Modeling Remaining Service Life and Structural Health Monitoring of Roads with Machine Learning and Deep Learning

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***Abstract*— The integration of machine learning (ML) and deep learning (DL) in structural health monitoring (SHM) and remaining service life (RSL) has revolutionized the ability to assess and maintain critical infrastructure. This review looks at the current state of SHM methods that use ML and DL. This is done by providing a detailed taxonomy that groups these methods into groups based on algorithmic strategies, data sources, and specific SHM and RSL applications. Using Scopus as the primary source for literature, we conducted a systematic review following PRISMA guidelines to ensure thorough screening and quality assessment of most relevant studies. The review covers key areas that include supervised and unsupervised learning techniques, neural networks, and their applications to structural damage detection, failure prediction, improving precision in monitoring. Based on the trend analysis and highlighting of some of the challenges in this context, this review has identified a few future opportunities for applying advanced learning techniques to SHM to improve infrastructure safety and management.**

Keywords—machine learning, deep learning, remaining service life, structural health monitoring, civil engineering, data science, big data, generating AI, systems engineering, information sciences, infrastructures, information systems, informatics, structural engineering, XAI, remaining service life, survey, predictive modeling, structural assessment, infrastructure monitoring, condition-based monitoring, smart cities, automated damage detection, infrastructure durability, sensor networks, data-driven engineering, machine vision, time-series forecasting, advanced analytics, computational mechanics, digital infrastructure, intelligent systems, unsupervised anomaly detection, mathematics, mathematical modeling, mathematical model, applied mathematics, applied informatics, hybrid learning models

I. INTRODUCTION

Engineering structures including buildings, bridges, and tunnels require structural health monitoring (SHM) to ensure their safe working conditions in various environmental conditions over aging [1]. SHM is a process of collecting data using sensors, analyzing them, and monitoring the condition of structures with the help of diagnosis tools [2]. The aim of SHM is to monitor the stress that leads to the aging of structures and detect real-time degradation for preventive maintenance to improve the safety and reliability of such structures. SHM helps to estimate the remaining service life (RSL) of a system, and it is very important when failure risk is high, and damage can be controlled [3]. In recent years, major road work in the European union is for maintenance, with only a fracture for building the new roads. Lack of information for road maintenance, leading to road damage. Poor maintenance results in more repair costs and a higher vehicle operating cost. It also harms the environment by using more resources and increasing emissions. Real-time monitoring is required to identify maintenance checks, which will help to reduce the costs and extend the service life of roads [4]. It is important to detect the damage in early stages. Common problems in pavements are cracking and sinking usually caused by heavy traffic and overloading. In order to provide safe and durable structures, modeling is necessary. The modeling of SHM is important because it allows engineers and researchers to simulate and analyze the behavior under different conditions and predict the RSL of structures [4,5]. The SHM system gives useful information about a structure's condition and helps choose the optimal maintenance actions. Hence, the need for SHM has grown over time and remains important today. However, the complexity of pavement materials and diffident environmental conditions make it challenging to develop efficient models for detecting and monitoring road damage [6,7]. Conventionally, the SHM relied heavily on physical inspections, manual data collection, empirical methods, and mathematical models. This traditional approach often involved time-consuming processes, requiring skilled inspectors to physically access and examine structures. While effective to some extent, this method was prone to errors and often limited by factors such as accessibility, time, and cost. Real-time inspection and maintenance have become increasingly essential in today's infrastructure management to reduce costs and extend the remaining service life (RSL) of various structures. Timely insights allow for preventive actions, which can mitigate deterioration and avoid costly repairs. Recently, however, advancements in technology have drastically transformed SHM by shifting from manual procedures to more efficient, automated techniques. With the rise of machine learning (ML) and deep learning (DL) methods, along with real-time condition monitoring, SHM has become significantly more advanced. The integration of these technologies enables continuous data collection and analysis, leading to higher accuracy, real-time insights, and cost-effective decision-making. As a result, these intelligent monitoring systems allow for predictive maintenance strategies, which not only prolong the lifespan of structures but also optimize maintenance schedules to reduce downtime and expenses [4]. One prominent application of SHM using DL is in road infrastructure, where sensor-equipped vehicles collect large volumes of data to evaluate road conditions. The collected data undergoes preprocessing and analysis through sophisticated DL algorithms, which can identify patterns and extract relevant features, such as cracks, roughness, and subsidence. Based on these features, the algorithms predict the overall structural health and quality of the roads, enabling maintenance teams to prioritize repairs and plan for long-term infrastructure sustainability. This approach offers a highly efficient alternative to traditional road inspections, as it can process massive amounts of data in real time, resulting in faster, data-driven decisions. A graphical representation of SHM, demonstrating its components and benefits, is shown in Fig.1, adapted from [8]. This illustration highlights how automated systems are transforming SHM processes and providing unprecedented insights into structural conditions through modern, data-intensive approaches. The growing demand for ML and DL-driven SHM methods illustrates the industry's recognition of their potential to revolutionize infrastructure management.

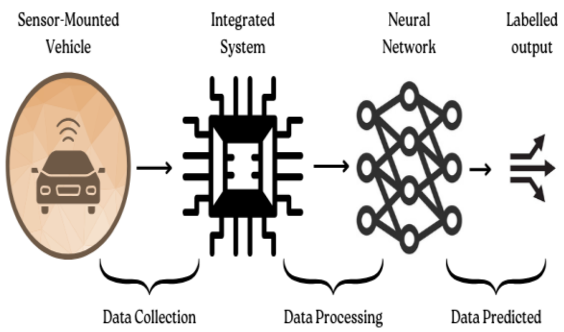

Fig. 1. Graphical representation of SHM for roads.

In the fields of mechanical, aeronautical, and civil engineering, fiber optic sensors (FOS) are important devices for monitoring strain and temperature in different types of structures. Their high precision and lightweight design are some of their advantages. For this, [4] demonstrated the use of fiber Bragg grating (FBG) optical sensors with a real-time monitoring system for the SHM of roads. In addition to it, [5] embedded these sensors in pavements to collect strain and temperature data. This setup effectively determines the stiffness of the road's upper layers using strain values, allowing for the monitoring and prediction of the RSL of large-scale roads. In a work by (Gao et al., 2018) a damage model was developed for asphalt pavements to efficiently predict the RSL. They conducted indirect tensile tests (ITTs) on asphalt mixtures of different ages to measure the damage based on the energy lost during loading. Following this, [6,7] developed a fatigue assessment method for a bridge in China. The data is collected from the SHM system to develop a three-dimensional finite element model. The findings showed that this approach effectively determines varying traffic loads and irregular fatigue damage. In studies by (Saleh, 2014&2016) [9,10] a falling weight deflectometer (FWD) is used to measure the pavement surface deflection in his studies to predict the RSL of pavements. In a related work by [11] a new method was developed to assess the RSL of highway roads using data from a traffic speed deflectometer (TSD). This methodology addresses important problems like road cracking and estimate the remaining fatigue strength.

Pavement management are often expensive, laborious, and time consuming process. For this Khahro et al., (2021) [11] developed an automated sensor-based cloud application to assist pavement management. The data is collected from a 1,000 km road network. The proposed system successfully identifies several road sections for maintenance. In a related study by [12] developed a road health monitoring system that uses android phone sensors to measure and analyze road roughness. The data is collected using accelerometers and gravity sensors. Wei et al., [14] used the Markov chain method to monitor the service life of airport runways over time. A duration function model is developed to categorize the condition of runway pavement based on the Pavement Condition Index (PCI). The results indicated that the Markov transition matrix effectively predicts the RSL of airport runways. (Garcia et al., 2024) evaluated the RSL and assessed the strength of airfield pavement under different load conditions using lightweight deflectometer (LWD) which showed potential for monitoring pavement degradation. Similarly, [13] developed a model for predicting the RSL of airfield pavement slabs using strain gauge data. After mentioning the conventional methods for SHM and RSL, it is worth presenting the literature that highlights the use of ML and DL. In a study by [8], a road health monitoring system was developed using a deep learning-based technique with sensors that can run on smartphones. The proposed solution optimizes the deep neural network (DNN), and the results show that the system can effectively identify road types with high accuracy. Nabipour et al., (2019) [15] aimed to improve the prediction of the RSL of pavements using support vector regression (SVR), SVR optimized fruit fly optimization algorithm (SVR-FOA), and gene expression programming (GEP). The results showed that GEP was the most accurate method for predicting RSL, achieving the best performance across multiple evaluation metrics. Similarly, [16] developed a SVR model to efficiently predict the RSL of road pavements. It was tested using data from heavy weight deflectometer (HWD) and ground-penetrating radar tests. The SVR model outperformed other models, e.g., artificial neural networks (ANN), and multi-layered perceptron (MLP), with an accuracy of 95% accuracy. To further explore this topic, [17] used a random forest (RF) and a genetic algorithm trained RF (RF-GA) to predict the PCI using roughness and distress data. The data is collected using road surface profiler (RSP) from Tehran-Qom Freeway in Iran and PCI is determined. The models were tested and RF-GA showed better performance than standard RF method. In a study by [20, 21] an ANN-based model was developed to predict the RSL of flexible and composite pavements. The model was effective at modeling pavement deterioration, particularly under different traffic conditions, thicknesses, and degradation patterns. [18] focused on addressing road damage like potholes and rutting, which can lead to serious accidents and increased maintenance costs. They developed an ML algorithm using an RF to classify different types of road damages. The results provided high accuracy of 97% in identifying and classifying road damages. Zhang et al., (2024) [19] studied the temperature distribution in road-rail bridges. They developed a long short-term memory (LSTM) model to predict the effective temperature (ET) and temperature difference (TD) based on environmental conditions. This model is compared with conventional linear regression models and achieved 40% improved in accuracy.

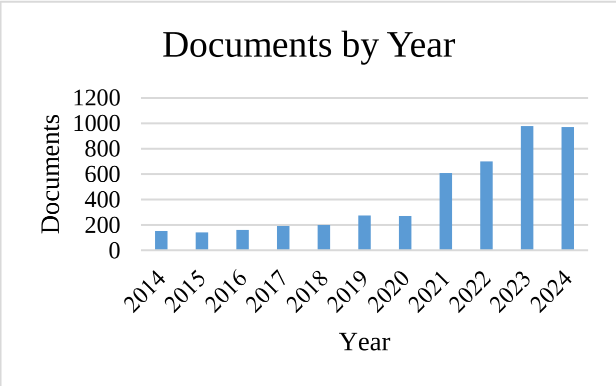

Fig. 2. A graphical representation of the initial database based on general applications from the period of 2014 to 2024.

Based on the findings from the above literature, it is clear that traditional methods for predicting RSL and conducting SHM for roads are less efficient. Researchers have used ML and DL methods less frequently for such tasks. Additionally, there is less literature available on ML and DL approaches compared to traditional methods, indicating a need for further exploration. Therefore, this study will focus specifically on ML and DL methods for RSL and SHM and will provide a taxonomy to help understand the studies and their contributions to these applications. This research highlights gaps in using ML and DL for SHM and RSL. Specifically, there is a need for larger datasets, improved integration of learning techniques, and real-time modeling. This research gap can be filled by developing datasets, using multimodal approaches, creating real-time monitoring systems. This can improve the clarity of model outputs and ensure researchers use effective methods for safe structure management. This study focuses on reviewing the most utilized ML and DL methods for conducting SHM and predicting RSL of the structures. This study aims to understand how ML and DL improve the monitoring and maintenance of buildings, bridges, and other infrastructures. To improve the accuracy of damage detection and RSL predictions the advantages of using ML and DL are also highlighted. This research will provide valuable insights that can help engineers and researchers to implement better strategies for maintaining crucial structures. The structure of this study is as follows: Section 2. follows the research methodologies. Section 3. highlights the significant applications of ML and DL methods for SHM and RSL. The findings from this study along with future directions are concluded in Section 4.

II. METHODOLOGY

The literature search for this review was conducted using the Scopus database, which was chosen for its extensive e-coverage of peer-reviewed publications in engineering, technology, and applied sciences. A set of keywords, including "Structural Health Monitoring," and "Remaining Service Life," "Machine Learning," "Deep Learning," and others related to ML/DL methods, included for the search. The search was restricted to English-language publications and included articles, conference papers, and reviews from January 2014 to October 2024. A total of 5243 studies were identified in the initial search, all focusing on the application of ML and DL to SHM and RSL systems as shown in Fig.2. The search query follows: (title-abs-key ("structural health monitoring" or" remaining service life") and title-abs-key ("machine learning" or "deep learning" or "artificial intelligence" or "neural network*" or "support vector" or "lstm" or "decision tree*" or ensemble or "random forest")). Then we narrowed the subject to road to include pavement, highway, and autobahn and eventually reduced the articles to 150. Full-text reviews were conducted on the remaining studies, with eligibility criteria centered on the direct application of ML/DL techniques in SHM. Key considerations included the use of ML/DL models for tasks like damage detection, anomaly prediction, and failure forecasting. Quality assessments were applied to each study to ensure methodological rigor, leading to the inclusion of 128 high-quality studies for analysis. After employing Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) and screening we reduced the references to 28. In this article we review and consider these 28 articles. A graphical representation of these articles from the period of 2014 to 2024 are illustrated in Fig.3.

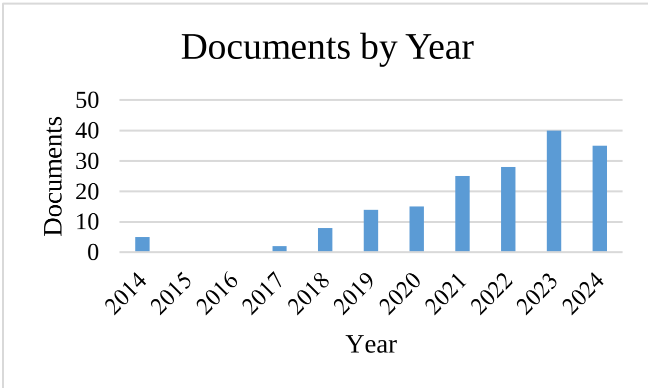

Fig. 3. A graphical representation of the most relevent articles based on RSL and SHM on roads from the period of 2014 to 2024.

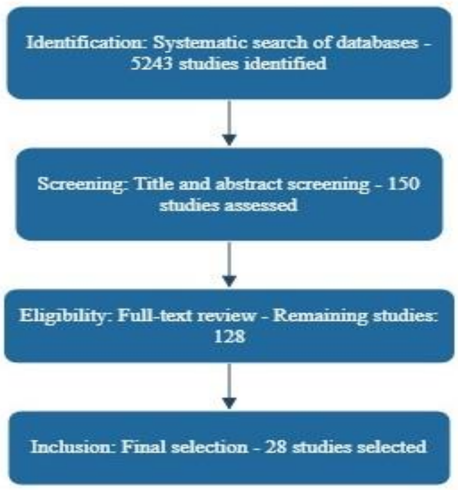

Fig. 4. Adapted PRISMA Flow Diagram.

The review process followed PRISMA guidelines to ensure a systematic and transparent methodology. The screening process began with an initial review of titles and abstracts to filter out irrelevant studies, particularly those unrelated to SHM or focused on other domains like medical monitoring. The phases of PRISMA methodologies are presented in the Fig.4. The selected studies were categorized into a taxonomy based on algorithmic strategies, data sources, and application areas. This taxonomy provided a structured overview of how ML and DL techniques are employed in SHM, categorizing studies into groups such as supervised learning, unsupervised learning, and DL applications. Data sources like vibration data, strain gauges, and acoustic signals were also classified. This approach helped identify key trends, emerging techniques, and challenges within the field, providing a comprehensive analysis of how these methods are advancing SHM and pointing to future opportunities for further development.

III. STATE OF THE ART REVIEW

This review explores how machine learning and deep learning transform the monitor the maintenance of roads and bridges. It highlights applications such as predicting traffic loads, pavement durability, and structural health using smart sensors, supervised learning, and advanced optimization techniques. Topics include innovative methods like using drones and infrared thermography for real-time monitoring, automated defect detection in bridges, and leveraging unsupervised learning for condition assessment. By examining these cutting-edge approaches, the review studies how ML and DL can enhance infrastructure safety, improve monitoring efficiency, and resilient roads and bridges.

TABLE I. ML AND DL APPLICATIONS FOR STRUCTRUAL HEALTH MONITORTING

Authors	Source title	Application	Methods
Burrello et al., 2022	Sustainable Computing	Traffic Load Estimation using supervised learning	RF, MLP, SVR
Karballaeezadeh et al., 2019	Engineering Applications of Computational Fluid Mechanics	Predicting pavement durability with SVM optimization	SVM, ANN, MLP
Karballaeezadeh et al., 2020	Coatings	Monitoring flexible pavements using smart sensors	RF, RF-GA
Kaya et al., 2020	Transportation Research Record	Flexible and composite pavement analysis	ANN
Jansen and Geißler, 2021	Bauingenieur	Defects detection using ML in road bridges	ML, PCA
Soni et al., 2023	IEEE Conference	Monitoring rural roads using sensor based smartphones	SVM
Dugalam and Prakash, 2024	Expert Systems with Applications	Innovative road monitoring with RF algorithms	RF, SVM, KNN
Nabipour et al., 2019	Mathematics	RSL prediction of flexible pavement using ML	GEP, SVR
Skokandic et al., 2018	IABSE Symposium	Optimizing bridge monitoring with WIM and ML	DT
Medhi et al.,2019	Nondestructive Evaluation	Real time structural monitoring using ANN	ANN
Belcore et al.,2022	Computer and Information Science	Automated classification of bridge defects	RF
Asthana et al., 2022	IEEE Zooming	Autonomous sensor design for SHM	NN, SANNs
Kulkarni et al., 2023	Automation in Construction	Infrared Thermography with DL for roadway health	YOLO
Zhang et al., 2024	Engineering Structures	Predictive modeling for road-rail bridge	LSTM
Zoric et al., 2024	Unmanned Aircraft Systems	SHM using DL and drones technologies	RCNN
Mishra et al., 2021	IEEE Sensors Journal	Real-time road monitoring using DL	DNN
Chen et al., 2021	Systems and Informatics	Comparative analysis of TL Methods in SHM	TL
Calderon et al., 2023	Lecture Notes in Civil Engineering	Automated bridge condition assessment	CVAE
Malik et al., 2022	Procedia Computer Science	Active damage detection with UAVs and DL	CNN
Cho et al., 2024	Buildings	Improving data quality in SHM	LSTM
Rosso et al., 2023	Proceedings of IABMAS	Integrating DL with SHM Technologies	CNN, RNN
Ranieri et al., 2023	Structural Health Monitoring	DL approaches for automated road surface assessment.	CNN
Hassani et al., 2024	Information Fusion	Optimizing SHM with data fusion	LLMs

Current developments in ML and DL have greatly improved the SHM of structures. In a study by [22] a Traffic Load Estimation (TLE) method is investigated using data from accelerometers on road structures. They compared different supervised learning approaches, such as Linear Regression (LR), K-Nearest Neighbors (KNN), Convolutional Neural Network (CNN), RF, MLP, and SVR. The results showed that the SVR achieved the highest accuracy, with a Mean Absolute Error (MAE) of 0.47 for light vehicles and 0.21 for heavy vehicles. The author plans to explore the integration of different TLE methods to further improve accuracy while ensuring the reliability and security of the system. [16] developed a new model to predict the RSL of road pavement using the SVR method. The results were compared with SVM, ANN, and MLP models. The SVR model demonstrated promising result with actual RSL values from non-destructive HWD tests, confirming its effectiveness and accuracy. The authors believe this method can be effectively utilized, especially with real time environmental and pavement thickness data. Additionally, it could reduce costs and traffic disruptions compared to other traditional testing methods. In a similar study by [15], the authors focused on the International Roughness Index (IRI) and the PCI using ML. They used the RF and RF-GA to predict PCI values. The results showed that the RF-GA method had better correlation coefficients (CC), scatter indices (SI), and Willmott's indices (WI), indicating improved model performance compared to the standard RF method. The author stated that advanced ML techniques and non-destructive testing methods can improve the SHM process, leading to lower costs and better efficiency in pavement management. [20] developed ANN model to predict pavement performance and RSL for roads and compared it with statistical methods. The results showed that ANN models were more effective for larger networks. The author aims to develop efficient automation methods for pavement management. [23] introduced the R-signature method with principal component analysis (PCA) to identify structural damage in bridges. The proposed anomaly detection procedure successfully identified damage. Further advancements in the R-signature method by integrating it with other anomaly detection techniques and enhancing its effectiveness using various sensor data are discussed. [24] developed a road health monitoring system using smartphone sensors to collect data on road conditions in rural areas of Punjab and Haryana, India. They used the SVM method to classify different road types and compared the conditions in both states. The model achieved over 96% accuracy in predicting road roughness. Similarly, [18] developed a new road damage classification algorithm using a RF classifier. Data was collected from accelerometers and a smartphone camera mounted on a vehicle. The algorithm achieved 97% accuracy in classifying road damage like potholes, speed bumps, and rutting. It also performed better than other models like SVM, KNN, Naive Bayes, and Decision Tree (DT) and was used to estimate repair costs. The authors suggest testing the model in different environmental conditions and using data from various geographic areas to improve the SHM process. [15] developed a new approach to predict the RSL of flexible pavements using surface distress instead of traditional non-destructive methods. They utilized ML techniques such as GEP, SVR, and an optimized version of SVR called SVR-FOA. Result showed that GEP outperformed the others with the highest accuracy in predicting RSL. The authors suggest that GEP can optimize pavement management systems by improving accuracy and reducing costs. [25] employed assessment techniques, alongside Value of Information (VoI) analysis, to connect SHM data using weigh-in-motion (WIM) measurements integrated with DT. The findings indicate that WIM measurements improve the reliability of bridge assessments and potentially extend the predicted RSL of these structures. [26] developed a computer vision-based system for monitoring the health of structures using a high-speed camera and an ANN. They used a “blob detection algorithm” to track the location and movement of structural features. The system was tested and can predict the condition of structures with good accuracy. The authors suggest that using high-speed video imaging for regular monitoring will ensure the safety of structures and extend their RSL. [2] proposed an automated method for detecting bridge defects using drone images. They used a RF technique to classify different defects successfully. The authors noted that improving the dataset with infrared-sensitive sensors and exploring spectral calibration will further improve the model’s performance. [1] designed an autonomous IoT system for SHM of roads and bridges using advanced NNs. The research employed Self-Repairing Spiking Astrocyte Neural Networks (SANNs) integrated with self-powered sensor nodes to improve SHM. The findings demonstrated that the proposed system could effectively detect defects while maintaining low power consumption. This study will inspire the use of autonomous monitoring systems helping to develop more sustainable infrastructure.

After discussing several ML methods in SHM, it is important to explore the DL methods in this field. Several studies demonstrate the effectiveness of DL techniques in analyzing complex and scalable data from various sensors placed on structures. DL has become a significant approach in this area. Researchers have effectively detected problems and predict the RSL of structures by using advanced DL algorithms. For example, Kulkarni et al., [27] developed an automated method for detecting potholes in roads using drone-captured infrared images. They utilized principal component thermography (PCT) analysis to improve the detection accuracy and DL based EfficientDet technique to automate the inspection process. Their model achieved a mean average precision (MAP) of 0.85 in detecting defects, outperforming the fifth version of the You Only Look Once (YOLO V5) algorithm by 24% in less time. This approach is limited to detecting shallow defects. The author highlighted the importance of environmental factors in improving infrared image quality to improve the accuracy of road damage detection methods. [19] investigated the temperature distribution in road-rail steel bridge. They used LSTM network to predict ET and TD based on environmental factors. This DL based method improved the prediction accuracy by 40% as compared to other traditional methods. The results showed that rise in temperature significantly affects the structural health of bridge. The effect of light reflection on temperature distribution by developing the three-dimensional structure of the bridge are discussed. [28] explored the use of multirotor aerial vehicles (MAVs) and DL techniques to improve the inspection of roads and bridges. They trained two neural networks (NNs) such as Mask recurrent neural network (Mask-RCNN) and Real-Time Multi-Task Detection-small (RTMDet-s) to detect and categories the cracks from SHM datasets. The results showed that these networks effectively localized cracks. The author highlights the need to improve object tracking and conduct real-time testing to develop the system. Mishra et al., (2021) [8] developed a road health monitoring system that uses sensors to classify different types of roads using a DL based classifier. The proposed system successfully identifies road types. The authors recommend developing devices, like smartphones, that use DNN models to send real-time data about road and vehicle conditions. Chen et al., (2021) [7] explored the use of DL in SHM to detect defects, focusing on the challenge of limited data. They applied transfer learning (TL) to address the issue of limited datasets in SHM. The results show that TL improves model performance and reduces the need for high computing resources. The study suggests that integrating TL with smartphones and drones for real-time defect detection in SHM will improve its effectiveness. [29] assessed bridge damage using DL based approach with convolutional variational auto encoders (CVAE). This method detects damage by analyzing vehicle acceleration data in real time through Continuous Wavelet Transform (CWT) images. The results demonstrated the method’s ability to classify bridges as either healthy or damaged under various conditions. [36] analyzed cracks using unmanned aerial vehicles (UAVs). They compared traditional ML methods with TL to build CNN models for damage detection. Their results showed that the proposed device enables effective real-time damage detection. The authors suggest using Generative Adversarial Networks (GANs) to improve the training data and improve the model accuracy. [32] focused on improving defect detection in SHM using Internet of Things (IoT) sensors. Three methods were tested such as, Interquartile Range (IQR), LSTM with AE, and time-series decomposition. IQR struggled to detect complex defects, while LSTM-AE performed better by capturing data patterns over time. Time-series decomposition was the most effective, identifying more defects. The study suggests that continuous data collection, along with regression and ANN will further improve SHM systems for better structural management. [39] investigated the use of DL techniques such as CNN, RNN, capsule neural networks (CapsNet), and neural transformers (NT) to improve the SHM of road bridges for improved maintenance and safety. The results demonstrated more accurate and comprehensive assessments of bridge conditions over time. The authors suggest that further developments in DL technologies for SHM will improve the accuracy and scalability of different structural systems. [38] reviewed different learning methods for detecting potholes and cracks in road pavements. They highlighted the use of semantic segmentation in images to identify these issues. They also noted that DL techniques, especially CNNs, are effective for analyzing road images to detect damage. The authors concluded that recent advancements in DL can reduce costs and make monitoring more scalable. They suggested that using Red Green Blue-Depth (RGB-D) technology and high-resolution cameras would provide better data for NNs to improve the accuracy of damage detection. [35] reviewed new data fusion techniques for SHM, that use different data sources to improve the decision-making process. They examined traditional and DL based methods. They suggest that integrating DL with large language models (LLMs) will boost efficiency and reduce costs in SHM applications. After evaluating the significant ML and DL methods and their applications in conducting SHM and predicting RSL of structures are briefly summarized, and the taxonomy of this study is presented as shown in Fig. 5. And results of these studies are evaluated and presented in Table.2.

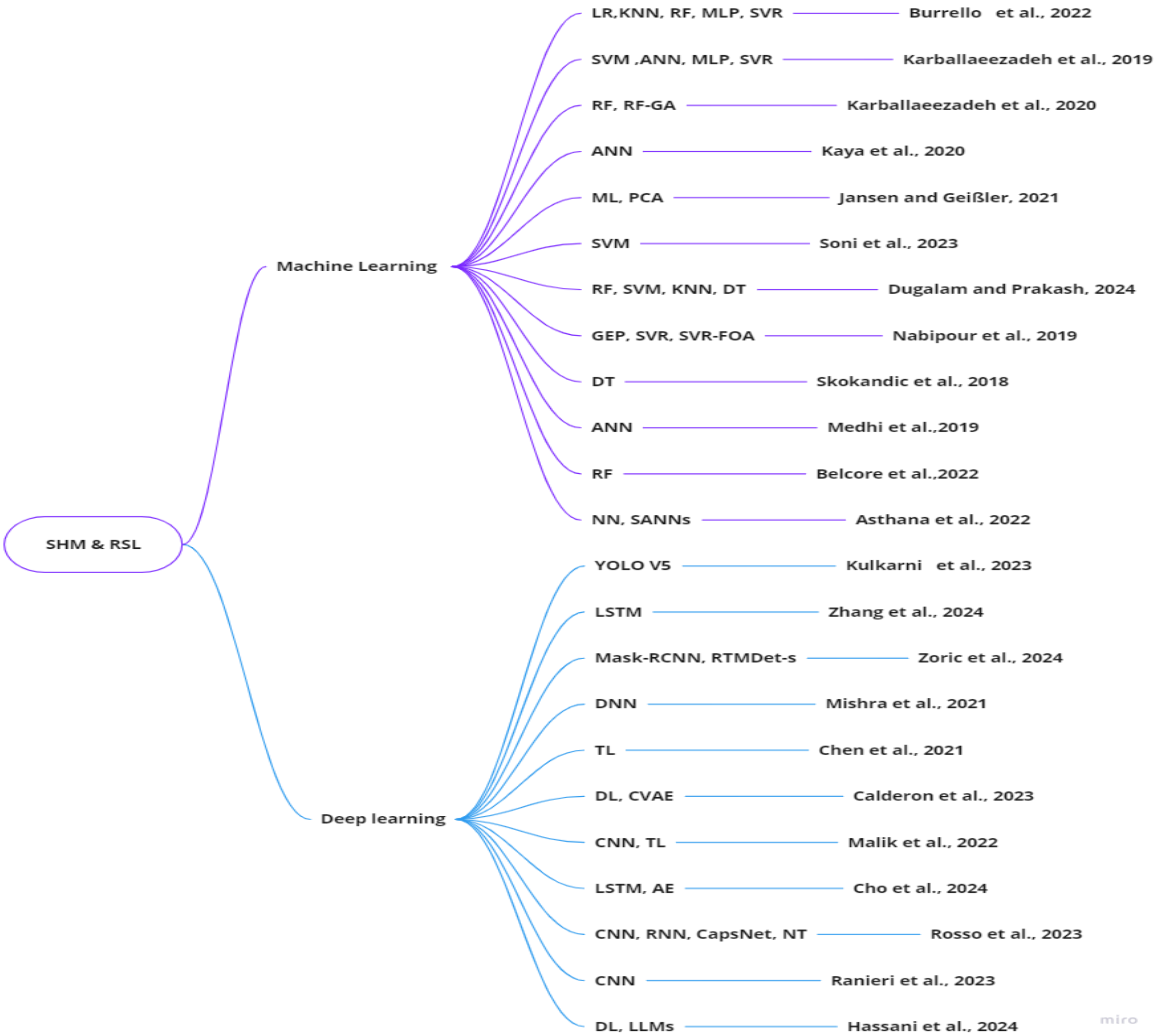

Fig. 5. The taxonomy of ML and DL methods based on their application in SHM.

Authors	Method	Avg. Accuracy	RMSE	Avg. MAE	CC	F1-score
Burrello et al., 2022	SVR	-	-	0.34	-	-
Karballaeezadeh et al., 2019	SVR	95%	0.14	-	-	-
Karballaeezadeh et al., 2020	RF-GA	-	-	-	-0.031	-
Soni et al., 2023	SVM	96%	-	-	-	-
Dugalam & Prakash, 2024	RF	97%	-	-	-	-
Nabipour et al., 2019	GEP	-	-	-	0.874	-
Belcore et al.,2022	RF	-	-	-	-	0.750
Kulkarni et al., 2023	YOLO	85%	-	-	-	-
Zhang et al., 2024	LSTM	-	1.1974	-	-	-
Mishra et al., 2021	DNN	90%	-	-	-	-
Malik et al., 2022	CNN	85.5%	-	-	-	-

TABLE II. EVALUATION OF RESULTS FROM REVIEWD STUDIES

As shown in the above Table.2, various studies have been evaluated and presented. These studies highlight the role of significant ML and DL methods in monitoring the structural health of buildings and predicting their RSL. Conventional ML methods like SVM and RF achieve high accuracy with low computational costs. For example, SVM models by [24] and RF model [18] achieved promising accuracies. However, DL models demonstrate optimal results in complex applications. Such as, EfficientDet and YOLO model by [27] and CNN model by [36] are effective in pattern recognition and image analysis. While LSTM networks [19] perform well with time-series data. The DL methods effectively learn complex and nonlinear relationships even with limited data [38-41]. In contrast, ML models are often less efficient, making them less suitable for handling large datasets and real-time detection. This comparison highlights DL's transformative role in advanced pattern recognition applications.

IV. CONCLUSIONS

This study aimed to provide a methodology to systematically review the research on the use of ML and DL in SHM and predicting the RSL of buildings. The most significant ML and DL techniques for monitoring structural health and predicting the RSL of buildings are reviewed using the PRISMA methodology. Based on our findings, both ML and DL have proven to be significant approaches in the field of SHM. Several studies have demonstrated the effectiveness of these methods in detecting structural defects and predicting the RSL of structures such as buildings and bridges. Specifically, DL techniques, including advanced neural networks like CNNs, AE, GAN and LSTM networks, are most effective in analyzing complex sensor data. These techniques are transforming SHM by improving the accuracy, scalability, and efficiency of monitoring systems. These approaches not only improve the accuracy of damage detection but also enable real-time monitoring. This is very important for maintaining the safety and durability of critical structure. The integration of ML and DL into SHM marks a big advancement in smart and sustainable structural management. Integration of DL with LLMs, UAVs, IoT, and Smart Sensors will shape smart and sustainable infrastructure for the future. The future research aims to develop a DL based model to effectively monitor the structural health and predict the service life of buildings.

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ABBREVIATIONS

Abbreviation	Definition	Abbreviation	Definition
ML	Machine Learning	CNN	Convolutional Neural Network
DL	Deep Learning	MAE	Mean Absolute Error
RSL	Remaining Service Life	IRI	International Roughness Index
SHM	Structural Health Monitoring	CC	Correlation Coefficients
FOS	Fiber Optic Sensors	SI	Scatter Indices
FBG	Fiber Bragg Grating	WI	Willmott's Indices
ITTs	Indirect Tensile Tests	PCA	Principal Component Analysis
FWD	Falling Weight Deflectometer	DT	Decision Tree
TSD	Traffic Speed Deflectometer	VoI	Value Of Information
PCI	Pavement Condition Index	WIM	Weigh-In-Motion
LWD	Lightweight Deflectometer	SANNs	Spiking Astrocyte Neural Networks
DNN	Deep Neural Network	PCT	Principal Component Thermography
SVR	Support Vector Regression	MAP	Mean Average Precision
GEP	Gene Expression Programming	MAVs	Multirotor Aerial Vehicles
SVR-FOA	SVR Optimized Fruit Fly Optimization Algorithm	NNs	Neural Networks

HWD	Heavy Weight Deflectometer	Mask-RCNN	Mask Recurrent Neural Network
SVM	Support Vector Machines	RTMDet-s	Real-Time Multi-Task Detection-Small
ANN	Artificial Neural Networks	TL	Transfer Learning
MLP	Multi-Layered Perceptron	CVAE	Convolutional Variational Auto Encoders
RF	Random Forest	CWT	Continuous Wavelet Transform
RF-GA	Genetic Algorithm Trained RF	GANs	Generative Adversarial Networks
RSP	Road Surface Profiler	IoT	Internet Of Things
ET	Effective Temperature	IQR	Interquartile Range
TD	Temperature Difference	CapsNet	Capsule Neural Networks
PRISMA	Preferred Reporting Items For Systematic Reviews And Meta-Analyses	NT	Neural Transformers
TEL	Traffic Load Estimation	RGB-D	Red Green Blue-Depth
LR	Linear Regression	LLMs	Large Language Models
KNN	K-Nearest Neighbors		

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