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MACHINE LEARNING FOR PAVEMENT PERFORMANCE AND SERVICE LIFE PREDICTION

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Abstract The way we predict service life and model pavement performance gradually evolves due to the popularity of machine learning (ML). We now have better tools to handle complex, multi-dimensional and big data through applications of recent advancements in deep learning and large language models (LLMs). Thus, the pavement deterioration can be predicted earlier and with greater accuracy because of models' ability to identify patterns that conventional techniques might miss. In addition to support and continuous monitoring through automated analysis of sensor and visual inputs, ML helps through learning from historical data, traffic patterns, and environmental factors. In order to investigate current trends, we performed a literature analysis after conducting a systematic review in accordance with PRISMA guidelines. Our results state that although ML has gained popularity, the pavement engineering is still in its infancy. In this field, more sophisticated techniques, e.g., generative AI and LLMs have not yet been thoroughly investigated. Even though there are still issues, especially with data quality and model transparency, ML presents great potential in enabling intelligent infrastructure management.

Keywords: Artificial intelligence, Machine learning, service life of pavement, big data, deep learning, civil engineering, data science.

AMS Mathematics Subject Classification: 65R32.

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1 Introduction

In recent years, machine learning (ML) has emerged as a reliable computational method in the field of pavement engineering, particularly in the prediction of pavement performance and remaining service life. The traditional mechanical, physical and empirical models, although robust, are increasingly being supplemented or replaced by ML models that offer improved accuracy, adaptability, and cost-efficiency. The integration of ML with non-destructive testing (NDT) techniques has opened new pathways for comprehensive and real-time health monitoring of pavements, leading to proactive maintenance strategies and longer infrastructure lifespans [1-3]. Among various ML techniques, Random Forest (RF) and Support Vector Regression (SVR) models have demonstrated superior prediction performance for pavement deterioration and service life forecasting. For instance, RF models have shown a reduction in prediction error compared to M-E models [1]. Meanwhile, SVR, especially when optimized by algorithms such as the fruit fly optimization algorithm (FOA), has proven effective in estimating the remaining service life (RSL) of flexible pavements using inputs from Falling Weight Deflectometer (FWD) and Ground-Penetrating Radar (GPR) data [2]. These approaches enable more reliable performance prediction under diverse environmental and loading conditions. Machine learning also enhances the utility of NDT methods by enabling indirect estimations of pavement conditions. For example, tire noise analysis through ML classifiers like RF Classifier (RFC) and Support Vector Classifier (SVC) can predict crack damage with high accuracy, offering a cost-effective alternative to conventional inspections [3]. Additionally, advanced regression models such as XGBoost, enhanced with chaotic particle swarm optimization (CPSO), have been applied to predict deflection basin area using temperature and load variables, minimizing the frequency of costly physical tests [4]. These innovations significantly contribute to the efficiency of health monitoring systems. Beyond performance prediction, ML supports long-term planning through applications in Pavement Condition Index (PCI) estimation [5], life-cycle cost analysis (LCCA) [6], and the quantification of overweight traffic impacts on survival life [7]. Importantly, recent studies suggest that pavements rehabilitated using advanced methods like Full-Depth Reclamation (FDR) may last significantly longer than expected when assessed with high-accuracy ML models [1]. Nevertheless, challenges such as data heterogeneity and model generalizability persist. Future directions call for the integration of simulated datasets to enhance model robustness and the development of generalized frameworks capable of performing reliably across varied geographical and structural conditions [8,9].

Table 1: Summary of Machine Learning Applications in Pavement Engineering

Aspect	ML	Benefits	Ref
Prediction Accuracy	RF, SVR, XGBoost	Higher accuracy, reduced errors	[1], [2], [4]
Non-Destructive Testing	Tire Noise, Deflection Basin	Cost-effective, efficient, reduced testing frequency	[3], [4]
Health Monitoring	PCI Prediction	Improved maintenance timing and budgeting	[5], [6]
Impact of Traffic	Random Survival Forest	Quantifies impact of overweight traffic	[7]
Long-Term Performance	Life-Cycle Cost Analysis	Cost-effective pavement management	[6]
Data Quality & Integration	Synthetic Data, Simulations	Enhanced accuracy, reduced uncertainties	[8]
Model Generalization	Emphasis on Generalization	Better performance across different datasets	[9]

ML has emerged as a powerful tool for predicting pavement performance and optimizing infrastructure maintenance. Numerous studies have demonstrated its capability to forecast pavement deterioration with greater accuracy than traditional methods, thereby improving the allocation of maintenance and rehabilitation resources [10], [11]. For example, ML which utilize algorithms such as RF and CatBoost have successfully predicted the long-term performance of asphalt concrete overlays, with RF outperforms others in predictive accuracy [11]. Furthermore, time-series models like Long Short-Term Memory (LSTM) combined with Fully Convolutional Neural Networks (FCNN) have outperformed conventional approaches in capturing pavement condition trends, highlighting the advantages of deep learning (DL) in managing large-scale datasets [12]. Despite these advancements, challenges persist which include variability in model outcomes, data preprocessing complexities, and sensitivity to hyperparameter tuning, which must be addressed to ensure robust and generalizable performance [16,17]. A parallel development in pavement engineering is the integration of non-destructive testing (NDT) with ML and DL models to improve condition assessment and health monitoring. Advanced NDT techniques such as 3D imaging, laser scanning, and infrared sensing have been employed alongside ML algorithms to enhance damage detection accuracy [13]. Ground Penetrating Radar (GPR) and Road Surface Profiler (RSP) data have also proven valuable in evaluating subsurface and surface conditions, particularly in understanding how asphalt thickness variations influence International Roughness Index (IRI) values [14,15]. The combination of GPR and RSP has been used to estimate the remaining service life (RSL) of pavements through gene expression programming (GEP), while intelligent data analysis approaches continue to support decision-making for inspection and subsurface evaluation [10], [17]. Collectively, these integrated approaches show strong potential to transform pavement management systems, though ongoing research is essential to overcome existing limitations and ensure their broader applicability in real-world scenario. Although recent developments in ML have created exciting opportunities for predicting pavement performance, there are still a number of important research gaps that prevent ML's full potential in pavement engineering from being fully realized. A systematic review that directs the development and generalization of these models across various scenarios and datasets currently is not available. This is despite the fact that numerous studies have shown the capabilities of individual ML algorithms [18]. Adding to this problem, current research hardly ever assesses ML models on extensive, real-world datasets, which results in limited understanding of the models' scalability and resilience in real-world problems [19]. Furthermore, the integration of physical pavement behavior, which is essential for long-term accuracy and reliability, is frequently left out of current machine learning models, which frequently operate as black boxes [20]. The absence of standardized, high-quality datasets further undermines model reliability and reproducibility, which creates inconsistencies across different studies and applications [21,22].

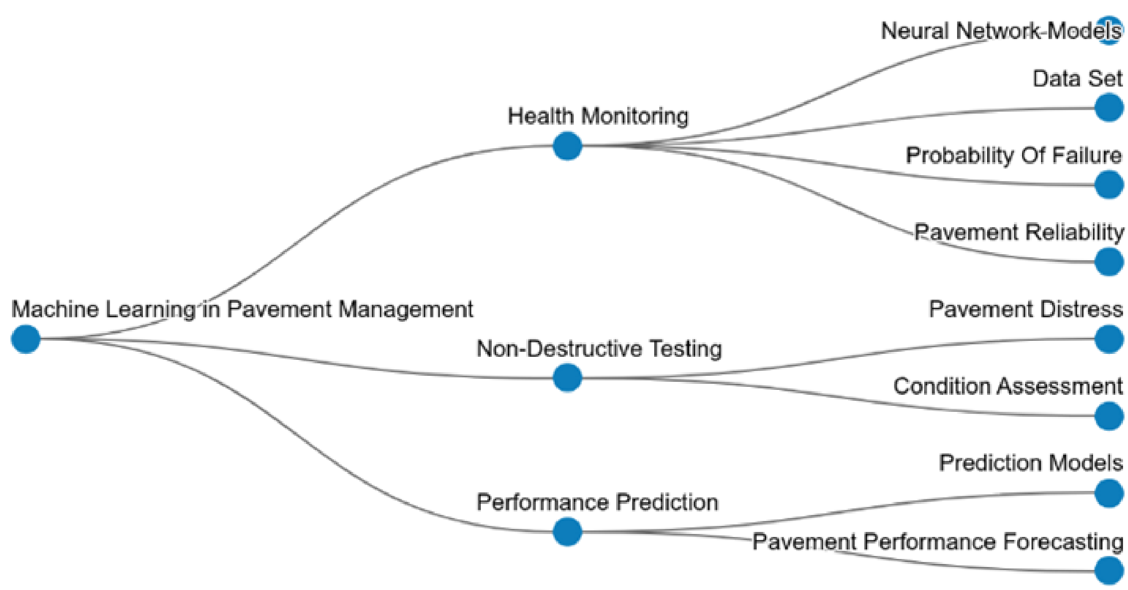

Figure 1: Taxonomy of ML methods for predicting RSL of pavements

In addition to the technical difficulties, the intricacy and weak interpretability of machine learning models limit their practical application in actual pavement management systems, which restricts their value for practitioners [23,24]. Predictive modeling attempts frequently ignore maintenance and rehabilitation history, despite the obvious influence these factors have on pavement performance [23]. Furthermore, many studies neglect to adjust models to particular pavement types, ignoring variations in preservation methods and deterioration mechanisms among materials and environments [25]. Last but not least, despite the growth of smart infrastructure, little is known about how to integrate smart transportation systems and evaluate pavement conditions in real time, which offers a huge chance to improve predictive capabilities and infrastructure responsiveness [26]. These gaps highlight the need for holistic, interpretable, and context-sensitive ML models in order to bridge data science with domain-specific engineering knowledge.

Table 2: Summary of Research Gaps

Research Gap	Description Summary	References
Systematic Approach	No unified framework to support multiple ML algorithms and ensure model generalization.	[18]
Large-Scale Dataset Comparison	Few studies compare ML models on comprehensive real-world datasets.	[19]
Integration with Physical Behavior	Physical pavement behavior is often excluded, reducing long-term accuracy.	[20]
Data Quality and Standardization	Low-quality and inconsistent datasets hinder model reliability.	[20], [21]
Model Interpretability	Many ML models are too complex and lack transparency for practical use.	[21], [22]
Maintenance History	Historical maintenance data is often omitted from model inputs.	[21]
Specific Pavement Types	Lack of model evaluation specific to pavement types and treatment methods.	[23], [24]
Real-Time Assessment	Limited research on real-time condition monitoring and smart systems integration.	[25], [26]

Several research gaps in the area of pavement performance prediction using ML listed in table II. These gaps point to areas that require more research and development in order to improve the precision, usefulness, and effectiveness of machine learning models in pavement engineering. Filling in these research gaps can result in ML models for pavement performance prediction that are more precise, dependable, and useful, which will ultimately improve pavement management systems and the lifespan of infrastructure. The roadmap should begin with the establishment of a standardized, superior pavement performance database in order to fill in the research gaps. Environmental, maintenance, structural, and functional data should all be included. Using fundamental machine learning techniques in new applications is a smart first step. This aids in introducing and popularizing machine learning among pavement engineers. The best models for the dataset should then be identified by comparing various machine learning approaches. More sophisticated approaches like ensemble learning, hybrid approaches, and generative models can then be used. Using responsible machine learning is also crucial. This entails making certain that models are fair, interpretable, and useful in the real world.

Fig 2 identifies the key research gaps in pavement performance prediction using across three categories, i.e., performance metrics, data utilization, and ML techniques. Current models often rely on isolated metrics like the International Roughness Index or Pavement Condition Indices, which fail to capture the full complexity of pavement deterioration, while ignoring synergistic indicators such as probability of failure. Data utilization remains constrained by issues of dataset quality and the limited integration of critical external factors like climate impacts, which are essential for long-term predictive accuracy. Furthermore, while advanced ML methods such as support vector regression, ensemble learning, and neural networks have shown promise, their application is hindered by a lack of comparative benchmarking, low interpretability, and overfitting risks due to narrow or unbalanced datasets. These gaps collectively underscore the need for a holistic, physically informed, and interpretable ML framework supported by standardized, high-fidelity data to enhance the reliability and

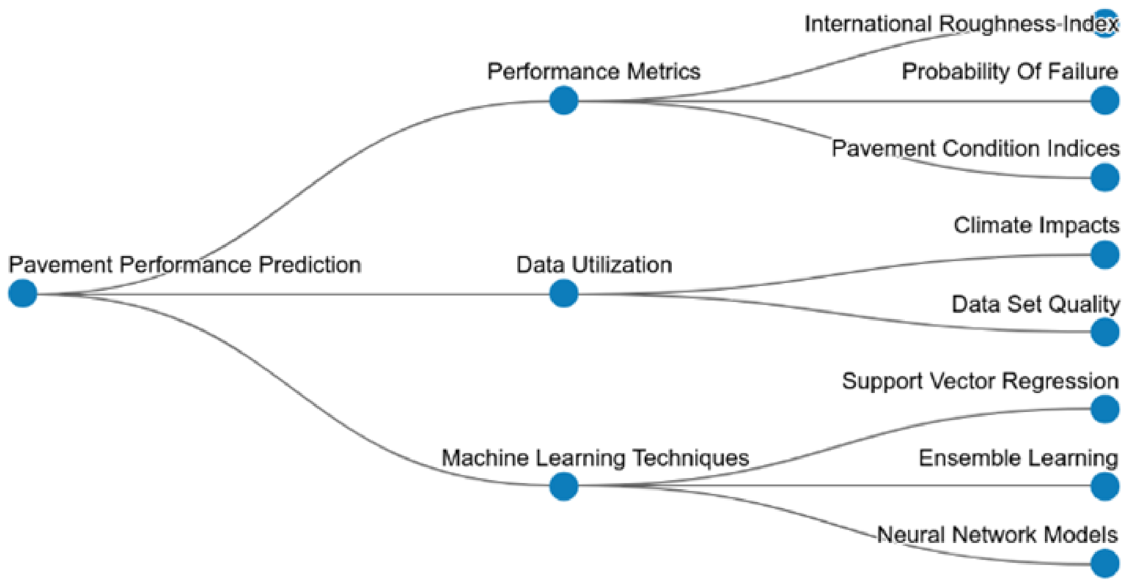

Figure 2: Research gap of predicting RSL of pavements

practical implementation of pavement performance predictions.

A: Research Gap considering LLM, Generative AI, DL, Ensemble ML, Hybrid ML and Physics-informed ML

Although generative AI (GenAI) has been utilized in urban transportation for scenario generation and decision-making, pavement performance prediction has not yet been implemented, which presents a research opportunity [27].

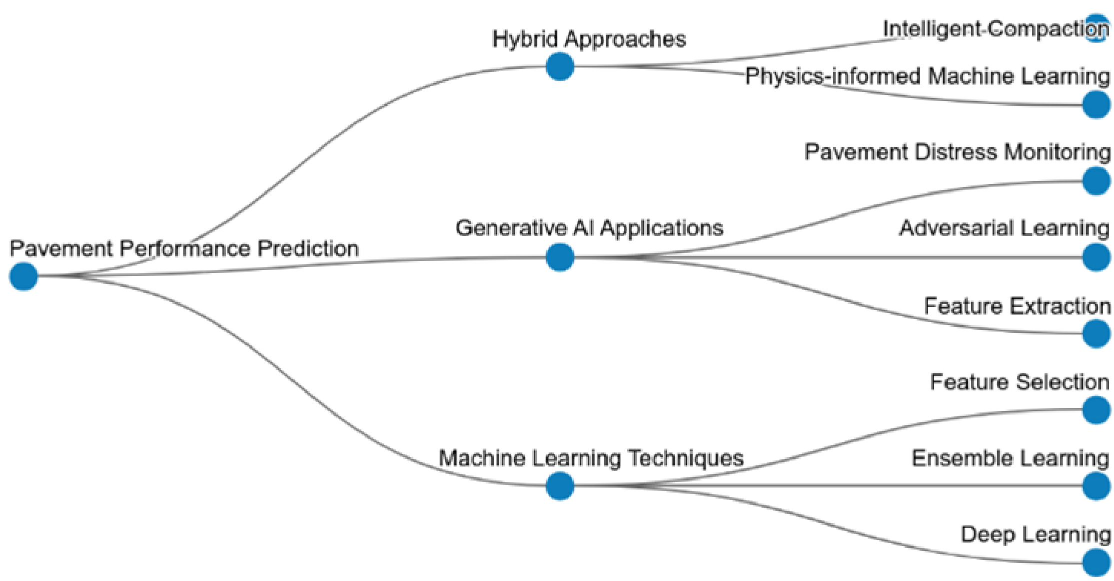

Figure 3: Research gap taxonomy of LLM, Generative AI, DL, Ensemble ML, Hybrid ML and Physics-informed ML

Pavement distress and transverse cracking can be accurately predicted using DL partic-

Table 3: Summary of Research Gap Considering LLM, Generative AI, DL, Ensemble ML, Hybrid ML and Physics-informed ML

ML Technique	Current Applications	Research Gaps	Ref	Expected Results
Large Language Models (LLM)	Not specifically mentioned in the context of pavement performance.	Need for exploration in pavement performance prediction and integration with existing ML models.	—	Improved automation in analysis and integration of unstructured infrastructure data.
Generative AI (GenAI)	Enhances decision-making for vehicles and infrastructure; generates realistic scenarios.	Application in pavement performance prediction is unexplored. Potential to improve reliability and adaptability.	[27]	Adaptive, scenario-based pavement performance forecasting.
DL	Used for predicting transverse cracking and pavement distress detection.	Optimization of models, dataset quality, and integration with digital twin technologies.	[28] [29]	More accurate distress prediction and seamless integration with smart infrastructure.
Ensemble ML	Applied in traffic prediction, pavement temperature, and performance modeling.	Challenges with overfitting, computational load, and scalability in real-time contexts.	[30] [31] [32]	Robust, high-accuracy models for real-time pavement condition monitoring.
Hybrid ML	Combines models like RF-MCMC for pavement temperature prediction.	Needs further research for long-term pavement performance forecasting.	[31]	High-accuracy, long-term performance models with uncertainty quantification.
Physics-informed ML	Not yet applied in pavement performance modeling, but rather materials design	Opportunity to integrate physical laws for improved prediction accuracy and interpretability.	[53]	Physically consistent, interpretable models with enhanced predictive power.

ularly deep neural networks (DNN) [28,29]. Nevertheless, there are still issues with data quality, model optimization, and integrating digital twins and other technologies [29]. In traffic and pavement temperature studies, ensemble machine learning techniques have increased prediction accuracy [30][31][32]. However, they have drawbacks, including overfitting and high computational costs [4]. Although hybrid models, such as those that combine RF and MCMC, provide high accuracy in predicting pavement temperature, their application in long-term pavement forecasting is still restricted [31]. Physics-informed ML has not yet been applied in this area, though it is expected to improve accuracy and interpretability. Overall, Physics-informed ML has been effective in related fields, but key gaps remain in its application to pavement performance and service life prediction. The detection of pavement distress and temperature prediction have been successfully accomplished through the use of DL and ensemble techniques. Nonetheless, issues with scalability, data quality, and model optimization still exist. Although hybrid machine learning techniques like RF-MCMC offer high accuracy, they are still not widely used to predict pavement performance over the long term. Although they work well for decision-making and urban mobility, generative AI and LLMs have not yet been used for pavement modeling. These techniques provide unrealized potential for processing unstructured infrastructure data and creating scenarios. In this area, machine learning informed by physics is conspicuously lacking. Its incorporation into data-driven models could improve interpretability and accuracy by incorporating physical laws. In order to facilitate effective pavement management, future research should concentrate on integrating these cutting-edge AI techniques which enhances data robustness, and creating interpretable, adaptive models.

2 Methodology

The primarily search of queries of ML and pavements in the database of Scopus returns 3017 documents. Using PRISMA guidelines for screening the number of documents is reduced to 552. Fig 4 presents the initial search which is a exponential rise of ML in pavement research. After careful screening we identified the 20 original research to review and add in this study.

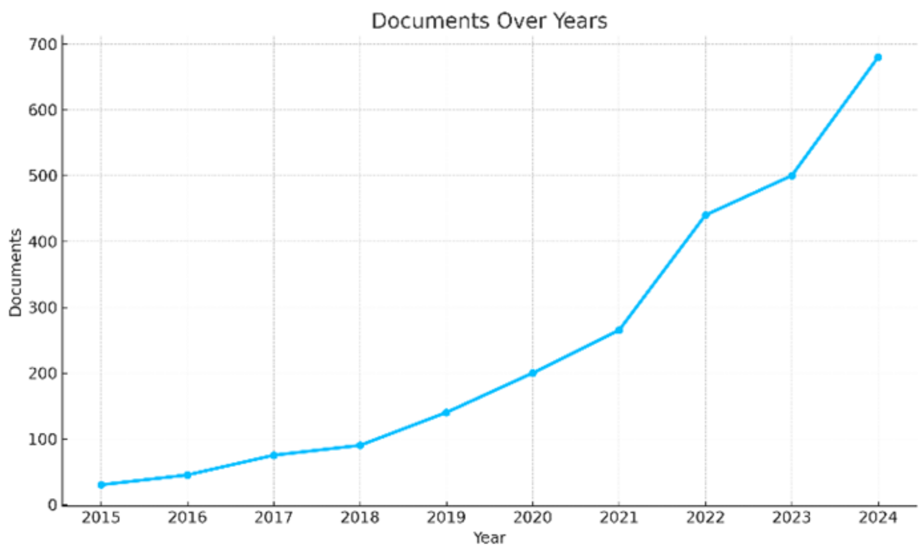

Figure 4: Progress of ML in pavement research

3 Results

Table IV and V demonstrate the effectiveness of various ML algorithms in pavement performance prediction, health monitoring, and service life estimation. RF, GBM, SVR, ANN, and XGBoost show strong performance in predicting IRI, PCI, and RSL. Newer models such as CatBoost, LightGBM, and ThunderGBM report improved accuracy in specific applications. DNN and RNN are increasingly applied in image-based analysis and time-series modeling for detecting pavement distress and degradation. These techniques are integrated into PMS and ITS, using data from sources like LTPP, 3D imaging, and geotagged datasets. The use of ML improves prediction accuracy, supports maintenance planning, and enhances infrastructure resilience through data-driven decision-making.

Table 4: Summary of Fundamental ML for Pavement Performance, Health Monitoring and Service Life Prediction

Machine Learning Algorithm	Description	References
RF	Used for predicting International Roughness Index (IRI) and other pavement performance metrics. Demonstrated high accuracy in several studies.	[34- 37]
Gradient Boosting Machine (GBM)	Effective in predicting pavement performance, particularly in terms of rut depth and IRI.	[38- 40]
Support Vector Regression (SVR)	Applied for predicting pavement performance and remaining service life (RSL). Optimized using various techniques like particle swarm optimization (PSO).	[41-43]
Artificial Neural Networks (ANN)	Utilized for predicting various pavement performance indicators, including PCI and cracking probability.	[44-47]
CatBoost	Found to outperform other models in predicting pavement performance with high accuracy.	[48]
LightGBM	Demonstrated superior performance in predicting pavement performance metrics.	[49, 48]
eXtreme Gradient Boosting (XGBoost)	Applied for predicting IRI and other performance metrics, showing high accuracy.	[49]
Decision Tree (DT)	Used in various studies for predicting pavement performance, often as part of ensemble methods.	[36, 39, 46, 49]
Ensemble Learning	Combines multiple algorithms to improve prediction accuracy. Effective in predicting pavement condition and RSL.	[38, 42, 48, 49]
Support Vector Classifier (SVC)	Applied for classifying pavement conditions based on various features.	[50, 51]
Multilayer Perceptron (MLP)	Used for predicting pavement performance and classifying road conditions.	[42, 50]
Gaussian Process Regression (GPR)	Demonstrated high accuracy in predicting pavement conditions.	[37,52]
Deep Neural Network (DNN)	Applied for predicting transverse cracking in pavements, showing high accuracy.	[47]

Table 5: Summary of Fundamental ML; Methods and Applications

Focus Area	**Methodologies**	**Key Findings**	**Ref**
Pavement Performance Prediction	RF Algorithm	Emphasizes generalization performance for predicting International Roughness Index (IRI)	[33]
Asphalt Pavement Friction Prediction	Linear Regression, Lasso Regression	Initial friction is crucial for friction evolution; scikit-learn is versatile	[34]
Pavement Performance Classification and Prediction	SVC, RNN	Two-stage model improves prediction accuracy	[35]
Urban Pavement Condition Prediction	RFR, SVR, GBR, ANN, RNN	Low prediction errors and RMSE for short-term condition prediction	[36]
Pavement Design, Analysis, and Optimization	Various AI Techniques	AI enhances efficiency in pavement design, cost analysis, and maintenance planning	[37]
Road Condition Monitoring	DL Techniques	Categorizes studies based on signal data types; highlights advancements in AI methods	[38]
Pavement Maintenance Classification	Azure ML (AML), MCNN	High accuracy in predicting maintenance needs using Multi-Class Neural Network	[39]
Pavement Management Systems (PMS)	Various ML Techniques	ML improves accuracy in pavement condition assessments and maintenance decisions	[40]
Pavement Health Monitoring	DL, Attention Mechanism	Efficient DL pipeline for image degradation detection and enhancement	[41]
Pavement Damage Detection	3D Imaging, AI Models	AI-driven 3D damage detection using laser scanners and stereo cameras	[42]
Intelligent Road Inspection	MLP, RBF Neural Networks	CMIS model outperforms others in predicting Pavement Condition Index (PCI)	[43]

Focus Area	Methodologies	Key Findings	Ref
Pavement Distress Identification	AI, DL Models	High accuracy in distress identification using UAS and photogrammetry	[44]
Pavement Crack Detection	Machine Vision, AI Techniques	Utilizes SVM and neural networks for efficient crack detection	[45]
Pavement Distress Detection	DNN	YOLOv7 and U-Net for automatic detection and assessment of pavement distress	[46]
Structural Health Monitoring	Explainable AI (XAI), 1D-CNN	Improved prediction accuracy and model convergence using XAI	[47]
Pavement Distress Detection	DL, YOLOv3 Algorithm	High accuracy in detecting and measuring pavement distresses	[48]
General AI Applications in Transportation	Various AI Techniques	AI enhances logistics, traffic flow, and predictive maintenance	[49]
Intelligent Transportation Systems	ML, DL	Enhances safety and efficiency in transportation through VANETs	[50]
AI in Healthcare and Biomedicine	ML, DL	AI techniques for disease prediction and treatment planning	[51]
Driver Sleepiness Detection	Machine Learning Techniques	Uses facial expressions and bio-indicators to assess driver condition	[52]

As summarized in Table IV, the ML techniques not only improve prediction performance (e.g., RMSE, R^2) but also support classification of road conditions using metrics like Precision and F1-score. Despite these advances, challenges remain in data availability, model generalization, and integration with existing PMS. Further emerging trends include the use of transfer learning, synthetic data generation, and hybrid models combining AI and traditional methods to enhance scalability and decision support across varying pavement environments. ML has revolutionized pavement performance prediction by enabling precise, data-driven insights into infrastructure health. Algorithms such as RF, GBM, SVR, ANN, and XGBoost are widely adopted for predicting IRI, PCI, and RSL, among other metrics, as summarized in Table IV. These methods benefit from datasets from LTPP, WIM, and geotagged imagery, which enables models to detect pavement distress, model degradation, and forecast maintenance needs with high accuracy. DNN and RNN are also gaining popularity for time-series and image-based analysis, which enhances the detection of cracking and deterioration patterns over time. For future studies we propose studying the modeling railroads, tunnels and effect of vehicles and engines vibrations on the pavements [54,55].

4 Conclusions

This study, which is based on a systematic review of 552 documents filtered from an initial 3017 using PRISMA guidelines, shows how ML is rapidly influencing pavement performance prediction and service life modeling. From this, 20 important research studies were thoroughly examined, we showed an exponential increase in ML applications, especially in the prediction of IRI, PCI, and RSL using RF, GBM, SVR, ANN, and XGBoost. Even with this expansion, advanced techniques like GenAI and LLMs are still mostly untested in pavement engineering. Our analysis validates ML's potential to enable real-time, sensor-based pavement monitoring in addition to increasing prediction accuracy. Nonetheless, there are still issues with data quality, model interpretability, and physical model integration. By utilizing hybrid, physics-informed, and generative approaches, future research will more concentrate on filling these gaps and eventually move toward infrastructure systems that are more intelligent, adaptive, and data-driven.

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