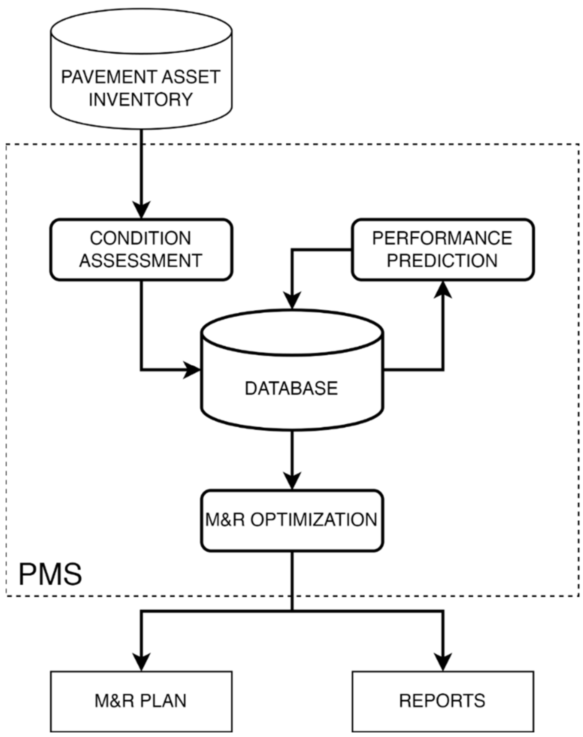

Figure 1. Simplified structure of a Pavement Management System.

Therefore, road agencies maintain an inventory of assets under their purview. The information from the existing infrastructure serves as an input for a PMS. In turn, the outputs consist of M&R plans, as well as cost and quality reports. This article examines the different modules of PMS, excluding the database. Thus, the emphasis will be on pavement condition assessment, performance prediction, and the optimization of maintenance and rehabilitation—topics elaborated upon in the following sections.

2.1.1. Pavement Condition Assessment

Pavement monitoring consists of collecting data on pavement conditions, such as surface distress, roughness, and structural capacity, using manual inspections or automated systems. Specialized equipment like road profilers and ground-penetrating radar is typically used for this task [39–41]. However, the necessary equipment can be costly and require specialized operators. Likewise, operators and equipment can influence data quality, leading to inconsistencies [8,9,11].

In the condition assessment, road agencies evaluate pavement conditions and identify distress, such as cracking, rutting, and potholes [42]. They employ various indices, including the Pavement Condition Index (PCI), the International Roughness Index (IRI), or the Present Serviceability Index (PSI), to quantify pavement quality and compare road segments [43].

The PCI scores pavements from 0 to 100, with deductions for observed distresses, start with a perfect score of 100 [44]. The PSI evaluation is based on a scale of 0 (impassable) to 5 (excellent) and evaluates roads based on visual observations and slope variance. The IRI measures pavement smoothness by analyzing the average longitudinal profile and gauging surface variations affecting vehicle vibrations, based on a theoretical response of a quarter-car at 80 km/h [44,45]. Moreover, research conducted by Hall and Muñoz [46] reveals a direct correlation between PSI and IRI.

Data collection in pavement condition assessment is progressively shifting toward automation [9]. With emerging technologies like smartphones, drone surveys, and Computer Vision (CV) techniques, the landscape of pavement monitoring is poised for significant transformation [47–49]. These advancements promise enhanced accuracy and efficiency in assessing road quality, lowering costs and the time to collect data.

2.1.2. Pavement Performance Prediction

Predicting pavement performance is crucial in pavement management, enabling road managers to proactively plan M&R activities, allocate funds for upcoming needs, and thus optimize costs. In summary, the performance prediction module in a PMS aims to describe pavement deterioration trends [17].

Pavements experience a systematic decline in quality over time. This degradation is attributed to several factors, including the vehicle load, climatic conditions, maintenance frequency, and construction quality. Notably, the deterioration process of pavements exhibits a non-linear trajectory. In its initial phases, the rate of deterioration is slow, ensuring the pavement retains a satisfactory condition. However, as time progresses, this rate of deterioration intensifies considerably [50].

The prediction of pavement quality over time is performed using pavement performance models, which can be divided into three main categories: mechanistic, empirical, and mechanistic–empirical [27]. While mechanistic models analyze pavement physics, focusing on traffic load reactions, empirical models leverage regression analysis to discern the impact of traffic, weather, and pavement age, making them suitable for ML applications [28]. On the other hand, mechanistic–empirical models integrate both approaches, relating pavement stress responses to performance deterioration.

Recent advancements in predicting pavement performance have integrated ML. These technologies process large datasets efficiently, enabling the modeling of intricate factors and adapting to new data, outperforming traditional models [28].

2.1.3. Maintenance and Rehabilitation Optimization

Decision-making in pavement management involves assessing factors such as budget, current pavement conditions, and performance while directing resources toward effective and efficient solutions. Project prioritization is also essential, allowing road agencies to address the most critical needs first [2]. However, the problem of scheduling highway maintenance is challenging due to limited budget resources [7], especially when coordinating the various activities associated with M&R, as well as considering the timely execution of the project, disruption periods, environmental impact, life cycle cost, and uncertainty while simultaneously maximizing benefits.

Different methods have been proposed to address this problem, such as specialized algorithms, logistic regression analysis, or rules based on the pavement condition [51–53]. Nevertheless, the problem of selecting road segments that need to be repaired, as well as the type and timing of the maintenance, can be seen as a combinatorial optimization problem [54].

Optimization is one of the most researched topics in general asset management [55], where agencies rely on historical data to build performance models that can forecast the future state of an asset and recommend the optimal maintenance action. Various methods, such as regression, mathematical optimization, neural networks, fuzzy logic, cloud Decision Trees, and different ML techniques, are applied to address the challenges of M&R optimization [56]. Each method has limitations: computational complexity, data demands, model precision, or solution quality. Some work reviews the diversity of techniques in detail [8,57–59], while we focus on how ML is applied to M&R Decision-Making in Section 3. In summary, pavement management includes assessing pavement conditions, performance predictions, and decision-making. By considering all these aspects, road agencies can develop effective strategies to maintain and rehabilitate their pavement networks, ultimately enhancing the safety and efficiency of the transport infrastructure [1,2,37].

2.1.4. Limitations of Traditional Road Pavement Management Systems

Despite their widespread use in transport agencies, traditional PMS have limitations. Data collection requires expensive equipment and skilled labor, while the frequency of data collection is often constrained by budget and resource limitations, leading to outdated or incomplete information [8,11,39–41].

Inaccuracies and subjectivity can occur in condition assessment when it relies on subjective visual inspections, which may not accurately reflect the pavement's actual condition [10,60,61]. Furthermore, traditional pavement distress indices are typically aggregate measures that may overlook localized or specific issues [60]. Additionally, it places inspectors at risk of working conditions on highways [25].

Performance models in traditional PMS often have limited abilities to predict pavement conditions. Based on empirical relationships or deterministic assumptions, they may not fully capture the complex and dynamic interactions between various factors affecting pavement deterioration, such as traffic loads, climate, and material properties [5,28,62]. Consequently, these models may provide unreliable predictions of pavement conditions and over or under-estimate the necessary M&R interventions.

Furthermore, adopting new technologies and upgrading existing techniques involves significant costs that cannot be overlooked. Technical staff often resist changing established practices, exacerbating the technology gap and leading to inefficiencies and delays in the adoption of new methods. Additionally, agencies frequently struggle to justify the initial investments required for process and equipment upgrades, despite the long-term benefits. This resistance underscores the need for clearly structured easily understandable studies that provide both technical and financial justification.

The limitations of traditional PMS highlight the need for more advanced and accurate tools to better address pavement management complexities [63–65]. In this context, AI offers promising solutions to overcome these challenges by providing data-driven techniques to learn patterns from large datasets and make predictions based on those patterns [27,37].

Thus, the integration of AI in road pavement management has the potential to revolutionize the field, as discussed in the following sections of this paper.

2.2. Machine Learning Fundamentals and Techniques

Machine Learning is an AI subfield designed to emulate human intelligence. The idea is to develop algorithms capable of learning and making predictions based on data [66–68]. ML techniques have gained popularity in various domains due to their ability to process large amounts of data and adapt to changing patterns [69,70]. Also, according to Russell and Norvig [71], ML techniques can be broadly classified into supervised, unsupervised, and Reinforcement Learning (Figure 2).

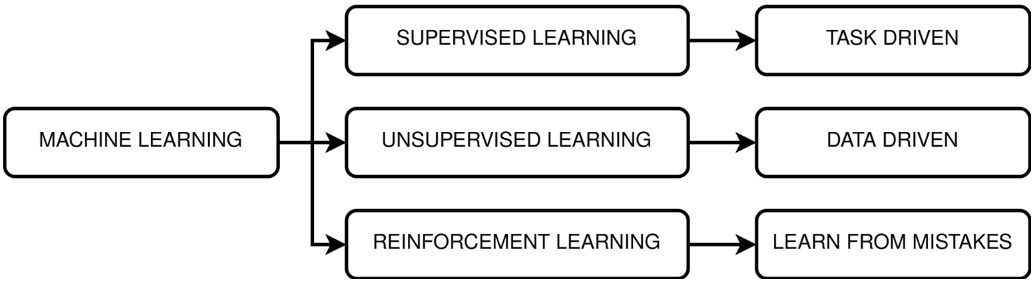

Figure 2. Machine Learning techniques (adapted from [28]).

Supervised learning is a task-driven type of ML that aims to make predictions using past data. Specifically, in supervised learning, the model is trained on input/output pairs or labeled data to produce a function that can approximate and predict new unseen data. This type of learning can be divided into regression and classification problems. Regression problems predict continuous outputs, while classification problems predict categorical outputs [72]. Moreover, supervised learning is widely used in pavement management [28].

Supervised learning models in pavement management utilize historical data, including traffic patterns, material properties, and maintenance and repair (M&R) activities, to forecast pavement conditions [28,37]. Regression models, for example, are employed to predict the rate of pavement deterioration. In contrast, classification models are used to identify potential types of pavement distress, facilitating timely and targeted interventions [12,20,73]. Also, technological advancements in supervised learning algorithms have significantly enhanced the accuracy of these predictions. These algorithms can now process vast datasets with numerous variables, which has led to improved prediction accuracy, enabling more effective pavement management decisions [28,72,74].

Unsupervised learning is a data-driven type of ML where the algorithm is trained on unlabeled data. This means that models are designed to find patterns in the data with no specific orientation or direction [75]. Thus, the algorithms aim to discover patterns and perform grouping, dimensionality reduction, or density estimation [74,76]. In pavement management, unsupervised learning can be useful for identifying pavement degradation patterns or grouping similar road segments.

Reinforcement Learning (RL) is a type of ML where an agent learns to perform actions in an environment to maximize a reward. The agent receives feedback from the environment through rewards or punishments for its actions and, consequently, learns through trial and error to find the behavior that maximizes its reward [77,78]. Interestingly, although RL has yet to be widely explored in pavement management, it has the potential to be applied to problems such as maintenance schedule optimization or resource allocation.

Unsupervised learning and RL applications in pavement management are scarce. Thus, the next section will solely focus on supervised learning algorithms.

Common Machine Learning Techniques for Pavement Management

In recent years, ML has emerged as a powerful tool for addressing various challenges in pavement management, including data collection and analysis, performance prediction, and decision-making. In pavement management, data are often structured in tables with rows and columns, referred to as tabular data. Supervised learning techniques are particularly effective for this data format [79], as explored in this section.

Chavan et al. [80] highlight that Convolutional Neural Networks (CNN), a type of neural network, represent the state-of-the-art pavement condition assessment. According to Xu and Zhang [17], this perspective can be complemented by noting the application of support vector machines in identifying pavement distress. Justo-Silva et al. [27] discuss the predominance of Decision Trees and neural networks in supervised ML methods for regression, particularly for predicting pavement performance. Additionally, Marcelinho [37] concurs that neural networks are the preferred methodology for projecting pavement performance. For M&R optimization, Xu and Zhang [17] identify neural networks, tree-based algorithms, and RL as key methods.

In this section, we focus on linear regression, support vector machines, tree-based algorithms, neural networks, and Reinforcement Learning as common ML methods in pavement management. The main machine techniques covered in this document are represented in Figure 3.

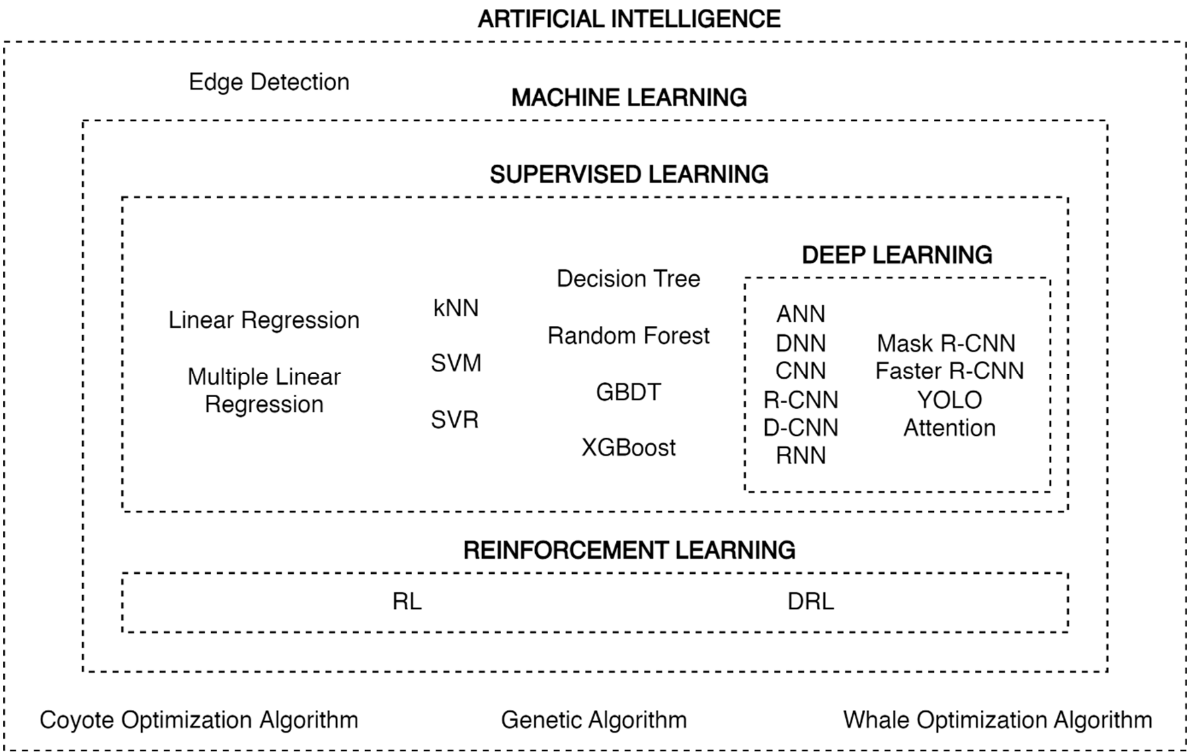

Figure 3. Machine Learning techniques used in the reviewed articles.

Linear Regression (LR) predicts a continuous dependent variable (y) based on one independent variable (x), establishing a linear relationship between them. LR predicts outcomes based on a single predictor and is represented by Equation (1), as follows:

$$y = A + Bx \quad (1)$$

where A is the intercept—indicating the value of y when x is zero—and B is the slope, measuring the change in y for a one-unit increase in x. This relationship is depicted as a straight line through the data, showing where the line crosses the y-axis and defining the line's direction and steepness of the line (Figure 4).

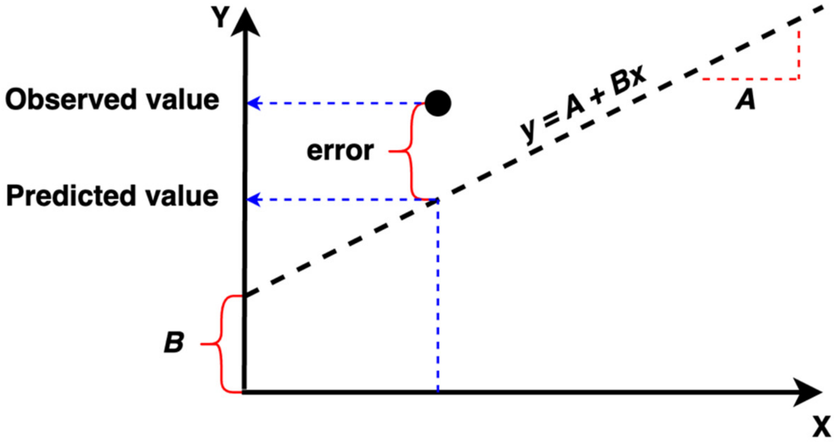

Figure 4. Example of linear regression.

In contrast, Multiple Linear Regression (MLR) involves multiple independent variables to provide more accurate predictions. LR and MLR are used in pavement management for simple assumptions or as a benchmark [81].

The Support Vector Machine (SVM) is a supervised ML algorithm widely used for classification tasks, which operates by identifying the optimal decision boundary, known as a hyperplane, which maximizes the margin between distinct classes in the feature space, ensuring enhanced accuracy, generalization, and minimized classification errors [82,83]. SVM has been utilized in pavement management for performance prediction, condition assessment, and the classification of distress types [73,84–87].

Tree-based algorithms such as Decision Trees (DT), Random Forests (RF), and Gradient-Boosted Decision Trees (GBDT) form a fundamental part of supervised learning, creating a hierarchical structure for data classification and regression. These models consist of nodes that represent features, branches that denote possible feature values, and leaf nodes that indicate outcomes (Figure 5). Built on the principle that a prediction for a target value Y is made from an input X, these models are particularly adept at handling structured data and have been successfully applied to pavement management challenges including decision-making and performance prediction [37,88–93]. Likewise, ensemble models are recommended for problems involving structured data, as they handle this type of data effectively [79].

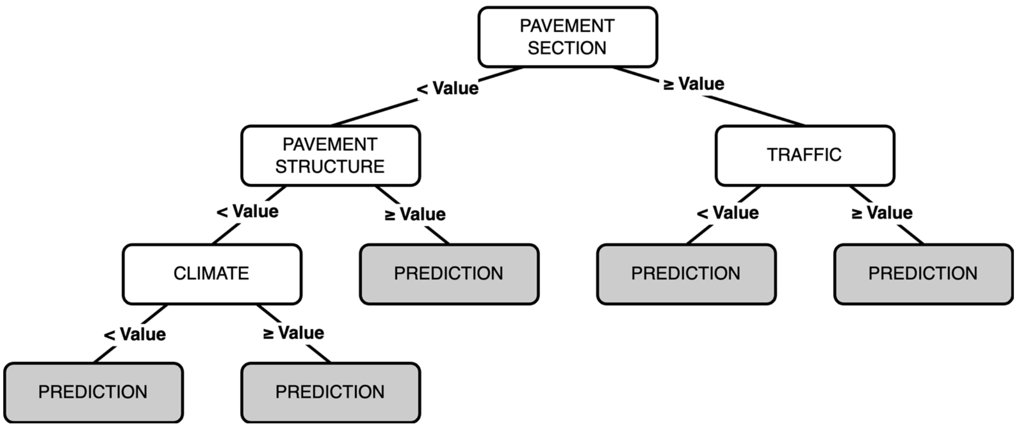

Figure 5. Example of a Decision Tree.

The Artificial Neural Network (ANN) is a type of ML that consists of layers of interconnected processing nodes, in which each node is connected to all the nodes in the previous layer, and each connection is associated with a weight [67,94] (Figure 6). Deep Learning (DL) models like CNN and Recurrent Neural Networks (RNN) have been used in pavement management for various tasks, including automated pavement distress detection and pavement performance prediction [13,14,95–97]. Furthermore, ANNs are particularly useful for analyzing unstructured data such as images and videos [67].

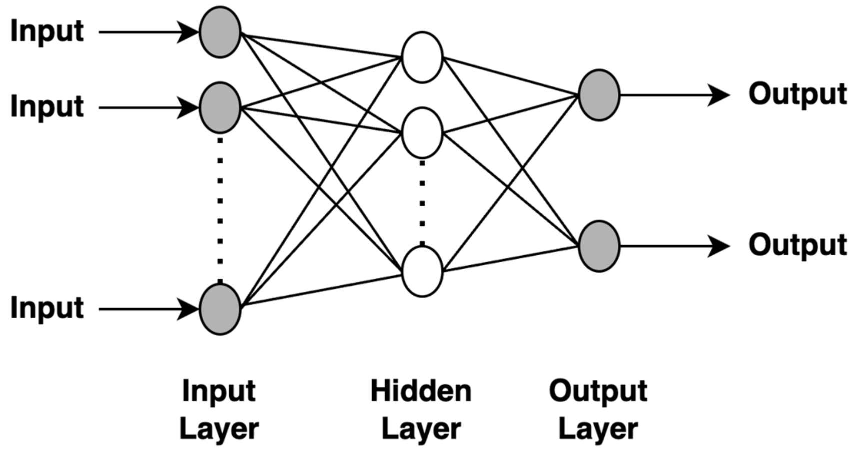

Figure 6. Example of an Artificial Neural Network.

Reinforcement Learning is a Machine Learning approach where an agent learns to make optimal decisions through trial-and-error interactions with a dynamic environment (Figure 7). The agent selects actions based on the current state of the environment, which then responds by transitioning to a new state and providing a reward signal. The agent uses this feedback to refine its policy, aiming to maximize cumulative rewards over time [77,78]. This iterative process balances the exploration of new actions and exploitation of known strategies, enabling the agent to learn complex behaviors in various applications, including game-playing, robotics, and decision-making.

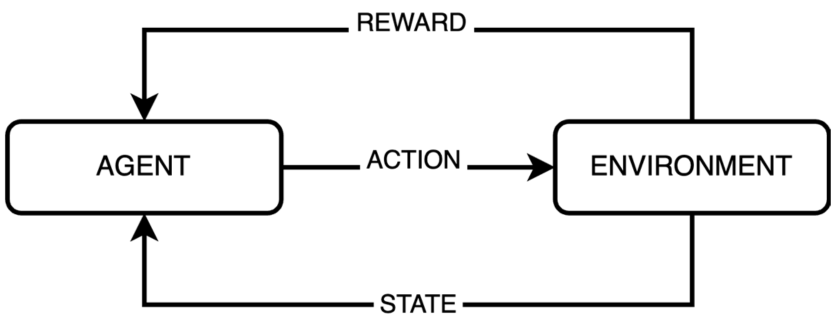

Figure 7. Reinforcement Learning diagram.

Consequently, ML techniques offer robust and flexible tools for addressing various challenges in pavement management. The following section of this review will delve into the methodology used to select the documents underpinning this article.

3. Methodology

To conduct the literature review, the PRISMA method [33] was applied; three branches were defined: pavement condition assessment, pavement performance prediction, and M&R Decision-Making. Selection criteria were created for each of these three topics, as described in Table 1. Then, the literature review was conducted in the Web of Science (WoS) database, with the searches carried out on 6 December 2023.

Table 1. Criteria for article selection.

Topic	Criteria	Query
Common for all topics	Peer-reviewed articles [1]. Written in English [1]. Published after 2018.	The period is added to the query using: PY = 2018–2023
Pavement condition assessment	Employs AI techniques to assess pavement conditions.	TS = ("pavement*" AND ("condition assessment" OR "condition evaluation" OR "distress analysis" OR "defect detection")) AND TS = ("machine learning" OR "artificial intelligence" OR "deep learning" OR "neural network*") AND PY = 2018–2023
Pavement performance prediction	Apply AI for pavement performance prediction.	TS = ("pavement*" AND ("performance prediction" OR "deterioration model*")) AND TS = ("machine learning" OR "artificial intelligence" OR "deep learning" OR "neural network*") AND PY = 2018–2023
M&R Decision-Making	Uses AI at some stage of M&R Decision-Making	TS = ("pavement*" AND "maintenance" AND ("optimization" OR "planning" OR "strategy optimization" OR "decision making")) AND TS = ("machine learning" OR "artificial intelligence" OR "deep learning" OR "neural network*") AND PY = 2018–2023

[1] The search was filtered to include only peer-reviewed articles and those published in English.

Table 1 in this review outlines the filters and query criteria used to select articles for analysis. The overarching theme of these articles revolves around the application of AI in different aspects of road pavement management, described as follows:

1. Pavement Condition Assessment: The search targeted articles employing AI techniques to assess pavement conditions, focusing on condition assessment, evaluation, distress analysis, and defect detection;
2. Pavement Performance Prediction: This category included papers applying AI to predict pavement performance, focusing on performance prediction and deterioration modeling;
3. M&R Decision-Making: The final topic involves articles that utilize AI in some stages of M&R Decision-Making, especially in optimization, planning, and strategy.

For all these categories, the search was filtered to include only peer-reviewed articles written in English and published after 2018. The period (PY = 2018–2023) was explicitly added to the query to ensure the inclusion of only the most recent studies. Using the asterisk (*) as a wildcard character in the search queries enabled the inclusion of all variations stemming from the root of each term, thus broadening the scope of the search. In the query used for this research, terminologies and operators from the WoS database are employed. "TS" stands for "Topic Search," which includes the searches in article titles, abstracts, and keywords. Likewise, the "AND" operator in the search narrows down results by only showing articles that meet all listed criteria. Meanwhile, the "OR" operator broadens the search by including articles containing specified terms.

The analysis outcomes and the steps for selecting articles based on the PRISMA guidelines are presented in Figure 8, where articles are categorized based on their focus: pavement condition assessment is labeled "PCA", articles on pavement performance prediction are marked as "PPP", and M&R Decision-Making is tagged "M&R".

The Web of Science search yielded 79 articles for Query 1, 37 for Query 2, and 80 for Query 3. Furthermore, we expanded our search through a snowballing method, adding 17, 11, and 1 articles, respectively. Each paper added was subject to the same selection process. Likewise, articles considered low relevance or borderline related were discarded. Ultimately, 37, 19, and 10 articles were selected for this review.

The snowballing technique expanded the selection by including articles that offered new insights or discussed techniques not covered in the initially selected literature. It also added relevant documents that fell outside the predefined filters. Moreover, this review offers a comprehensive and nuanced understanding of ML developments and applications in road pavement management.

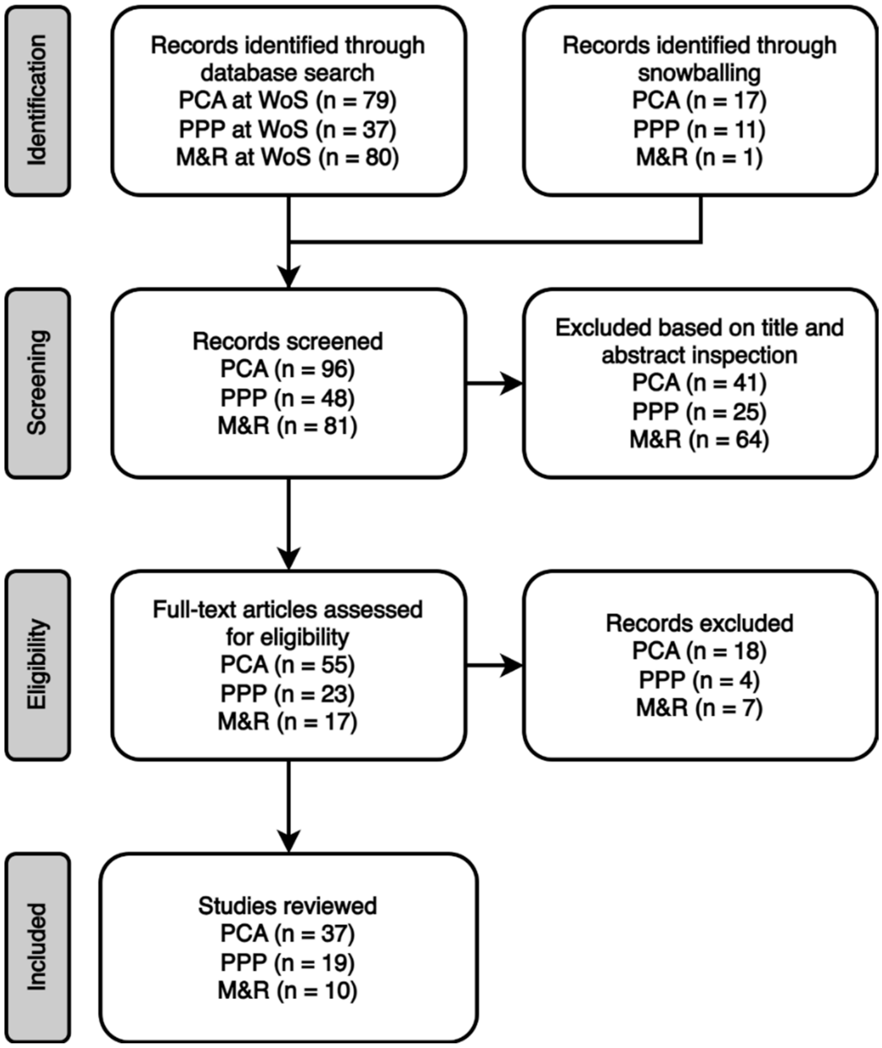

Figure 8. Steps for selecting reviewed articles.

4. Applications of Machine Learning in Road Pavement Management

Integrating ML techniques into road PMS can potentially revolutionize the field by addressing various challenges associated with traditional methods. This section presents an overview of the applications of ML in pavement management, discussing aspects such as pavement condition assessment, performance prediction, and M&R Decision-Making.

4.1. ML Applied to Pavement Condition Assessment

Traditional manual and visual inspections for pavement management are time-consuming, labor-intensive, and insufficient for new standards, leading to a growing interest in automated data collection and analysis methods [9,10,12,23,60,61]. Machine Learning techniques have been applied to classify pavement distress types and severity levels based on image, sensor, or survey data [19,98]. Commonly employed techniques are rooted in object detection or semantic segmentation of images [19,99,100].

The implementations initially focused on edge detection. Wang et al. [101] proposed pavement distress segmentation through the application of wavelet edge detection, specifically using the à trous algorithm (also known as the holes algorithm). Still focusing on edge detection, Ying and Salari [102] presented a refined approach using the beamlet transform technique. This novel implementation addressed the variation in background illumination. Following this, Cui et al. [103] proposed a pavement distress detection method using RF, capturing richer information through color gradient features. This approach effectively reduces noise in edge detection applications, enabling real-time pavement measurements. Later, Shi et al. [104] introduced the CrackForest framework, building upon this concept.

The advent of DL marked a significant evolution in pavement crack detection, with Zhang et al. [105] and Gopalakrishnan et al. [106] demonstrating the effectiveness of CNN in achieving high-accuracy results. This progression continued with Song et al. [107] introducing the CrackSegan, an end-to-end CNN framework, signaling a departure from traditional methods toward more sophisticated data-driven approaches. Historically, traditional edge detection methods in CV were commonly used for crack detection. However, with the introduction of DL in recent years, these new implementations have quickly ascended to become state-of-the-art. Llopis-Castelló et al. [108] further extended the application of CNNs to encompass the identification, classification, and quantification of urban pavement distresses, proposing an automated assessment methodology that aimed to reduce the subjectivity associated with visual surveys.

Continuing this trajectory, Han et al. [109] developed CrackW-Net, enhancing road crack detection by addressing segmentation challenges with a novel CNN structure. Wen et al. [110] developed Pavement Crack Detection Net (PCDNet), a DL framework combining CNN and a pixel-level crack seed algorithm for precise 3D pavement crack detection. Concurrently, Ji et al. [111] developed an integrated approach using DeepLabv3+, a Deep Convolutional Neural Network (D-CNN)- based system, for detecting and quantifying pavement cracks at the pixel level. Zhao et al. [112] introduced DASNet, a D-CNN designed for automated road defect detection, overcoming challenges like irregular shapes and scale differences.

Different implementations of You Only Look Once (YOLO) algorithms have been proposed over the years to detect distress. YOLO is a real-time object detection algorithm that divides an image into a grid, simultaneously predicting bounding boxes and class labels in a single inference [113]. Mandal et al. [114] improved crack detection with YOLOv2, followed by Liu et al. [115], who combined modified YOLOv3 with U-Net for a two-step detection and segmentation process. Du et al. [116] used a YOLO-based Deep Learning framework for object detection and distress classification in a large-scale dataset. Liu et al. [117] proposed a novel YOLOv3-ResNet50vd-DCN model for detecting concealed cracks in Ground-Penetrating Radar (GPR) images.

Zhu et al. [49] used YOLOv3 for pavement distress information collection and maintenance planning using Unmanned Aerial Vehicles (UAV) with a high-resolution camera. Jiang et al. [118] introduced a two-stage pavement crack detection and segmentation method using optimized YOLOv4 and an enhanced deeplabv3+ with the Ghost module and Convolutional Block Attention Module (CBAM), improving accuracy and inference speed over single-task DL approaches.

Liu et al. [119] enhanced YOLOv5s for faster more accurate road defect detection, optimizing the model's parameters and incorporating novel modules for improved efficiency and smaller size. Following this advancement, Yi et al. [120] proposed a pavement distress detection method using an improved YOLOv7 integrated with the Simple parameter-free Attention Module (SimAM) and Ghost module, optimizing accuracy and speed for real-time pavement defect detection and outperforming traditional and other DL models. Tamagusko and Ferreira [121] conducted a comparative analysis of YOLO models for pothole detection, revealing YOLOv4's superior performance, with YOLOv4-tiny being particularly suited for mobile applications, and YOLOv5 demonstrating the potential for scalability and ease of implementation.

A faster Region-based Convolutional Neural Network (R-CNN) has also been extensively utilized. Tran et al. [122] proposed a supervised ML network model using Faster R-CNN (RetinaNet) for crack detection and classification. Similarly, Song and Wang [97] used Faster R-CNN for pavement distress detection and achieved better results than CNN. Moreover, Ibragimov et al. [123] introduced a pavement distress detection method to analyze full-size pavement images, targeting various types of cracks, such as longitudinal, transverse, alligator, and partial patching cracks.

In exploring alternative methods, Hoang and Nguyen [73] evaluated SVM, ANN, and RF and found that SVM performed best. Additionally, Fan et al. [124] proposed the U-Hierarchical Dilated Network (U-HDN), an end-to-end DL algorithm for crack detection. Tong et al. [125] integrated a fully convolutional network with a Gaussian-Conditional Random Field (G-CRF) for pavement defect detection.

Furthermore, Guan et al. [126] introduced a framework for automated pixel-level pavement distress detection using stereo vision and a modified U-Net for crack and pothole segmentation. Also, Wen et al. [127] presented a pavement distress segmentation network (PDSNet), a DL framework for automated asphalt pavement distress segmentation. Besides these methods, He et al. [128] leveraged Mask R-CNN and transfer learning for accurate pavement defect detection in complex backgrounds, demonstrating superior precision and efficiency compared to Faster R-CNNs.

Expanding upon UAV applications in pavement condition assessment, Khilji et al. [129] and Loures and Azar [130] utilized UAVs and DL to detect road surface distress on unpaved roads. Khilji et al. [129] applied Deep Neural Networks (DNN) for segmenting road pixels and identifying defects such as potholes with high accuracy. Loures and Azar [130] provided cost-effective solutions using UAVs and DNN algorithms to detect key road distresses, enhancing rural and remote community access. Both studies demonstrate the efficacy of combining UAV imagery and ML in pavement maintenance.

Ranyal et al. [131] developed a novel computationally efficient system for detecting and assessing pothole severity on pavements using an optimized RetinaNet architecture and a depth estimation algorithm based on 3D modeling. Zhang et al. [132] introduced ECSNet, a DL model for efficient real-time pavement crack detection, balancing accuracy with speed and low computational demand.

Yang et al. [133] and Chen et al. [134] have advanced pavement defect detection by implementing Attention network structures. Yang et al. [133] introduced the Multi-scale Triple-Attention Network (MST-Net), designed for pixelwise crack detection and segmentation that effectively handles complex backgrounds and class imbalance issues. Concurrently, Chen et al. [134] developed the Multiscale Mobile Attention-based Network (MANet), employing deep learning techniques for automatically detecting pavement defects, demonstrating the application of multiscale convolution and Attention mechanisms in enhancing pavement maintenance strategies. Ding et al. [135] also introduced PCSNet, a novel network for pixel-level pavement crack segmentation that enhances crack feature detection through richer Attention modules and hybrid pyramid structures.

The availability of high-quality data is crucial for training ML models, yet the field has historically lacked a standardized dataset for model training and evaluation. Addressing this gap, Eisenbach et al. [136] introduced the German Asphalt Pavement distress (GAPs) dataset, a large and freely available pavement distress dataset. Following this initiative, Majidifard et al. [137] proposed the Pavement Image Dataset (PID) method that uses Google Maps imagery for automated pavement distress detection using Deep Learning. The dataset includes both wide-view and top-down-view images of pavement segments. Building on these efforts for quality data, Arya et al. [138] released the RDD2020 dataset, which contains over 26,000 road images annotated with various road distresses. Finally, Table 2 summarizes articles reviewed on ML applications for pavement condition assessment.

The most promising results have come from Attention-based models and DNN, including Modified YOLOv5s and YOLOv7, which optimize speed and efficiency for real-time applications. These models, particularly those incorporating Attention mechanisms, represent the closest approaches to the state-of-the-art, offering enhanced pixelwise crack segmentation capabilities.

The revised algorithms enable the automation of defect detection in road pavements with high accuracy, thereby allowing skilled labor to focus on less repetitive and safer tasks. For instance, specialists who conduct field data collection or analyze pavement videos can work more efficiently and with reduced risk through the use of advanced computer vision techniques.

In conclusion, various ML and DL methods, including RF, CNN, YOLO frameworks, U-Nets, and Faster R-CNN, have shown promising outcomes in detecting and classifying pavement distresses. State-of-the-art methods increasingly employ neural networks and their variations, excelling in analyzing unstructured data like images, with impressive results in pavement condition assessment. Moreover, UAV and GPR images are being explored to enhance assessment efficiency. A trend toward implementations based on Attention algorithms is also emerging [133–135], indicating a shift toward more sophisticated analysis techniques in pavement condition assessment.

Table 2. Summary of ML applications in pavement condition assessment studies.

Algorithm	Key References	Application	Key Findings
Wavelet with À Trous Algorithm	Wang et al. [101]	Pavement distress detection	Process images of pavements with complex backgrounds and filter image noise
Beamlet transform	Ying and Salari [102]	Pavement distress detection	Improved distress detection in pavements through the minimization of background illumination variations
Random Forest (RF)	Cui et al. [103], Shi et al. [104]	Pavement distress detection	Edge detection for distress has been enhanced by incorporating richer information using color gradient features
Convolutional Neural Network (CNN)	Zhang et al. [105], Gopalakrishnan et al. [106], Song et al. [107]	Pavement distress detection	High accuracy results
Deep Convolutional Neural Network (D-CNN)	Zhao et al. [112], Ji et al. [111]	Pavement distress detection	Detects, locates, and quantifies road defects
You Only Look Once version 2 (YOLOv2)	Mandal et al. [114]	Pavement distress detection	Improved crack detection efficiency
Modified YOLOv3 & modified U-Net	Liu et al. [115]	Pavement crack detection and segmentation	Two-step pavement crack detection method
YOLO-based framework	Du et al. [116]	Pavement distress detection	Created a large-scale pavement distress dataset
Deep Neural Networks (DNN)	Khilji et al. [129], Loures and Azar [130]	Pavement distress detection	UAVs can identify distress on unpaved roads
YOLOv3-ResNet50vd-DCN	Liu et al. [117]	Pavement concealed crack detection	Detection in ground-penetrating radar (GPR) images
YOLOv4 with Convolutional Block Attention Module (CBAM)	Jiang et al. [118]	Pavement crack detection and segmentation	Two-step pavement crack detection method
YOLOv3	Zhu et al. [49]	Pavement distress detection	UAVs with high-resolution cameras can support maintenance planning
YOLOv3, YOLOv4, YOLOv5	Tamagusko and Ferreira [121]	Pavement distress detection	YOLOv4 has better accuracy than YOLOv3 and YOLOv5
Modified YOLOv5s	Liu et al. [119]	Pavement distress detection	Optimized YOLOv5s for speed and efficiency
YOLOv7 with Simple parameter-free Attention Module (SimAM)	Yi et al. [120]	Pavement distress detection	Optimized accuracy and speed for real-time pavement distress detection
Faster region-based convolutional neural network (R-CNN)	Tran et al. [122], Song and Wang [97], Ibragimov et al. [123]	Pavement distress detection	Outperforms traditional methods in detecting and classifying various pavement distress

Table 2. *Cont.*

Algorithm	Key References	Application	Key Findings
Support vector machine (SVM), Artificial Neural Network (ANN), RF	Hoang and Nguyen [73]	Pavement distress detection	SVM performed best
U-Hierarchical Dilated Network (U-HDN)	Fan et al. [124]	Pavement distress detection	End-to-end framework
Fully Convolutional Network with Gaussian-conditional Random Field (G-CRF)	Tong et al. [125]	Pavement distress detection	Improved detection results
Stereo Vision and Modified U-Net	Guan et al. [126]	Pavement distress detection	Pixel-level crack and pothole segmentation
Pavement distress segmentation network (PDSNet)	Wen et al. [127]	Pavement defects detection and segmentation	Efficient framework
Mask Region-based Convolutional Neural Network (Mask R-CNN)	He et al. [128]	Pavement defects detection and segmentation	Good accuracy under complex backgrounds
RetinaNet CNN architecture and depth estimation algorithm	Ranyal et al. [131]	Pothole detection and depth estimation	Implemented depth estimation with good accuracy
Efficient Crack Segmentation Neural Network (ECSNet)	Zhang et al. [132]	Pavement crack detection and segmentation	Real-time pavement crack segmentation
Attention based	Yang et al. [133], Chen et al. [134], Ding et al. [135]	Pavement crack detection and segmentation	Improved performance in pixelwise crack segmentation

4.2. ML Applied to Pavement Performance Prediction

Machine Learning algorithms have been significantly improving the prediction of pavement performance. Techniques such as ANN, SVM, DT, and Boosted Trees address the limitations of traditional empirical and deterministic models by developing data-driven models for predicting pavement performance and deterioration over time [8,87,139]. Furthermore, ML techniques can accurately estimate pavement performance, considering factors such as traffic loads, climate, pavement structure, and material properties [28,140].

Some authors utilized SVM to predict pavement performance. Ziari et al. [86] found that SVM demonstrated high accuracy in short-term and long-term performance prediction. Subsequently, Wang et al. [141] introduced a hybrid technique combining Gray Relation Analysis (GRA) and Support Vector Regression (SVR) for long-term pavement performance prediction, showcasing higher precision and operability.

RF algorithms have shown promising results. For instance, Gong et al. [89] explored the application of RF models, which proved more accurate and precise than linear regression when predicting IRI values. Furthermore, Marcelino et al. [37] presented a systematic ML approach for developing pavement performance prediction models in PMS. This concept effectively incorporates structural, climatic, and traffic pavement data by utilizing algorithms such as RF and focusing on predicting IRI using the Long-Term Pavement Performance (LTPP) database. Additionally, Naseri et al. [142] introduced a pavement M&R optimization technique using the RF for IRI prediction. By merging the Whale Optimization Algorithm with RF, their method outperformed conventional models like MLR.

Similarly, neural networks have been applied to pavement performance predictions as well. Hossain et al. [143] developed an ANN model to predict the IRI for flexible pavements across different climate zones, utilizing climate and traffic data from LTPP. In the same vein, Choi and Do [144] developed an RNN algorithm to predict road pavement deterioration in

Korea, reducing prediction errors and achieving high determination coefficients, optimizing maintenance timing and budgets. Younos et al. [145] developed models using MLR and ANN to predict pavement performance by considering climate and traffic loading, demonstrating their effectiveness in similar climatic and traffic conditions. Also, Abdelaziz et al. [146] compared ANN to MLR and found that ANN yielded relatively better results. Zeiada et al. [96] investigated the factors influencing pavement performance in warm climates, contrasting them with cold regions. Among various ML models, they determined that ANN provided the most accurate results.

Furthermore, Yao et al. [13] developed a framework for modeling the evolution of pavement performance using techniques such as BorutaShap for feature selection, Bayesian Neural Networks (BNNs) for model development and uncertainty quantification, and Shapley Additive Explanations (SHAPs) [147] for model interpretation. They tested the framework for predicting transverse cracking in pavements and found that the predictions were relatively accurate. Similarly, Sirhan et al. [148] demonstrated that DNN models, trained on a large dataset, outperform traditional linear and nonlinear regression methods in predicting PCI values, suggesting their potential integration into PMS for enhanced accuracy.

Piryonesi and El-Diraby [42] investigated the performance of different classification algorithms in analyzing asphalt pavement deterioration data, showing that ensemble learning techniques and segmenting data by climatic region can improve prediction accuracy. The algorithms tested include Decision Trees, naïve Bayes classifier, naïve Bayes coupled with kernels, logistic regression, k-Nearest Neighbors (kNN), RF, and Gradient-Boosted Decision Trees (GBDT). Subsequently, Piryonesi and El-Diraby [62] further examined the impact of different performance indicators on flexible pavement deterioration modeling, achieving high accuracy levels using algorithms like RF and GBDT.

Some authors used tree ensembles for pavement performance predictions. For example, Song et al. [149] proposed a new ThunderGBM-based ensemble learning model with the SHAP method to predict IRI. Likewise, Luo et al. [150] compared the prediction accuracies of GBDT, extreme gradient boosting (XGBoost), SVM, and MLR models for pavement performance prediction using LTPP data. Damirchilo et al. [90] predicted the IRI of pavements using the LTPP dataset and ML algorithms, finding that XGBoost provided the best results. Similarly, Guo et al. [91] used LTPP data to create a GBDT model for predicting pavement performance, namely the IRI and rut depth. The developed model performed better than the ANN and RF benchmarks, while the results were further interpreted using SHAP. Additionally, Luo et al. [150] also predicted IRI using LTPP data, evaluating models including GBDT, XGBoost, SVM, and MLR. The authors introduced a stacking fusion model, combining GBDT and XGBoost with bagging as meta-learners, and achieved superior performance over isolated models.

Lastly, Ekmekci et al. [151] proposed a comparison between structural equation models and auto-Machine Learning (AutoML) for pavement deterioration prediction, finding that AutoML was superior in prediction, but its "black box" nature made it less practical for field applications. They suggest a hybrid approach to enhance the transparency and utility of the model.

Table 3 summarizes the articles reviewed on ML applications for pavement performance prediction.

As shown in Table 3, ANN emerges as the most frequently deployed ML technique for pavement performance prediction, acclaimed for its wide-ranging applicability and prowess in forecasting performance accurately [13,96,143–146,148]. Concurrently, ensemble models and AutoML are spotlighted for their promising contributions to the field. By integrating multiple ML strategies, ensemble models significantly bolster prediction accuracy, capitalizing on the synergistic effects of diverse techniques [90,91,149,150]. Meanwhile, AutoML propels the predictive capabilities to new heights, simplifying the model development cycle. Nonetheless, the practical utility of AutoML is somewhat diminished by its "black box" nature [151].

Table 3. Summary of ML applications in pavement performance prediction studies.

Algorithms	Key References	Application	Key Findings
Support Vector Machines	Ziari et al. [86], Wang et al. [141]	Pavement performance prediction	High accuracy in short-term and long-term performance; higher precision and operability
Random Forest	Gong et al. [89], Marcelino et al. [37], Naseri et al. [142]	Pavement performance prediction	Importance of initial IRI value in prediction, and promising results
Neural Networks	Hossain et al. [143], Choi and Do [144], Younos et al. [145], Abdelaziz et al. [146], Zeiada et al. [96], Yao et al. [13], Sirhan et al. [148]	Predicting the pavement transverse cracking, Performance prediction	Accurate performance model and real-world applicability
Diverse regression algorithms	Piryonesi and El-Diraby [42,62]	Asphalt pavement deterioration modeling	Improved prediction accuracy with ensemble learning techniques and segmenting data by climate
Ensembles models	Song et al. [149], Damirchilo et al. [90], Guo et al. [91], Luo et al. [150]	Pavement performance prediction	Improved prediction accuracy and consistency
Auto-Machine Learning (AutoML)	Ekmekci et al. [151]	Predict pavement rutting	AutoML effectively predicts rut depth, but its "black box" nature warrants consideration.

Using ML to predict pavement quality improves the accuracy of these predictions. Traditional models typically had lower accuracy, leading to increased uncertainty and reduced network reliability. This lack of precision also negatively impacted long-term planning, as road managers received less reliable information about the condition of pavements over time.

Conclusively, ML showcases substantial promise in augmenting pavement performance predictions and refining pavement management methodologies. Ensemble and boosted tree models stand out among the array of ML approaches, especially in structured data applications like pavement performance forecasting [28,79]. However, leveraging ML's full potential necessitates overcoming several hurdles, such as securing high-quality data, addressing the variability in pavement performance, improving model interpretability, reducing computational demands, establishing standard datasets, and enhancing the reproducibility of research findings.

4.3. ML Applied to Maintenance and Rehabilitation Decision-Making

Maintenance and rehabilitation decision-making is a critical component of pavement management as it determines the optimal allocation of resources to ensure the longevity and functionality of road networks [1,2,4,5]. Machine Learning applications in road pavement M&R have been slowly increasing. The objective is to obtain optimized strategies that increase cost-effectiveness and promote the efficient allocation of resources.

Returning to the 2000s, Bosurgi and Trifirò [152] demonstrated that ANN and the Genetic Algorithm (GA) can optimize resources for resurfacing interventions on flexible pavements. Ferreira et al. [153,154] and Meneses et al. [155] demonstrated that GA can optimize the application of M&R interventions in the pavements of a whole road network. Years later, Elbagalati et al. [65] developed an ANN-based tool integrating structural and functional conditions for improved time-efficient pavement M&R decisions, achieving high prediction accuracy. Likewise, Hafez et al. [156] utilized ANN to optimize pavement M&R alternatives for low-volume roads while considering expert recommendations. They developed two ANN prediction models using pavement condition data, condition indices, and road lengths, providing a decision-making tool that evaluates maintenance practice variability in the Colorado Department of Transportation region and suggests tailored alternatives based on pavement management needs and predicted performance.

Yao et al. [29] developed a Deep Reinforcement Learning (DRL) method for creating maintenance strategies that maximize long-term cost-effectiveness in pavement maintenance decision-making. The case study results show that the DRL model can learn more effective strategies, ensuring acceptable pavement conditions while optimizing maintenance costs. Similarly, Han et al. [157] introduced an intelligent decision-making model for pavement maintenance plans that utilized RL and data mining techniques to enhance the benefit–cost ratio and address the challenges of manual decision-making based on experience. The model, tested on a highway maintenance decision in Jiangsu Province, achieved better decision-making accuracy compared to an ANN.

Morales et al. [158] presented an ML-based methodology to enhance road maintenance prediction and intervention planning, utilizing DT, kNN, SVM, and ANN, which focuses on identifying the type and likelihood of required interventions for each road segment, ranked by technical severity. The study highlights the critical role of precise asset condition data and the consideration of variability in maintenance characteristics.

Furthermore, Naseri et al. [159] developed a multi-objective optimization model for pavement maintenance planning, aiming to improve network conditions and reduce CO_2 emissions simultaneously. This model utilizes a combination of single-objective (Coyote Optimization Algorithm and GA) and multi-objective metaheuristic algorithms (Multi-Objective Coyote Optimization Algorithm and Non-Dominated Sorting GA) to achieve its goals. In the same vein, Naseri et al. [142] proposed a method for optimizing pavement M&R plans, using RF to predict pavement IRI, and compared its performance to MLR. They employed the Whale Optimization Algorithm (WOA) as a metaheuristic optimization algorithm to find optimal M&R solutions, with the hybrid model significantly outperforming the GA in identifying cost-effective solutions.

Finally, Jooste et al. [160] created a model to predict pavement treatment types using multi-classification ML algorithms, assisting pavement engineers in decision-making. Based on inventory and condition data, the model accurately predicted pavement treatment types (reseal, overlay, or rehabilitation).

In conclusion, the evolution of ML in optimizing maintenance has come a long way, offering significant improvements in cost-effectiveness, resource allocation, and decision-making for road pavement management. Researchers have been relentless in pursuing innovative solutions, from early applications of ANN and GA to more recent developments in RL and hybrid algorithms. Due to the complexity of decision-making activities for M&R, fewer studies focus on this area, leaving the door open for further development and exploration in this field.

Table 4 presents the reviewed articles on ML applications in M&R Decision-Making.

The application of ML techniques in road pavement management, particularly in M&R Decision-Making, highlights a trend toward diverse sophisticated approaches. ANNs are extensively utilized across various studies for tasks such as optimizing resurfacing interventions and enhancing the maintenance of low-volume roads [65,152,156]. Furthermore, GA is recognized for its efficiency in complex optimization problems within pavement management. Also, further advancements in DRL and RL have demonstrated significant success in developing cost-effective maintenance strategies and refining M&R plans [29,157]. Notably, a hybrid methodology has surpassed most conventional techniques, illustrating the effectiveness of combining multiple ML methods for improved decision-making in M&R [142].

The integration of AI in M&R Decision-Making has progressed slowly, primarily due to the complexity and many variables involved. For example, transport managers must account for factors like traffic patterns, weather conditions, material wear, and budget constraints. Each variable can significantly impact the prioritization and timing of maintenance actions, thus complicating the decision-making process.

In summary, the sector continues to value GA and ANNs for their broad applicability. However, there is a clear shift toward more complex, hybrid, or ensemble models that merge the capabilities of various ML techniques.

Table 4. Summary of ML applications in M&R Decision-Making.

Algorithm	Key References	Application	Key Findings
Artificial Neural Network (ANN), and Genetic Algorithms (GA)	Bosurgi and Trifirò [152]	Resurfacing interventions optimization	Effective use of ANN and GA
ANN	Elbagalati et al. [65]	Pavement M&R Decision-Making	ANN can be used to optimize treatment selection based on structural and functional pavement conditions
ANN	Hafez et al. [156]	Low-volume road maintenance optimization	Developed tailored decision-making tool using ANN
Deep Reinforcement Learning (DLR)	Yao et al. [29]	Pavement M&R plans optimization	DRL optimized costs and improved strategies
RL	Han et al. [157]	Pavement M&R plans optimization	Improve maintenance decision-making
Decision tree (DT), k-Nearest Neighbors (kNN), ANN, and Support Vector Machines (SVM)	Morales et al. [158]	Decision tree (DT), k-Nearest Neighbors (kNN), ANN, and Support Vector Machines (SVM)	
Coyote Optimization Algorithm and GA	Naseri et al. [159]	CO_2 emission reduction in pavement M&R	Optimization aids CO_2 reduction in road M&R
Random Forest (RF), Multiple Linear Regression (MLR), and Whale Optimization Algorithm (WOA)	Naseri et al. [142]	Pavement M&R plans optimization	Hybrid model outperformed GA in cost-effectiveness
Ensemble trees	Jooste et al. [160]	Pavement M&R plans recommendation	Predicting pavement treatment types with high accuracy

5. Challenges of Applying ML to Road Pavement Management

Several challenges delay the effective integration of AI in road pavement management. This section explores the obstacles associated with implementing ML techniques in this context.

5.1. Technical Challenges

The main challenge in using ML techniques for pavement management is ensuring the quality and availability of data. The quality of input data significantly affects the performance of ML models [161,162]. However, the amount of data used is also an important factor, albeit to a lesser extent [161,163,164]. Data collection, standardization, and sharing should be a priority in pavement management. The objective is to ensure that the models have the necessary quality to learn the complex relationships between various factors that influence pavement performance.

A key issue often associated with training data is bias. Bias in ML models can emerge from numerous sources, such as historical data, sampling errors, and the biases of those selecting features [165,166]. When data are not representative or balanced, it can lead to skewed results. Moreover, there exists the challenge of algorithmic bias. This type of bias may be introduced inadvertently during the model design process. For example, assigning higher importance to certain features might result in the unintentional exclusion of specific groups. This highlights the critical need for careful and inclusive model design to prevent unfair outcomes.

The expense of continuously monitoring road pavements is a significant factor to consider when implementing a pavement management system across a large network. Advances in image processing and CV have reduced some challenges but necessitate the involvement of specialized teams such as data engineers, scientists, and pavement experts, which increase costs. Additionally, maintaining databases, updating and servicing ML models, and managing data collection, analysis, and diagnosis pipelines also incur considerable expenses. Despite these costs, the benefits of making informed and timely decisions often justify the investment in these comprehensive monitoring systems [167]. The principle of reproducibility stands as a cornerstone in rigorous scientific inquiry, as articulated by Zwaan et al. [168]. This precept underscores the need for independent verification of methodologies, datasets, and computational models, reinforced by Ioannidis [169] as foundational to the progression of scientific disciplines. Regrettably, a substantial number of the reviewed articles exhibit a scarcity of detail regarding their methods, often limiting their disclosure to specific models and selected parameters. Additionally, many do not openly share their codes, data, or models, instead indicating they are "available upon request." Such limitations hinder replication, validation of results, and further scholarly advancements built on prior research.

Another challenge is the interpretability and explainability of the models. Deep Learning algorithms can be considered "black boxes" due to their complexity and the difficulty users have in understanding decision-making processes [170,171]. Developing more interpretable and explainable models is crucial for gaining the trust of stakeholders and ensuring that they can use these models in their processes.

Road asset managers often hesitate to adopt technologies if they cannot explain the processes. This resistance highlights the importance of striking a balance between a model's complexity and its clarity. Ensuring the interpretability of a model builds trust among stakeholders and promotes its widespread adoption and effective integration into pavement management strategies. Results with lower accuracy but which are more straightforward to understand often end up being recommended. Due to this, linear and logistic regression, Decision Trees, naïve Bayes, or rule-based models are recommended. In addition to being easily interpretable, these models can serve as a baseline for more complex models.

Nevertheless, integrating ML techniques with existing PMS and workflows can also be challenging as it requires a thorough understanding of existing processes, tools, and data sources. Research is needed to develop strategies to effectively incorporate ML models into road agencies, minimizing disruptions and ensuring compatibility with established workflows. The importance of this factor is even greater in the current context, where there is a shortage of qualified personnel to deploy these ML models in real-world applications. The teams involved in this task must be multidisciplinary, covering knowledge in different domains, such as computer science, civil engineering, data analysis, and specific knowledge of pavement management domains.

Finally, implementing ML techniques in pavement management requires engineering experts and ML experience. Therefore, training and preparing a range of professionals to acquire the necessary skills and knowledge to apply ML concepts in managing road pavements is essential. Besides the technical challenges, there are other obstacles to consider. However, these challenges in the area can be minimized by ensuring quality data, creating explainable models, and fostering proficiency in AI techniques among professionals in the field.

5.2. Ethical and Societal Considerations

For the effective use of ML algorithms in pavement management, it is crucial to consider the ethical and social implications of implementing them. In particular, bias and fairness in decision-making are critical factors.

Bias, in its relation to ethics and prejudice, significantly influences ethical considerations within ML models. For example, models trained on data from regions historically neglected in pavement maintenance are likely to continue ignoring these areas. This results in an unjust distribution of resources and services. Furthermore, such models may perpetuate existing inequalities simply because they rely on data that are inaccurately labeled as good [172,173].

To address this issue, it is essential to take a mindful approach when developing and implementing ML models in pavement management. This may involve using techniques such as resampling and reweighting to minimize the impact of bias on training data. Also, one technique that is gaining ground is the use of synthetic data to rebalance datasets. In addition, researchers and stakeholders must actively collaborate to identify potential sources of bias during model development, validation, and deployment. To create unbiased models, experts must provide representative data for diverse samples.

A crucial aspect to ensure fairness in algorithmic decision-making is transparency and interpretability. Although complex ML models like DNN can deliver accurate predictions, their "black box" nature makes understanding and explaining them difficult [170,171]. This lack of transparency can hinder the identification of potential biases and assurance of fairness. By using interpretable models and integrating explainable techniques, it is possible to comprehend the factors influencing model decisions and detect potential unfairness.

In addition to fairness and bias, privacy concerns can arise when using ML to manage pavements. Using data from various sources such as sensors, cameras, and mobile devices can infringe on individual privacy. To mitigate these concerns, it is essential to establish strict data governance policies and employ privacy-preserving techniques such as anonymization, federated learning, or even data encryption [174]. The use of synthetic data appears to be a promising solution for data limitations. Both Hossain et al. [143] and Tamagusko et al. [175] demonstrated the effective integration of synthetic data to train ML models when faced with limited data scenarios. This approach also promotes data privacy and reduces bias.

Addressing the ethical challenges inherent in utilizing AI within pavement management requires a concerted effort to educate and prepare stakeholders. These professionals should possess a comprehensive understanding of AI, encompassing not only its technical aspects but also its limitations, potential biases, fairness, and possible adverse impacts. Educational programs and professional training should incorporate comprehensive modules on ethical AI usage, encouraging critical thinking regarding algorithmic decision-making processes and their broader societal ramifications. Fostering open dialogue between AI experts, urban planners, civil engineers, and the public can contribute to more ethically informed and socially aware AI solutions.

Moreover, the increasing dependence on ML-based PMS may cause concerns about labor displacement and the potential loss of human expertise. While there is no definitive answer to this issue, disruptive technologies have historically emerged, creating new work activities beyond these technologies. However, this relationship is complex and non-linear [176,177]. One thing is certain: a data-driven approach supported by ML can result in improved pavement management decisions.

In conclusion, addressing ethical and social considerations in pavement management is essential to ensure the responsible and equitable adoption of AI technologies. By proactively identifying and addressing biases, promoting transparency and interpretability, and addressing privacy and workforce issues, stakeholders can work together to create a fairer and more effective PMS.

6. Discussion

Incorporating AI into road pavement management has emerged as a promising paradigm, potentially revolutionizing the domain. ML introduces transformative benefits, including enhanced accuracy in damage detection, predictive maintenance capabilities, significant cost reduction, and improved safety through automated data analysis. However, a significant gap remains between academic research and practical implementation in road agencies.

This study has explored a range of AI algorithms, beginning with simpler methods such as edge detection for pavement condition assessment, SVM, and DT for predicting pavement performance, and the GA for M&R optimization. As AI has evolved, the implementations have become more complex and accurate. However, they have also become more difficult to interpret and implementation requires a higher level of expertise. Figure 9 arranges the AI algorithms discussed above categorically according to their respective application areas, providing us with an overview.

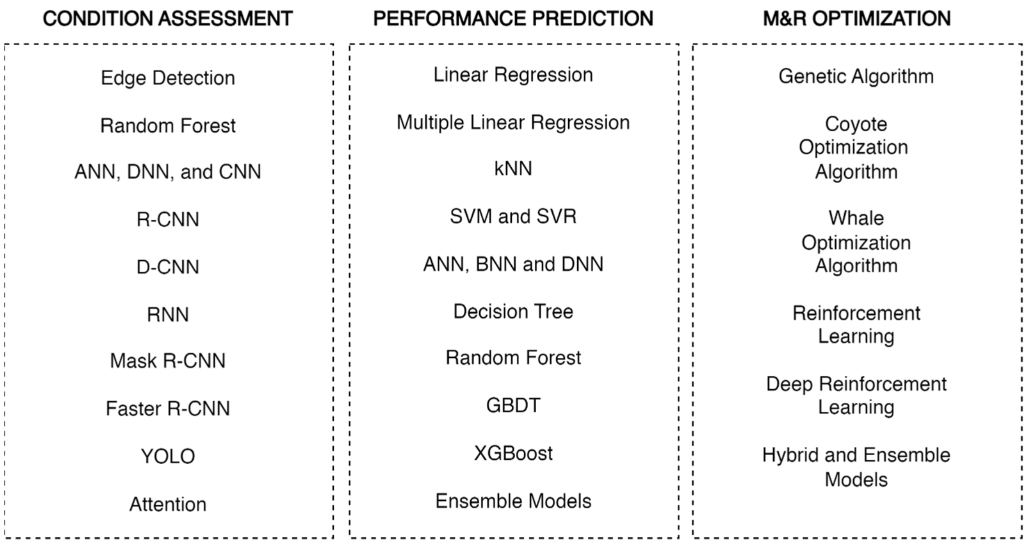

Figure 9. AI algorithms by application area.

Pavement condition assessment has undergone a transformative evolution. Previously anchored in manual inspections, the domain has seamlessly embraced automated data collection and analysis techniques. Traditional pavement data collection methods are costly, labor-intensive, and time-consuming [8–12]. Additionally, these methods often face challenges related to consistency and replicability [9,60]. The current landscape thus underscores the need to bed in CV techniques, especially given that visual inspections present a fertile ground for such integration, subsequently enhancing the precision of pavement assessment [61].

As the field of CV advances, techniques such as CNN, YOLO frameworks, U-Nets, Faster R-CNN, and Attention models have established their prominence, bolstered by their effectiveness in detecting and segmenting distress in pavements [22,105–107]. The ascendance of variations in DNN, particularly in object detection and image semantic segmentation tasks, and the integration of Attention mechanisms, consolidate them as state-of-the-art. This outcome aligns with the findings of El Hakea and Fakhr [20] and Gopalakrishnan [22], which revealed that a significant portion of the analyzed studies utilized ANN and DNN variations. However, using neural networks for pavement condition assessment faces challenges, including the need for large datasets, which increases computational demands, costs, and energy usage. Additionally, extensive data collection raises privacy and data quality concerns. Moreover, the "black box" nature of ANNs complicates the understanding and interpretation of decision-making processes, raising further ethical considerations. Addressing these issues is crucial for the ethical and sustainable use of neural networks in this field.

CV algorithms are increasingly recognized as the future of data collection in road pavement management. These algorithms rely heavily on supervised learning techniques, which necessitate high-quality labeled data to train the models effectively. This process, where technicians and experts provide the necessary labels, is crucial for ensuring the accuracy and reliability of the models.

However, recent advancements have seen the development of foundation models and zero-shot models, which do not require labeled data. Despite their potential, these models are currently less effective for specialized applications like road pavement management due to the unique and varied nature of the data involved. For these types of models to become viable in pavement management tasks, there must be access to large volumes of high-quality data to train them effectively. This would enable the creation of robust models capable of handling the specific challenges posed by road pavement assessment and maintenance.

Enriched by ML, pavement performance prediction offers opportunities for innovation. The front-runners in this field are the boosted and ensemble decision tree models, mirroring the rapid advancements in computational methodologies. The IRI emerges as the main indicator, outlining pavement quality. Models like SVM and DT are now viewed as outdated. Additionally, while ANNs yield commendable outcomes, they encounter challenges, especially regarding interpretability. Notably, they tend to underperform compared to boosted trees in predictions involving tabular data [79]. Consequently, boosted trees and ensemble models are recognized as state-of-the-art [28]. Once more, the key issues are related to the quality of training data, underscored by a substantial need for improvements in data integrity, management, and ongoing validation within the pipeline. Similarly, Xu and Zhang [17] also emphasizes this demand for high-quality data.

Given the unlikely recurrence of programs on the scale of the LTPP project, acquiring more data of similar scope will be challenging. Additionally, algorithmic predictions in pavement management have already achieved high accuracy, often exceeding 90%. With the vast number of variables and the continual changes in traffic and weather conditions, further significant improvements in accuracy may be limited to incremental advances. As a result, the focus is likely to shift toward enhancing data processing techniques, including data augmentation and the use of synthetic data. Efforts are also expected to concentrate on fine-tuning models to better accommodate diverse regional and climatic conditions and on leveraging external transfer learning to improve model applicability.

However, the widespread application of Machine Learning in predicting pavement qualities continues to be hindered by the limited open and standardized availability of the models developed in various studies. This restriction impacts the potential for broader validation and adoption of these technologies in pavement management, indicating a critical area for future research and development.

Within M&R Decision-Making, there is a focus on judiciously allocating resources to maximize pavement longevity. Integrating ML into pavement M&R is gradually revealing pathways for implementing optimized and cost-effective approaches. Bosurgi and Trifirò [152] demonstrated the synergistic potential of ANNs and GA. Following this trajectory, studies by Hafez et al. [156] and Yao et al. [29] have fortified the role of ML in sculpting tailored cost-efficient solutions. Recent forays, including hybrid models and ensemble techniques, presented by scholars like Naseri et al. [142] and Jooste et al. [160], indicate the dynamic evolution in the field. Furthermore, Yao et al. [29] and Han et al. [157] employed RL to enhance M&R planning decisions, yielding promising outcomes. Nonetheless, research in this domain remains sparse and is still in its early stages.

To enhance the application of ML in M&R of road pavements, it is crucial to conduct research in an open and transparent manner. Currently, many existing implementations are yet to make their models publicly available, making replication difficult or even impossible. This lack of transparency hinders progress, as the opacity of the studies conducted obstructs advancements. Furthermore, research in this field should address the practical challenges faced by stakeholders responsible for road pavement management. By aligning studies more closely with real-world issues, the solutions developed can be more directly applicable and beneficial in the everyday operations of pavement management. This approach not only enhances the relevance of the research but also increases the likelihood of its adoption in practical scenarios.

An increasing amount of research concentrates on interpretability and explainability in ML models [178–181]. Future studies should aim to create interpretable and explainable ML models that can facilitate acceptance and adoption in pavement management. This could involve exploring inherently interpretable models, such as Decision Trees, rule-based systems, or linear and logistic regression models and investigating post hoc explainability techniques like Local Interpretable Model-agnostic Explanations (LIME) [182] or SHAP [147]. Additionally, researchers should strive to develop new explainability methods tailored to the unique challenges and requirements of pavement management, including visualization tools and metrics for quantifying explainability.

The replicability of ML models developed in road pavement management is challenging due to the lack of transparency. Still, the ability to replicate findings is a critical component of scientific research [168]. Also, the independent validation of data, models, and methods plays a vital role in the progression of science [169]. However, numerous articles examined in this study lack sufficient detail about their methods, data, key parameters, and models. Furthermore, most do not grant access to their code, data, and models. This makes it extremely challenging to replicate results, verify findings, and do further research. To advance scientifically, a collaborative and open environment must be created.

Advancements in this field necessitate the creation of standardized datasets and benchmarks, similar to ImageNet [183] or Microsoft Common Objects in Context (MS COCO) [184]. While numerous pavement performance prediction models utilize LTPP data, discrepancies arise due to their reliance on varied versions, sections, and filters, rendering them non-comparable in most cases.

Developing road networks that are resilient to climate change and the resulting catastrophic events is essential for maintaining reliable transport infrastructure. Some researchers have examined the influence of climatic factors on road pavement design and deterioration, but these efforts may not be sufficient to address the challenges posed by recent climate changes. Designing and building roads that can withstand extreme weather conditions, floods, landslides, and other natural disasters can help minimize the risks associated with these events. Building resilient road networks also maintains connectivity between communities, ensuring medical care and support are provided in extreme situations. This can be achieved by developing intelligent information systems and using ML to predict events arising from climate change.

7. Conclusions

This article has demonstrated the transformative potential of Machine Learning (ML) for enhancing efficiency, effectiveness, and sustainability in road pavement management. Our analysis reveals a clear shift from traditional manual methods toward automated data-driven approaches, with promising advancements in pavement condition assessment, performance prediction, and optimization of M&R activities. While a variety of ML techniques are being explored, Deep Learning (DL), particularly using Convolutional Neural Networks (CNN), has emerged as the dominant approach for automated condition assessment, achieving impressive accuracy in detecting and classifying pavement distress. For performance prediction, ensemble methods and boosted tree models, such as Random Forests and XGBoost, have shown great promise in capturing the complex interactions of various factors influencing pavement deterioration.

However, realizing the full potential of ML in pavement management requires addressing key challenges. Ensuring high-quality standardized data is crucial, as ML models are highly dependent on the quality and representativeness of training data. Enhancing model interpretability and explainability is essential to build trust among stakeholders and ensure responsible implementation of ML-based decisions. Ethical considerations, such as addressing potential bias in data and models, protecting privacy, and mitigating job displacement, must also be carefully considered.

Based on our analysis, several critical areas for future research emerge:

1. Development of Standardized Datasets: Creating publicly available standardized datasets for pavement condition, performance, and maintenance history is necessary to enable robust model training and benchmarking, facilitating the development of more generalizable and reliable ML models;
2. Hybrid and Explainable ML Models: Exploring the development of hybrid models that combine the strengths of different ML techniques, as well as incorporating explainable AI (XAI) methods, can enhance model transparency and build confidence in ML-driven decision-making;

3. Integration with Smart Infrastructure: Further research is needed to seamlessly integrate ML with other smart infrastructure technologies, such as IoT sensors, Big Data analytics, and digital twins, to create intelligent Pavement Management Systems;
4. Climate Change Adaptation: Investigating the use of ML to predict the impact of climate change on pavement performance and develop adaptive management strategies is crucial for ensuring the long-term resilience of road infrastructure;
5. Lifecycle Cost Analysis of ML-Based Systems: Conducting comprehensive lifecycle cost analyses of ML-based Pavement Management Systems is vital to assess their economic viability and demonstrate their long-term cost-effectiveness to stakeholders.

In summary, integrating ML techniques into road pavement management shows great potential for transforming the field and improving decision-making processes. As stakeholders better further explore the challenges and opportunities presented by ML, the likelihood of achieving more effective and sustainable pavement management practices will increase. Ultimately, this will help develop efficient and resilient road networks that cater to society's growing needs.

Author Contributions: Conceptualization, T.T. and A.F.; methodology, T.T. and A.F.; validation, T.T., M.G.C. and A.F.; formal analysis, T.T.; investigation, T.T.; resources, T.T.; data curation, T.T.; writing—original draft preparation, T.T. and M.G.C.; writing—review and editing, T.T., M.G.C. and A.F.; visualization, T.T.; supervision, A.F.; project administration, A.F.; funding acquisition, A.F. All authors have read and agreed to the published version of the manuscript.

Funding: T.T. gratefully acknowledges the support provided by the Portuguese Foundation for Science and Technology (FCT), which awarded him the Ph.D. scholarship grant 2020.09565.BD. Similarly, M.G.C. was supported by the doctoral grant PRT/BD/152842/2021, financed by the FCT under the MIT Portugal Program. The authors are grateful to the Research Center for Territory, Transports, and Environment—CITTA (UIDP/04427/2020) for the financial support.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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