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DOCTORAL (PhD) DISSERTATION

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Artificial Intelligence for Modeling Ground-Penetrating Radar Data

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Contents

Abbreviations

Abbreviation	Full term
AC	Asphalt Concrete
AI	Artificial Intelligence
ANN	Artificial Neural Network
BS	Base/Subbase (context dependent)
CC	Correlation Coefficient
CNN	Convolutional Neural Network
DL	Deep Learning
GAN	Generative Adversarial Network
GPR	Ground Penetrating Radar
GWO	Grey Wolf Optimization
IoT	Internet of Things
LSTM	Long Short Term Memory
MAE	Mean Absolute Error
MATLAB	Matrix Laboratory (software environment)
ML	Machine Learning
PMS	Pavement Management System
PSO	Particle Swarm Optimization
RF	Random Forest
RMSE	Root Mean Square Error
RSL	Remaining Service Life
R^2	Coefficient of Determination
SGD	Stochastic Gradient Descent
SHM	Structural Health Monitoring
SHM	Structural Health Monitoring
SVM	Support Vector Machine
XGBoost	Extreme Gradient Boosting

Thesis Statement Overview

Table 0.1. Cross-Reference: Thesis Statements, Chapters, Results, and Publications

Thesis Statement	Chapter	Section	Key Result	Supporting Publication
T1	Ch. 2	2.1-2.5	PRISMA-guided ML review; 328 sources; research gaps identified	Azodinia, Shayakhmetov & Mosavi (2025). Eurasian J. Math. Comp. App., 13(4), 41-52
T2	Ch. 3	3.1-3.7	Cross-domain ML taxonomy for stress evolution modeling	Wang, Mosavi, Felde, Azodinia et al. (2025). Acta Polytechnica Hung., 22(12), 95-114
T3	Ch. 4	4.1-4.9	LSTM: lowest RMSE and highest CC for time-series pavement SHM	Azodinia et al. (2025). Decision Making: Appl. Mgmt. Eng., Vol. 8, Issue 1
T4	Ch. 5	5.1-5.9	RF: lowest error (above 1%); SVM: reliable (below 2%)	Azodinia et al. (2026). Decision Making: Appl. Mgmt. Eng., Vol. 9, Issue 1
T5	Ch. 6	6.1-6.5	LSTM: superior accuracy; GRU: efficient for real-time deployment	Azodinia, Mosavi & Besheyev (2026). J. Appl. Comp. Sci. Telecomm., 1(1), 38-42

Table 0.2. Publication-to-Thesis-Statement Mapping

Thesis Statement	Publication	Specific Contribution
T1 — Foundational literature contribution	Azodinia, Shayakhmetov & Mosavi (2025). Eurasian J. Math. Comp. App., 13(4), 41-52	PRISMA review: ML gaps in pavement performance and RSL prediction identified
T2 — Structured methodological synthesis	Wang, Mosavi, Felde, Azodinia et al. (2025). Acta Polytechnica Hung., 22(12), 95-114	Cross-domain taxonomy: supervised, unsupervised, DL for stress evolution
T3 — Independent scientific result	Azodinia et al. (2025). Decision Making: Appl. Mgmt. Eng., Vol. 8, Issue 1	LSTM optimal for time-series pavement SHM using temperature and layer depth
T4 — Independent scientific result	Azodinia et al. (2026). Decision Making: Appl. Mgmt. Eng., Vol. 9, Issue 1	Relief-based selection + SVM, RF, ANN evaluation on GPR pavement data
T5 — Independent scientific result	Azodinia, Mosavi & Besheyev (2026). J. Appl. Comp. Sci. Telecomm., 1(1), 38-42	GRU vs LSTM: accuracy-efficiency trade-off for RSL prediction

Artificial Intelligence for Modeling Ground-Penetrating Radar Data

This thesis is focused on artificial intelligence-based modeling for non-invasive structural health monitoring of pavements using ground penetrating radar data. The main objective is defined as support for informed and predictive decision making in road maintenance and infrastructure management. Pavement structural condition is estimated from subsurface sensing data, asphalt temperature, and pavement layer thickness, which are obtained from radiotechnical and sensor-based measurements. Nondestructive and high-resolution data acquisition is combined with artificial intelligence methods, which enables scalable and cost-efficient monitoring. Several machine learning and deep learning approaches are examined, including Support Vector Machine (SVM), Random Forests (RF), Artificial Neural Network (ANN), and long short-term memory models (LSTM). Model performance is evaluated by root mean square error (RMSE) and correlation coefficient (CC) during training, validation, and testing phases. Strong accuracy is achieved by SVM during training, while robust generalization is achieved by RF during testing. In addition, superior predictive accuracy and stability are demonstrated by LSTM across unseen datasets, hence this model is identified as the most effective approach for sequential pavement data. The results confirm that artificial intelligence enables automated, real-time, and continuous assessment of pavement structural condition. As a result, maintenance actions are scheduled in a timely manner, which leads to extended pavement service life and reduced lifecycle costs. Furthermore, integration of the proposed models into smart city and smart mobility platforms is supported, which enhances road safety and resource allocation. Therefore, this thesis establishes a unified foundation for artificial intelligence based, non-invasive pavement monitoring and sustainable urban transportation management.

Keywords: artificial intelligence, ground penetrating radar, non-invasive assessment, pavement structural health monitoring, machine learning,

1. Introduction

1.1 Introduction

Non-invasive subsurface investigation is required for safe and sustainable infrastructure management, which supports transportation systems, urban development, and environmental protection over long service periods. Ground Penetrating Radar (GPR) is widely applied because subsurface conditions are assessed without excavation, structural damage, or interruption of services, which is essential for operational infrastructure [1]. This capability supports continuous monitoring of pavements, bridges, tunnels, and buried utilities, where destructive testing is not acceptable. Artificial Intelligence (AI) is increasingly adopted because large volumes of GPR data are produced during routine surveys, network level inspections, and monitoring campaigns, which exceed the capacity of manual interpretation [2]. Furthermore, automated interpretation improves consistency across surveys conducted at different times and locations. As a result, AI based GPR modeling is regarded as a critical component of modern non-destructive evaluation and asset management systems.

GPR data interpretation is traditionally conducted through expert driven visual inspection, which relies heavily on operator experience and subjective judgment [3]. This process requires extensive training and long practical exposure, which limits scalability. In addition, interpretation results often vary between analysts, which affects reliability and comparability. Complex wave propagation phenomena, signal scattering, clutter, and heterogeneous subsurface materials further complicate interpretation tasks [4]. These factors increase uncertainty, particularly in urban and multilayered environments. AI methods, e.g., machine learning (ML) and deep learning (DL), are therefore introduced to automate feature extraction and pattern recognition from raw and processed GPR data [5]. Such methods enable systematic and repeatable analysis, which improves efficiency and supports standardized interpretation procedures.

Manual interpretation of GPR data is constrained by human bias, fatigue, and inconsistency among analysts, especially during long surveys [6]. Infrastructure networks generate extensive datasets over time, which require repeated analysis for condition tracking and trend evaluation. Conventional approaches are not efficient for such longitudinal assessment. In addition, signal attenuation, noise contamination, and overlapping reflections reduce detection accuracy, particularly in deteriorated or moisture affected structures [7]. These limitations restrict the reliability of manual decision making. Therefore, automated and data-driven modeling approaches are required, which address scalability, objectivity, and reliability constraints. AI based solutions are proposed to assist experts by providing consistent predictions, which enhance confidence in maintenance and rehabilitation decisions.

Existing AI based GPR studies often concentrate on isolated tasks, e.g., hyperbola detection, anomaly localization, or material classification [8]. These task-oriented approaches demonstrate strong performance under controlled experimental conditions or site-specific datasets. However, real-world applications require models to operate across varying soil conditions, antenna configurations, and survey parameters. Performance degradation is frequently reported when models are transferred to new environments [2]. Furthermore, many AI models lack interpretability, which limits acceptance by practitioners and decision makers [9]. Predictions are often produced without clear explanation of contributing signal features. Hence, a significant research gap is identified in developing generalized and transparent AI models that support non-invasive GPR interpretation across diverse scenarios.

Empirical evidence indicates that convolutional neural networks (CNNs) and advanced DL architectures achieve higher detection and classification accuracy than traditional signal processing and rule-based methods [9]. These models capture complex spatial and temporal patterns within radargrams, which are difficult to describe analytically. Successful applications are reported in underground utility detection, archaeological prospection, and bridge deck condition assessment [10]. These studies demonstrate reduced error rates and improved automation. However, sensitivity to training data characteristics, class imbalance, and noise levels is consistently observed [2]. Thus, available evidence highlights strong technical capability while also revealing unresolved challenges related to robustness and operational reliability.

An additional research gap is associated with data availability and data quality. High quality labeled GPR datasets are limited because annotation requires expert interpretation, domain knowledge, and significant time investment [2,10]. This limitation restricts supervised learning approaches and comprehensive validation. Simulation based data generation is commonly applied to address this issue, which allows controlled variation of subsurface parameters [10]. However, discrepancies between simulated and real-world data reduce model transferability. Moreover, physical principles of electromagnetic wave propagation, reflection, and attenuation are rarely embedded within AI architectures [10]. Therefore, hybrid approaches that integrate physical modeling with data-driven learning remain insufficiently explored and validated.

Recent evidence demonstrates that explainable AI (XAI) techniques enhance transparency and understanding of DL based GPR models [9]. Methods such as Grad CAM and LIMEs identify influential signal regions within radargrams, which supports model validation and error diagnosis. This capability enables experts to verify whether predictions align with physical expectations. In fact, interpretability facilitates communication between data scientists, engineers, and decision makers. However, XAI techniques are often applied only as post analysis tools and are limited to selected experimental cases. This evidence confirms that systematic and integrated use of interpretability in GPR modeling remains an open research challenge.

At the local level, aging infrastructure and increasing maintenance demands require frequent, reliable, and cost-effective assessment tools [6]. Budget constraints and safety considerations limit the use of invasive inspection methods. Non-invasive techniques are preferred because traffic disruption, excavation costs, and structural risks are minimized. AI based GPR analysis enables rapid condition evaluation over large areas, which supports early detection of defects such as voids, moisture ingress, and material degradation [6]. Consequently, preventive and predictive maintenance strategies are facilitated. This local context emphasizes the practical importance of AI driven GPR solutions for municipalities and infrastructure operators.

The objectives of this study are defined to address the identified technical and practical limitations in current GPR interpretation practices. AI models are developed for automated analysis of GPR data across diverse subsurface and operational conditions. Accurate detection and classification of subsurface features are prioritized, e.g., utilities, voids, and layer anomalies [3,7]. Furthermore, robustness and generalization capability are systematically evaluated across multiple datasets. Interpretability is incorporated through XAI techniques, which support transparent analysis and facilitate user trust [9]. These objectives ensure relevance for both research and practice. Consequently, the aim of this thesis is to advance AI driven non-invasive modeling of GPR data for reliable subsurface assessment. Integrated solutions are proposed, which combine accuracy, robustness, and interpretability within a unified analytical approach. Therefore, automated GPR interpretation is strengthened, which supports infrastructure evaluation, maintenance planning, and risk mitigation. In other words, this research contributes to improved reliability and acceptance of non-destructive testing practices in engineering and geoscience domains [2,6].

1.2 Thesis statements and Summary of New Results, and Organization of the Dissertation

In T1, a structured state-of-the-art review is presented for machine learning applications in non-invasive pavement assessment based on ground penetrating radar data. The novelty lies in the consolidation of fragmented studies into a coherent and critical synthesis. Clear limitations are identified in data quality and model transparency. In addition, limited adoption of advanced methods such as deep learning and large language models is established. In T2, a systematic and cross disciplinary review is introduced for stress evolution modelling using machine learning. A new taxonomy is proposed to classify supervised, unsupervised, and deep learning approaches under different loading and environmental conditions. The novelty lies in the integration of diverse applications into a unified analytical structure and in the definition of hybrid modelling directions that combine machine learning with conventional methods [T1, T2]. Chapters 2 and 3 are dedicated to state-of-the-art analysis through T1 and T2, respectively. They are presented as two separate chapters, each corresponding to a distinct peer-reviewed journal publication in a different scientific domain. Chapter 2 addresses machine learning for pavement performance and service life prediction [T1], and Chapter 3 addresses machine learning for stress evolution modeling and taxonomy [T2]. The general contribution of these two chapters lies in the establishment of a comprehensive knowledge base for machine learning applications in pavement engineering and materials science. A consistent methodology is applied through systematic review and structured evaluation. These chapters define current capabilities, identify research gaps, and set clear directions for future work. They provide a critical foundation for the subsequent experimental studies by clarifying limitations in existing methods and by proposing the need for more advanced and integrated modelling approaches [T1] [T2]. In T3, a data-driven method is developed for pavement structural condition assessment through integration of machine learning with sensor and traffic data. The novelty lies in the inclusion of physical variables such as asphalt temperature and pavement layer depth within predictive models. A comparative evaluation shows that the long, short term memory model achieves high predictive accuracy and strong generalization. The study also establishes a connection between predictive modelling and real- time monitoring within smart city systems, which supports continuous assessment and informed maintenance planning. This contribution strengthens the role of artificial intelligence in sustainable infrastructure management [T3]. In T4, an artificial intelligence based structural health monitoring model is developed through integration of non-destructive and high-resolution sensing technology with machine learning algorithms. The novelty lies in the use of a radiotechnical subsurface scanning device combined with Support Vector Machine, Random Forest, and Artificial Neural Network models. Strong predictive performance is achieved, especially for Support Vector Machine and Random Forest methods. The study introduces a scalable and cost-efficient solution for automated and continuous pavement monitoring. It also supports integration into smart city systems, which improves safety, efficiency, and long-term infrastructure resilience [T4]. In T5, a machine learning based approach is proposed for pavement condition prediction using field data from Heavy Weight Deflectometer and Ground Penetrating Radar tests. The novelty lies in the comparative evaluation of deep learning models for temporal pattern recognition. The Gated Recurrent Unit model is identified as the most effective, as higher accuracy and lower errors are achieved compared to the Long Short Term Memory model. This work confirms that deep learning supports reliable early maintenance planning and reduces operational costs. It also provides a balance between predictive accuracy and computational efficiency, which supports practical implementation in intelligent and sustainable infrastructure systems [T5].

2. Machine learning for pavement performance and service life prediction [T1]

2.1 State-of-the-art

This chapter presents the results that support Thesis Statement T1. This thesis has been published in a peer-reviewed journal. The article titled: Machine Learning for Pavement Performance and Service Life Prediction, investigates the state of the art of artificial intelligence for non-invasive modeling of ground-penetrating radar data [T1]. 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 an improved PRISMA guidelines for AI applications [1]. 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.

2.2 Novelty

This study provides a structured PRISMA compliant review of machine learning applications for non-invasive pavement assessment using ground penetrating radar data. The main contribution lies in a clear synthesis of fragmented research into a coherent body of knowledge. A critical evaluation of current methods is presented, where limitations in data quality and model transparency are systematically identified. The study advances the field by establishing that machine learning enables earlier and more accurate prediction of pavement deterioration through pattern recognition in complex and multi-dimensional datasets. A further contribution is the explicit identification of the limited use of advanced methods such as deep learning and large language models in pavement engineering. This gap is defined with clarity and supported by evidence from literature. The novelty of this work lies in its role as both a benchmark and a directional guide. It not only summarizes current practice but also sets a clear path for future research in intelligent infrastructure management through the adoption of more advanced artificial intelligence techniques.

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 T1.1. 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 utilizes algorithms such as RF and CatBoost have successfully predicted the long-term performance of asphalt concrete overlays, with RF outperforming 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].

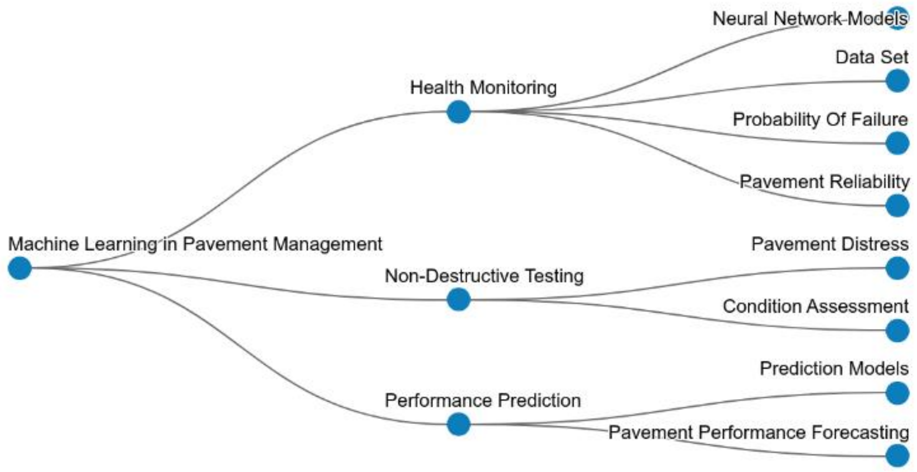


Figure T1.1. Taxonomy of ML methods for predicting RSL of pavements

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 T1.2. Summary of the Research Gap

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 are listed in Table T1.2. 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.

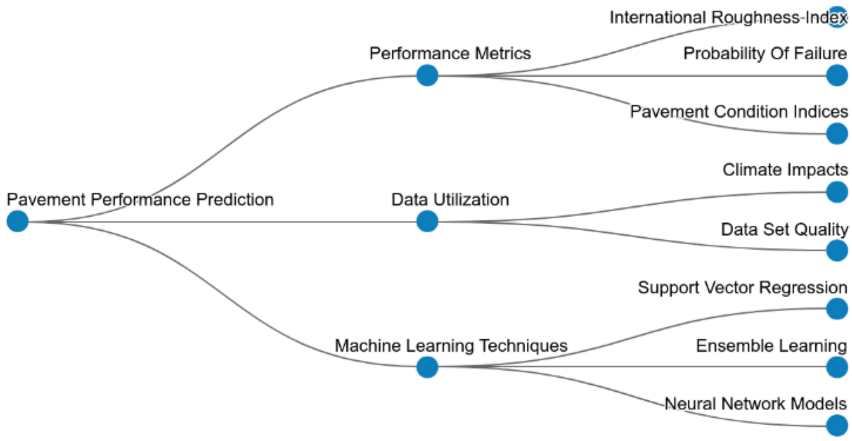


Figure T1.2. Research gap of predicting RSL of pavements

Figure T1.2 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 holistic, physically informed, and interpretable ML methods supported by standardized, high-fidelity data to enhance the reliability and practical implementation of pavement performance predictions. 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].

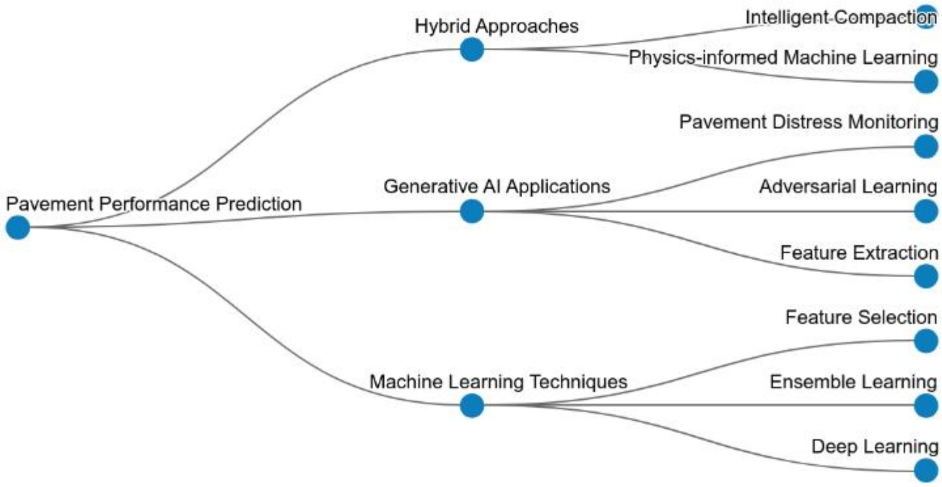


Figure T1.3. Research gap taxonomy of LLM, Generative AI, DL, Ensemble ML, Hybrid ML and Physics-informed ML

Table T1.3. Summary of Reseach 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.	[26]	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.

Pavement distress and transverse cracking can be accurately predicted using DL particularly 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 [30-32]. 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 enhance data robustness, and creating interpretable, adaptive models.

2.3 Methodology

The primary search of queries of ML and pavements in the database of Scopus returned 3017 documents for the period of the past decade. The query included the ML fundamental keywords, e.g., "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks" OR Transformer OR "Large Language Models" OR "Natural Language Processing" OR "Reinforcement Learning" OR "Transfer Learning" OR "Federated Learning" OR "Gradient Descent" OR "Support Vector Machine" OR "Decision Tree" OR "Random Forest" OR "Gradient Boosting" OR "Nearest Neighbors" OR "Naive Bayes" OR "Principal Component Analysis" OR Autoencoder OR "Generative Adversarial Networks" OR

"Ensemble Learning" OR "Edge AI" OR AutoML. The keyword of the pavement was included too. Using PRISMA guidelines [1] for screening, the number of documents is reduced to 552, through considering title, abstract and keywords relevance as described in several former reviews [P1]. To do screening, the articles had been divided between authors for screening the relevance. Figure T1.1 presents the initial search which is an exponential rise of ML in pavement research. After careful screening, we identified the 20 original research to review and added in this study. Only the original research that proposed a novel ML/DL method and published in reputable journals had been included.

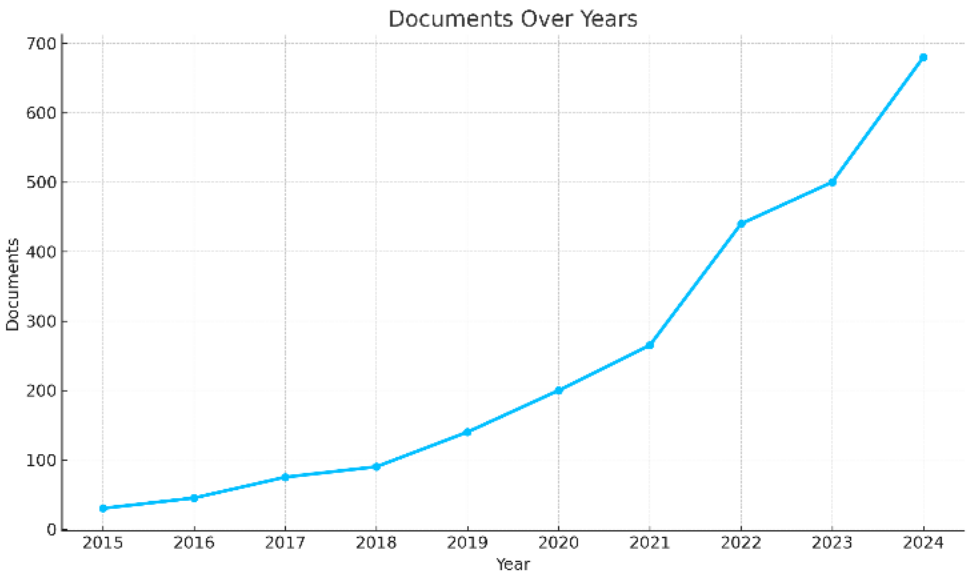


Figure T1.4. Progress of ML in pavement research

2.4 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. These techniques are integrated into PMS (Pavement Management System) and ITS (Intelligent Transportation Systems). PMS is used to monitor, assess, and manage pavement conditions for maintenance planning, while ITS applies communication and information technologies to improve transport efficiency and safety. They rely on data from sources such as LTPP (Long-Term Pavement Performance), which provides long-term records on pavement behavior, 3D imaging, which captures detailed surface conditions for accurate defect detection, and geotagged datasets, which include location information to enable spatial mapping and tracking of pavement performance. The use of ML improves prediction accuracy, supports maintenance planning, and enhances infrastructure resilience through data-driven decision-making.

Table T1.4. 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 T1.5. The summary of the analyzed papers by focus area: the methodologies used and the key findings

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]
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 T.1.5., 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 T1.5. 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 vehicle and engines vibrations on the pavements [54].

2.5 Conclusions

This study, which is based on a systematic review of 552 documents filtered from an initial 3017 using PRISMA screening guideline, shows how ML is rapidly influencing pavement performance prediction and service life modeling. From this, 20 fundamental research studies were thoroughly extracted and then examined. The study is limited to explore Scopus and only considered the studies which were original and proposed a ML/DL method for the first time. 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 concentrate more on filling these gaps and eventually move toward infrastructure systems that are more intelligent, adaptive, and data-driven.

3. Machine Learning for Modeling Stress Evolution [T2]

This chapter presents the results that support Thesis Statement T2, which is concerned with the classification and taxonomy of machine learning approaches for stress evolution modeling. This domain is scientifically distinct from the pavement performance context of Chapter 2, as the modeling challenge, relevant literature, and target output differ substantially. This work offers a comprehensive and systematically derived classification of machine learning approaches for stress evolution modelling across multiple scientific domains. The contribution lies in the development of a new taxonomy that organizes supervised, unsupervised, and deep learning methods based on their suitability under different loading and environmental conditions. A PRISMA based selection process ensures that the review remains transparent and reproducible. The manual screening had been performed by the authors following an adapted guidelines presented in e.g., [P1]. After records are identified through the Scopus database, titles and abstracts are screened using predefined inclusion and exclusion criteria to remove irrelevant studies. The remaining articles are then assessed through full-text review to confirm eligibility, and reasons for exclusion are recorded at this stage. Finally, the selected studies are included in the review, and the entire process is documented in a flow diagram that presents the stages of identification, screening, eligibility, and inclusion. The study advances knowledge by addressing the limitations of deterministic models in handling high dimensional and nonlinear data. A detailed comparison of machine learning methods is provided, where strengths and weaknesses are clearly stated. The importance of feature engineering, data quality, and model interpretability is examined in a structured manner. The novelty of this research lies in its cross-disciplinary scope and its integration of diverse applications into a unified analytical structure. In addition, future research directions are defined through the proposal of hybrid models that combine machine learning with traditional approaches to improve prediction accuracy and reliability.

3.1 Introduction

In material science, stress is crucial. When an object has external forces, internal forces are generated to keep force balance. The concentration of internal forces at a point is stress (Figure 1), which can be defined as Equation (1).

$$\sigma = \lim_{\Delta S \to 0} \frac{\Delta P}{\Delta S} \tag{1}$$

Where the normal stress coefficient (σ) is $\sigma = \Delta P / A$, ΔP is the normal force and A is the area. Shear stress coefficient (τ) is $\tau = \Delta S / A$, ΔS is the shear (tangential) force and A is the area. General stress components are normal stresses: σxx, σyy, σzz and shear stresses: τxy, τyx, τxz, τzx, τ.

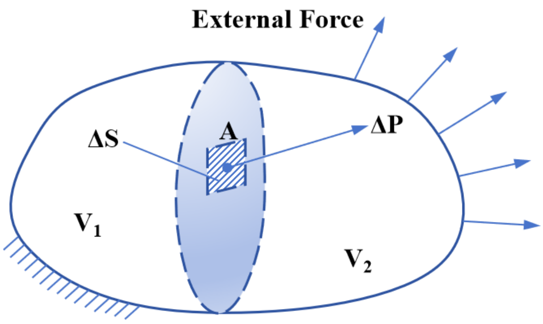


Figure T2.1. Definition of stress

The vector at point A is called the stress vector or traction vector. It represents the internal force that acts on an infinitesimal area element surrounding point A inside the body [55]. In the Figure, the solid body is divided by an imaginary internal surface of area ΔS into two regions, V_1 and V_2. External forces are applied on the outer boundary, and these loads create internal force transfer across the internal section. The resultant internal force on the small area element is denoted by ΔP. When the area element becomes very small, the ratio ΔP/ΔS approaches the stress vector at point A. This concept defines stress as force intensity at a specific location. The stress vector can be decomposed into one normal component, which acts perpendicular to the surface, and two shear components, which act tangentially to the surface. Normal stress is associated with tension or compression, while shear stress is associated with sliding deformation. Stress distribution inside a body is a key indicator of stiffness, strength, failure risk, fatigue life, and structural safety. It is affected by geometry, material properties, loading magnitude, loading direction, temperature, and internal defects [55]. Stress shows force concentration inside an object and is an important measure for mechanical properties, failure risk, and service life. Stress is affected by many factors, such as material processing technology and processes, material properties, and environmental conditions. The stress change inside an object, with time or process, is referred to as "stress evolution", as illustrated in Figure 2. Stress evolution refers to the dynamic changes in stress within materials subjected to external influences, such as mechanical loading, thermal effects, or environmental conditions. This concept is fundamental in understanding how materials deform, fail, or adapt under various scenarios. Understanding the evolution of stress is a basic prerequisite for predicting material behavior and optimizing performance in advanced materials and structures. The stress-strain relationship provides crucial insight into how materials respond to different loads, while techniques such as digital image correlation allow for precise measurement of local strains and stress distributions, especially for materials like concrete, bricks, and composites. Additionally, strength theories are critical for defining yield or failure criteria under complex stress states like biaxial or multiaxial stresses, ensuring material reliability in real-world applications. For example, in order to obtain the stress-strain relationship of quenched 7050 aluminum alloy under different temperature and strain rate conditions, the Gleeble hot compression experiment is implemented. Using the optimization algorithm for curve fitting, the stress-strain constitute model can be established in the form shown in Equation (2), and the difference between the experiment results and the model is shown in Figure T2.2.

$$\sigma = (\sigma_0 + B\varepsilon^n)[1 + C\ln(\dot{\varepsilon}/\dot{\varepsilon}_0)]\{1 - [(T - T_r)/(T_m - T_r)]^p\} \tag{2}$$

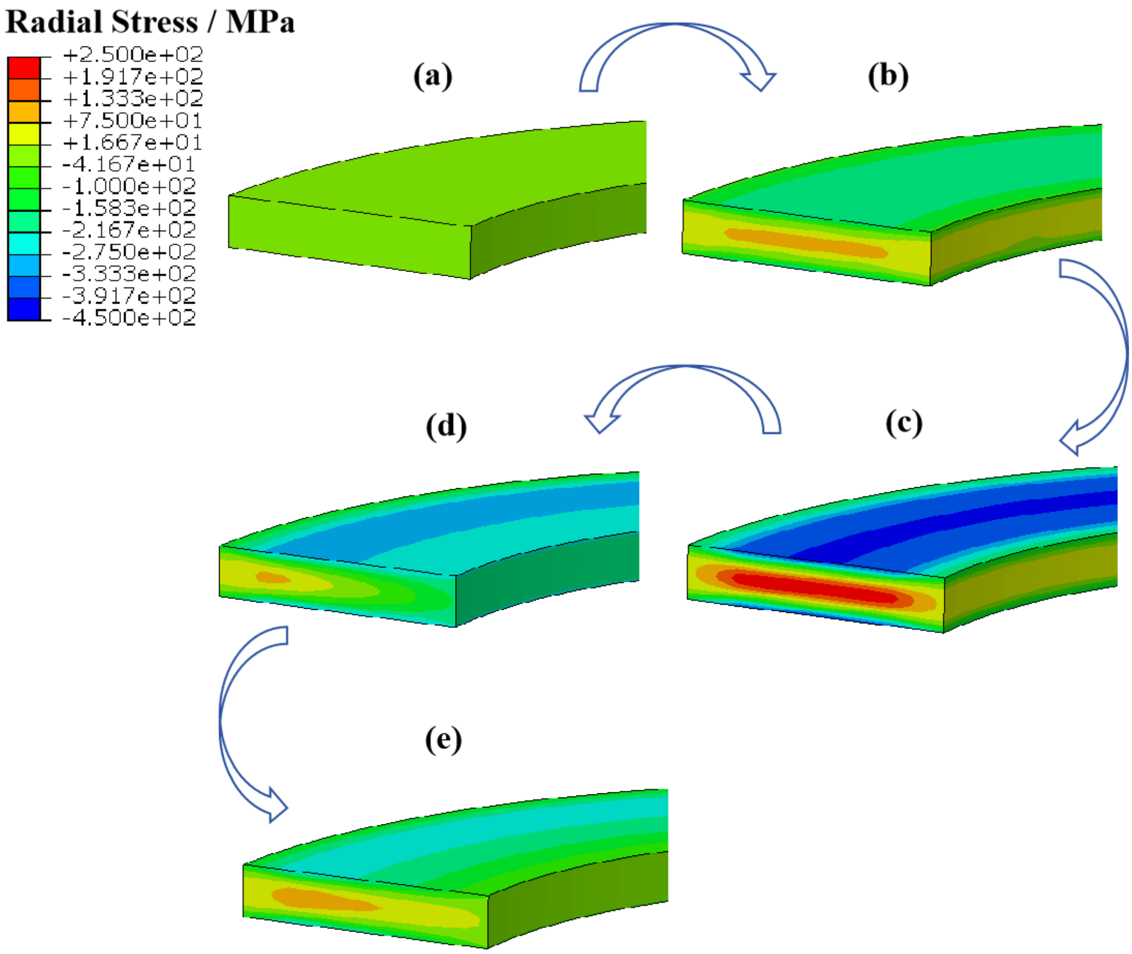


Figure T2.2. Radical Stress Evolution of 7055 Aluminum Alloy Ring during Processing: (a) Beginning of Quenching; (b) Quenching at 52 s; (c) End of Quenching; (d) Cold Bulging Loading; (e) Cold Bulging Unloading

Studying the laws of stress evolution is crucial in many fields. It helps to better understand the characteristics of materials during the forming process i.e., dimensional and shape accuracy, component cracking failures, service life, forming process, and the physical, chemical, mechanical properties. Engineers analyze the safety and stability of structures such as buildings and bridges using stress evolution laws to ensure life and property safety in structural engineering. In the geological sciences, using the knowledge of stress evolution in strata, it is possible to analyze the earth stress evolution and predict earthquakes. In life sciences, biomechanics studies stress evolution in living structures like cells, tissues and organs, to understand life activity laws and provide new insights for disease diagnosis and treatment. The more conventional methods for studying stress evolution include the Finite Element Method (FEM), Model Method and Experimental Method. FEM divides the continuum into discrete units and approximates the stress evolution of the entire domain by calculating physical quantities at unit nodes. The Model Method can be divided into a phenomenological model and a physical model. The phenomenological model generally establishes model equations based on experimental data and predicts stress evolution by fitting equation parameters; the physical model generally starts from basic theory, studies the influencing factors and their laws, and then establishes model equations to predict stress evolution. The Experimental Method is used to measure the stress distribution in the object in real-time on site, so as to obtain the stress evolution law of a certain process.

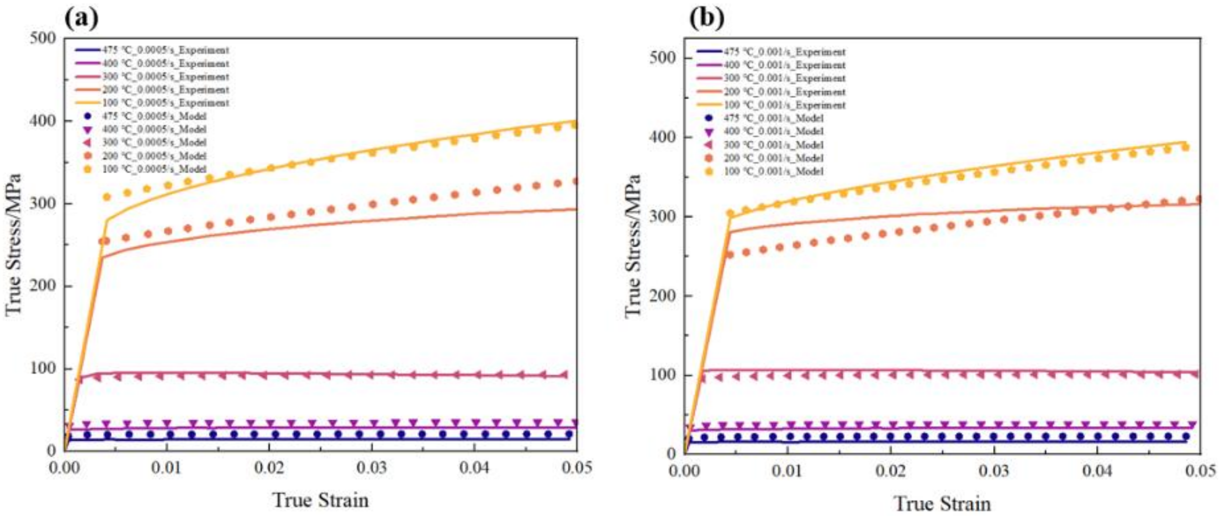


Figure T2.3. Stress-strain relationship of quenched 7050 aluminum alloy under different conditions: (a) Strain rate is 0.0005/s for different temperatures; (b) Strain rate is 0.001/s for different temperatures

The authors in [56] proposed a prediction model for the evolution of yield stress of cement-based paste in the early hydration stage from the perspective of microstructure. Taking into account the interaction between cement particles and the change of solid volume fraction during the hydration process, the original Yodel model was modified, and the prediction was more accurate. In another article, [57], the authors took the stress evolution law of low-alloy ferritic steel welding process as the target, improved the original K-M model equation according to the austenite-martensite transformation process, established a finite element model, and obtained the welding stress evolution law that conforms to the experimental data. Stress evolution is a highly complex and nonlinear problem with high data dimensionality and high modeling difficulty, in which using the traditional models have obvious limitations. For example, the finite element method requires an accurate stress-strain constitutive model of the material and requires a large number of grids to be divided. The model method requires a large amount of experimental measurement data to fit the equation parameters. The emergence of machine learning has brought new breakthroughs in the modeling and prediction of stress evolution, improving the accuracy of the model and the prediction. Machine learning can process and analyze a large amount of data to learn laws, characteristics, and models from it, thereby completing tasks such as prediction and decision-making. For example, [58] were inspired by the application of neural networks in the field of physics and proposed a novel model, i.e., space-time physics-informed neural network (STPINN) to calculate the stress evolution caused by electromigration in very large-scale integration (VLSI) circuits. Compared with the traditional finite difference method or finite element method, STPINN based on meshless technology does not require grid division, has lower computational complexity and higher efficiency, and can more accurately predict stress evolution by encoding physical laws into neural networks and adopting multi-channel structure design. The authors in [59] used an active ensemble learning (AEL) technology, utilized principal component analysis (PCA) to reduce data dimensions in the data sampling stage, and used light gradient boosting machine (LGBM) as a prediction model in the prediction stage, thereby improving the robustness, generalization ability and computational efficiency of predicting the evolution of early-age stress (EAS) in concrete. Consequently, this study conducts a detailed review, classification, and evaluation of machine learning methods for modelling and predicting stress evolution in various materials and systems, obtain their advantages and prospects over traditional methods, critically evaluate the limitations of these methods, emphasize the role of data quality, feature engineering, and model interpretability, determine the direction for future applications, and explore the potential of hybrid models that combine machine learning and traditional techniques to promote the understanding and prediction of stress evolution.

3.2 Background

Stress evolution models incorporate factors such as elasticity, plasticity, and viscosity, alongside material-specific properties, to predict stress distributions and their time-dependent behavior. These predictions help engineers and scientists design materials with improved performance and reliability, accounting for complex real-world conditions [60-62].

Machine Learning's Role in Stress Evolution Modeling

Machine learning (ML) has emerged as a transformative tool in stress evolution modelling due to its ability to process high-dimensional data and uncover patterns that traditional methods may overlook. For instance, ML models, such as fully convolutional networks (FCNs), can predict stress distributions faster than conventional Finite Element Methods (FEMs), significantly enhancing computational efficiency [63]. Supervised learning techniques, including regression trees and neural networks, have been employed to predict mechanical properties like strength and toughness from experimental datasets [64]. Furthermore, ML facilitates material optimization by identifying configurations that minimize stress and maximize performance. Techniques such as support vector machine regression enable the screening of extensive material databases for properties like high elasticity or hardness [65]. Hybrid approaches, combining ML with traditional methods like FEM, provide comprehensive modelling by integrating macroscopic and microscopic data, making them particularly effective in predicting fatigue properties and stress-strain behaviors [66,67].

3.3 Challenges and Future Directions in ML-Driven Stress Evolution Modeling

While ML offers significant advancements in stress evolution modeling, challenges remain. One critical issue is the need for extensive, high-quality data to train models effectively, which can be a limitation in certain engineering applications [68]. Ensuring that ML models adhere to physical principles such as thermodynamic consistency is another challenge [69]. Additionally, integrating ML with traditional approaches like finite element analysis (FEA) can enhance predictive accuracy but requires careful validation and feature selection [70,71]. Future directions involve the development of hybrid models that combine classical phenomenological approaches with data-driven methods to achieve accurate extrapolations even with limited data [68-71]. These advancements will help overcome current limitations, broadening the applicability of ML in stress evolution studies.

The constitutive model is an accurate tool for explaining the evolving state of the material under different kinds of mechanical and thermal loads. Data-driven approaches are indispensable in developing this model, particularly through the use of machine learning. Machine learning algorithms help in analyzing and predicting many complex behaviors, such as deformation, failure, and adaptation. This enables material design and furthers engineering applications [72,73]. Machine learning significantly improves stress evolution modeling. ML constitutes an economic surrogate to predict stress fields while quantifying uncertainty. These models yield accurate predictions over a wide range of material microstructures, considering relatively lower computational cost compared to finite element analysis. They are helpful in stress predictions in three-dimensional structure or under complex loading conditions. However, challenges remain. Large, varied datasets must be generated, and thermodynamic principles must be rigorously imposed [71,72].

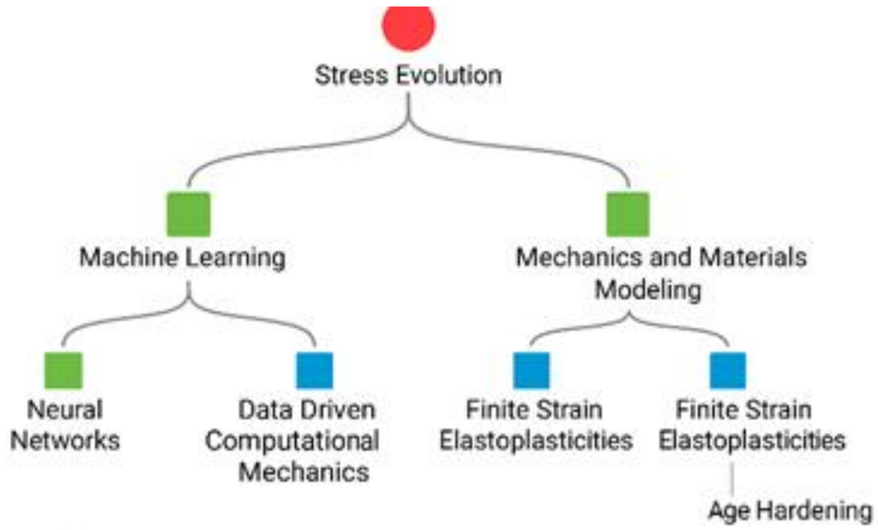


Figure T2.4. Taxonomy of stress evolution

Despite that, ML is still improving the accuracy of stress evolution predictions. Applications of machine learning in modeling stress evolution are numerous. For example, in the prediction of the behavior of engineering materials in tension, compression, and shear with real-world conditions, according to [70]. ML also improves the quality of additively manufactured parts by enabling real-time monitoring and defect prevention during fabrication. Some of the challenges include the cost associated with the collection of high-quality data and the implementation of ML models when data is scarce. Their resolution will contribute to increased applications in other engineering areas of ML-driven stress evolution modeling. Stress evolution in mechanics and materials is governed by several core principles. The stress-strain relationship is fundamental, illustrating material behavior under load and key thresholds, like the yield limit, where elastic deformation shifts to plastic [70]. Constitutive models, both phenomenological and data-driven, enhance predictions by considering factors like strain hardening and thermal effects, even in data-scarce scenarios [78,88]. Thermomechanical coupling, including thermal activation and viscoelastic properties, captures the time-dependent strain responses crucial for processes like curing. Microstructural evolution, such as dislocation mechanics and nano-porous growth, also plays a critical role in flow stress and material behavior [77,82]. Damage mechanics addresses material degradation through models like Continuum Damage Mechanics (CDM), while cyclic loading highlights fatigue damage and hysteresis loops' importance in long-term performance [81]. Finally, configurational forces, exemplified by the Eshelby stress tensor, provide insight into energetic changes and adaptability in fracture mechanics and interface evolution [80]. These principles collectively form the basis for advancing material design and engineering applications.

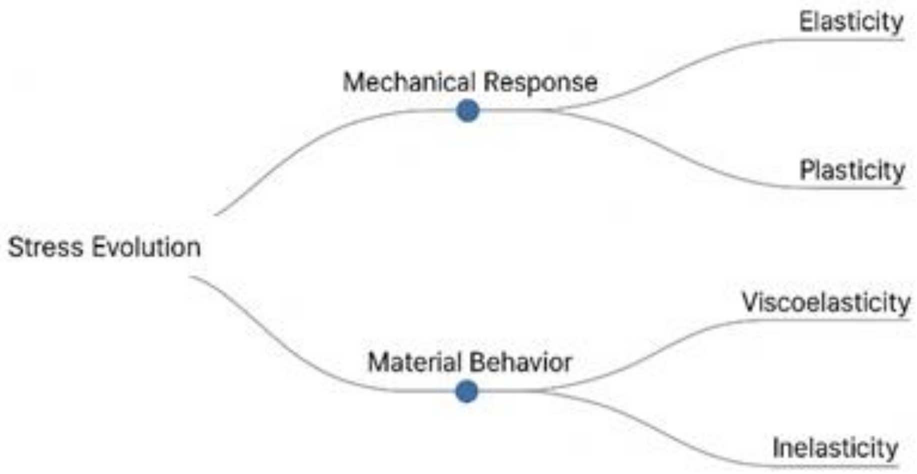


Figure T2.5. Key Principles of Stress Evolution in Mechanics and Materials

Table T2.1. Principal and description of methods

Method	Description	Supporting References
Stress-Strain Relationship	Describes material behavior under load, highlighting key thresholds like the yield limit where elastic deformation shifts to plastic.	[81] [82] [83]
Constitutive Models	Enhance predictions using phenomenological and data-driven approaches, accounting for strain hardening and thermal effects, even with limited data.	[84] [85] [86]
Thermomechanical Coupling	Captures time-dependent strain responses involving thermal activation and viscoelastic processes; essential for processes like curing.	[87] [88] [89]
Microstructural Evolution	Explores dislocation mechanics and nano-porous growth in flow stress and material behavior.	[90] [91]
Damage Mechanics	Analyzes material degradation using CDM, emphasizing fatigue damage and hysteresis loops for durability predictions.	[92] [93]
Configurational Forces	Provides energetic insights into fracture mechanics and interface motion, leveraging the Eshelby stress tensor.	[94] [95]

3.4 Materials and Methods

In order to establish how ML approaches are employed to model stress evolution in materials, a systematic literature review was completed. The Scopus database was used as the main point of reference for the study because it contains a wealth of peer-reviewed publications in engineering, materials science and computational methods. Also, the study focused on publications between 2015-2025 and used keywords like “stress evolution”, “machine learning”, “stress-strain modeling” and “finite element analysis”. Upon conducting the search, 2,768 documents were retrieved. In order to maintain methodological rigor, the PRISMA framework was utilized. Through several screening steps, duplicates and non-relevant publications were removed. Abstracts and full texts were adequately scrutinized for relevance and quality. After this filtering process, 9 articles were identified which met the stringent inclusion criteria and were subjected to final analysis. These studies were divided based on three core ML categories, i.e., supervised learning, unsupervised learning, and deep learning. Each of these categories was analyzed according to their modeling techniques, input data (microstructure, simulations, sensor readings), target outputs (stress fields, yield points) and material systems. We further evaluated each ML method using common performance indicators, including predictive accuracy, generalization ability, computational efficiency, and model interpretability. Special focus was given to hybrid models those combining ML with traditional physics-based approaches like FEA or CDM. These hybrid methods showed notable potential in capturing complex, nonlinear stress behavior with improved cost and time efficiency.

3.5 Review and Results

ML and DL are transforming the understanding and prediction of stress evolution in materials science and mechanics. AI applications, such as predicting mechanical properties, stress-strain relationships, and stress distribution, have demonstrated significant accuracy and efficiency. For instance, Deep Learning Surrogate models (DLS) can predict mechanical performance with over 98% accuracy, outperforming traditional FEA methods [78]. Machine learning and deep learning techniques also enhance the prediction of composite material properties, stress-strain behavior in anisotropic materials, and flow stress in high-entropy alloys, significantly advancing structural engineering and material safety [30]. The advantages of AI and DL lie in their speed and precision. Neural networks generate predictions in seconds, reducing the computational burden of traditional simulations, while achieving accuracy levels with less error [81,87]. Techniques like convolutional neural networks (CNNs) and U-Net architectures efficiently predict stress fields in complex material systems, offering rapid solutions for dynamic events like impact analysis [84-88]. Moreover, advanced AI frameworks such as multi-scale modeling and transfer learning improve the precision of predictions in both experimental and real-world applications, enabling breakthroughs in material design. Despite their potential, challenges remain. Reliable predictions depend on high-quality and abundant training data, requiring robust datasets and effective data augmentation strategies [89]. Integration of AI with experimental methods is critical to validate and enhance the practicality of these models. Combining computational predictions with experimental validation will ensure accurate, scalable, and real-world solutions [85].

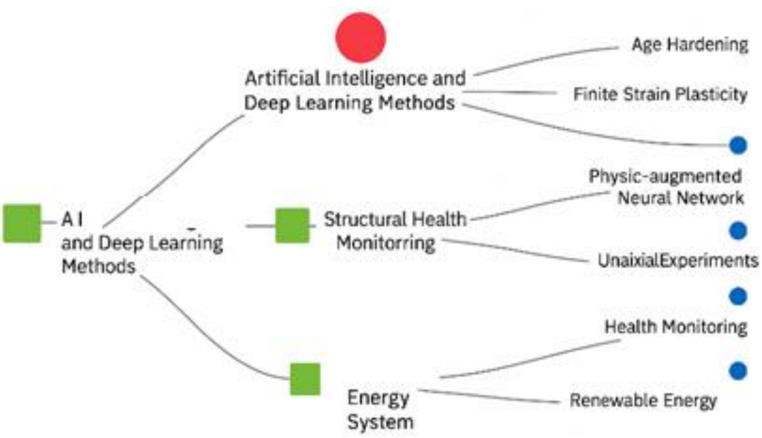


Figure T2.6. Proposed taxonomy focused data-driven methods and applications

AI are revolutionizing materials science by providing efficient, accurate, and rapid tools for stress evolution analysis, paving the way for accelerated progress in engineering applications. The use of AI and deep learning has revolutionized studies into the development of stresses in material science and mechanics. These technologies can make very accurate predictions about their mechanical properties, such as the stress-strain relationship, including yield strength and ultimate strength, using data from simulations and experiments. Deep learning models coupled with FEA are used for the prediction of stress distributions with high accuracy that helps in overcoming high computational costs and accelerating the analysis process. Surrogate models, like deep learning surrogate models (DLS), provide efficient predictions of maximum stress values under complex conditions, making them valuable for material screening and design [78,81]. AI also plays a crucial role in failure prediction by using high-fidelity simulation data to forecast fracture propagation and material degradation with precision [88]. In other words, AI integrated into real-time monitoring systems can enhance the manufacturing process of materials with consistent quality and uniformity in properties. AI models analyze microstructural features that in turn help in understanding their influence on mechanical performance, thus helping to design materials with customized properties. These are promising developments that, in most cases, bring faster and cost-effective options rather than experimental testing methods. However, the accuracy of AI models heavily depends on high-quality standardized training data. There is a need for robust data augmentation techniques to enhance the reliability of predictions under variable conditions. It also requires further collaboration between AI researchers and materials scientists to make the algorithm tuning appropriate for engineering applications, as per [85]. Despite their potential, there are challenges on computational efficiency and experimental validation aspects. The optimization of AI models with respect to speed and accuracy without compromising reliability is very important for practical applications. Merging the AI-driven predictions with experimental validation ensures accurate, scalable results that could be useful in real life. Overcoming these challenges will widen the role of AI in material design and industrial applications. AI and deep learning remain in continuous development for analyzing stress evolution by offering efficient and fast solutions accurately; however, further work is required to realize their full potential.

Deep learning has emerged as powerful tools that predict stress evolution in mechanics and materials, providing greater speed and accuracy than their experimental counterparts. The techniques can handle a considerable amount of data and, through the use of complex correlations existing between material properties and stresses, provide quite accurate predictions about the mechanical performance of materials. While traditional methods have relied on very time-consuming experimental procedures or complex modeling calculations, AI-based approaches-like deep learning surrogate models-can accurately reproduce the results of FEA simulations much faster. This speeds up material screening and design toward optimization of synthesis conditions, besides enhancing real-time monitoring. The outstanding challenges are obtaining enormous amounts of data during training, expensive computations, and model robustness assurance for guaranteed quality data. The solving of such problems is indicative of the possibility of using this method on a wider scope with regard to AI and applications in material optimizations and mechanical engineering.

Table T2.2. Summary table of the key findings

Ref	Study Focus	Materials/Applications	Machine Learning Approach	Key Findings
[91]	Flow stress modeling	Titanium aluminide (TiAl) alloy TNM-B1	Data-driven model, hybrid model	MLM more accurate and faster than PM, better extrapolation
[92]	Predicting material response	Titanium alloys, magnesium alloys, composites	Neural networks	Accurate predictions under arbitrary thermo-mechanical loading
[93]	Constitutive models for path-dependent processes	Structural materials	Hybrid framework (phenomenological + data-driven)	Accurate extrapolation, thermodynamically consistent
[94]	Microstructure-sensitive design	Copper, Ti-7Al alloy	Physics-informed neural network (PINN)	Improved accuracy and efficiency, small-data problems
[95]	Flexible composites design	Ag/poly (amic acid) composite	BP neural network with DE algorithm	High accuracy, optimized fabrication conditions
[96]	Stress hotspot prediction	Hexagonal close packed materials	Random forest	Predicts hotspots, identifies microstructural features
[97]	Strain-stress behavior prediction	Nitinol alloys	Various algorithms (kNN, Random Forest)	kNN highest accuracy, predicts mechanical responses
[98]	Ratchetting prediction	AZ31 magnesium alloy	Physics-informed ML model	High prediction accuracy and generalization
[99]	Additive manufacturing process modeling	Various materials	Physics-informed ML models	Robust and interpretable framework, integrates physical insights

ML techniques presented in the context of stress evolution in engineering materials in the previously discussed Table II, marking a clear progression from primitive methods. Research shows that ML models like neural networks, k-nearest neighbors, and random forests dominate in estimating flow stress, strain-stress behavior, and ratchetting in alloys like titanium, magnesium, and Nitinol [91,92,97,98]. These models surpass phenomenological models in accuracy and calculations, especially in the presence of intricate or multi-axial loading conditions [91,92]. Hybrid techniques that combine data-driven and physics-informed models, while maintaining thermodynamic equilibrium, are remarkably strong in low-data scenarios [93,94]. Physics-informed neural networks (PINNs), apply microstructure-sensitive design processes to enhance physics-informed frameworks where sparse experimental data strengthens the design [94-99]. The most difficult hurdles of a lacking dataset, generalizability of the model, and interpretability through a physics lens of purely driven ML predictions still very much poses an issue. A problem optimal ML approach would face includes a bounded dataset where extrapolation beyond the confinement threshold would render retraining difficult [95,96]. To address these challenges, new research emphasizes the development of interpretable, hybrid, and physics-constrained models that can excel in low-data regimes [93,95]. The way ahead should be with the integration of ML followed by experimental validation, enhanced explainability and algorithm customization based on material type [92,98]. Through overcoming these limitations, ML will continue to revolutionize materials science, for real-time prediction, optimized design, and accelerated discovery of new materials [92,97]. ML and AI significantly support the analysis of stress evolution in mechanics, structures, and material science. These methods learn from big data from either experimental and simulated data and apply them to predict stress evolution in materials under many conditions. They are able to calculate faster and more effectively than many traditional methods. They also sometimes combine physics-based models with data-driven models to predict conditions more accurately even for situations beyond the training. This makes them ideal for structural health monitoring, material design optimization, and high-end simulations that involve considerations of cost and time. This, therefore, reduces trial and error in experiments and enables engineers to be more assured of their designs. AI models will be increasingly integrated with simulations and real-time monitoring systems in the future. This can assist in designing new materials that are suited for particular stress situations and in anticipating failure before it occurs. The primary benefits are speed, flexibility, and the capacity to identify patterns that humans might miss. There are still issues, though, like the requirement for high-quality data, substantial computer power, and close coordination between material scientists and AI experts. These problems may be resolved in the upcoming years with the aid of cloud-based computing, more effective algorithms and improved data sharing. Stronger materials, safer structures and more environmentally friendly engineering solutions could result from the proper applications of AI and material science.

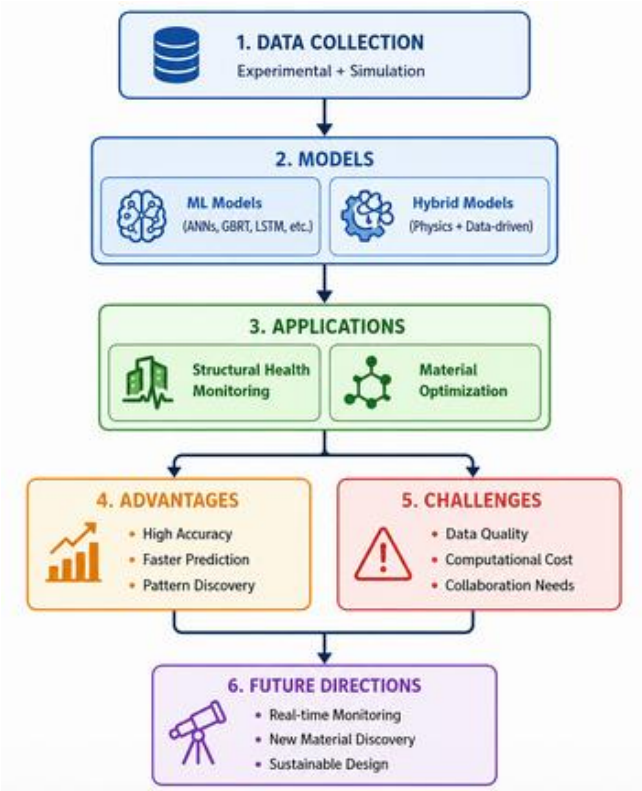


Figure T2.7. Detailed analysis of AI and machine learning in stress evolution

In T2.7., we illustrate how machine learning and artificial intelligence aid in modeling stress, in structures and materials. Data collection from simulations and experiments is the first step. Either AI models or models that combine AI and physics, can use this data. The outcomes are applied to practical tasks like enhancing materials and keeping an eye on the condition of structures. There are unquestionable advantages along the way, such as faster and more precise forecasts and fresh insights, but there are also drawbacks, like requirements for better data and significantly greater processing power. Future objectives like real-time monitoring, the discovery of new materials and the development of more environmentally friendly designs are indicated by the process.

3.6 Discussion

Research into the evolution of stresses in materials indicates significant developments within a set of disciplines. The interaction between high strain rates and temperature is very important in driving forward the microstructural evolution in alloys, especially in highly entropic samples. These will directly affect the mechanical properties and stress-relaxation behavior, and surely, future work will aim toward the optimization of these interactions, leading to better performing and more durable alloys [74]. Advanced computational approaches now replace the conventional ways of stress-strain predictions, including the finite element analysis and ML techniques. ML techniques provide enhanced prediction accuracy in complicated loading conditions and offer precise modeling of localized deformation in heterogeneous microstructure. Integration of these ML-based models with classical computational techniques opens up exciting possibilities for handling a wide range of mechanical conditions, with far greater efficiency [75]. Another critical area of research that has emerged comprises titanium alloys, where innovative methods like laser shock peening and phase transformations are being explored to bring improvements in the mechanical performance. Stress-induced relaxation and nanodomain engineering are prospective pathways to further refine their strength and reliability [76]. Besides, stress localization due to grain boundary effects will be increasingly important in polycrystalline materials. It has been revealed in studies that grain boundaries have a significant effect on the distributions of stress under different modes of deformation; future studies are needed to understand such mechanisms for improvement in stress evolution modeling and reliability in materials [90]. All these developments together guarantee a bright outlook for the design of materials, with specified mechanical properties and better stress performance. Design optimization has also benefited from stress evolution principles, drawing inspiration from nature's load-bearing strategies. Bio-inspired approaches, such as self-repair and optimal construction seen in biological materials like bones, provide new pathways for creating materials capable of withstanding higher stress levels. Principal stress line analysis, though underutilized, offers a powerful tool for guiding structural topology optimization by identifying optimal material continuity paths. Advanced computational modeling methods, such as the regularized extended finite element method (Rx-FEM), have also improved damage modeling in composite materials, including delamination and matrix cracking, enabling more effective designs. Microscale stress analysis further enhances performance predictions by examining stress load-sharing mechanisms in materials with microscale particles [76]. The practical applications of stress evolution include addressing challenges such as creeping, a time-dependent strain under constant stress. Modeling creep in materials like concrete and masonry enhances predictions of stress redistribution and structural integrity [87]. Similarly, the development of ultra-high-strength steels and other advanced materials meets modern structural demands for greater performance. However, successful material selection must balance performance needs, cost and environmental factors [88]. Together, these advances drive the design of safer, more efficient and innovative engineering solutions.

3.7 Conclusions

Implementing ML in modeling the evolution of stress techniques has proven to be an effective optimization opportunity, for forecasting various material and mechanical systems. These methods make it possible to predict important mechanical attributes such as the stress-strain curve, yield strength, and fracture growth and for measuring vast amounts of data obtained from simulations and experiments. AI model surrogates and deep learning models working in conjunction with FEA tend to capture some level of sophisticated stress distributions while incurring significantly lesser costs and time. In fact, AI provides many opportunities to monitor and control the structural material characteristics during the manufacturing process, in real-time, which significantly improves accuracy, consistency and overall quality control. Although these breakthroughs provide a considerable amount of growth opportunity, persistent gaps still exist, most notably, the dependence on high quality training data, strong data augmentation, and efficient computation framework to manage streamlined, high dimensional data sets. These problems in AI development should be optimally tailored through collaborative efforts with material scientists. There is an increasing need to address these gaps to properly utilize AI within material designing and mechanical engineering. Future models should focus on complex systems that combine traditional logic methods with AI algorithms to improve estimation values and trustability. Combining AI with traditional approaches like FEA and continuum damage mechanics holds great promise for solving problems related to stress evolution under different types of loading and changing environmental conditions. In addition, new methods on microscale analysis or bio-inspired design principles open fresh frontiers for enhancing material properties or structural performance. All AI models undergo a validation process, which ensures their dependability and interpretability. It is essential for practical applications and these models need to be refined through experimental processes. The advancement of AI models can significantly change the paradigm of material optimization by doing so quickly and at a lower cost, which in turn, will increase engineering safety and efficiency.

4. Deep Learning for Structural Health Monitoring of Pavements [T3]

4.1 Introduction

This research introduces a data-driven approach for pavement structural condition assessment through the integration of machine learning with sensor data and traffic information. The contribution lies in the inclusion of key physical variables such as asphalt temperature and pavement layer depth within predictive models. This integration improves the representation of real-world pavement behavior. A comparative evaluation of machine learning methods is conducted, where the long, short term memory model demonstrates superior performance in both training and validation phases. The study advances the field by proving that this model offers strong generalization when applied to unseen data. The novelty is reflected in the connection between predictive modelling and real-time monitoring within smart city systems. This link supports continuous assessment and informed decision making for maintenance planning. The work also provides practical implications for transport authorities, where artificial intelligence-based monitoring systems are recommended for efficient resource allocation, improved safety, and long-term infrastructure sustainability.

Structural health monitoring and predictive pavement analysis play a central role in ensuring the safety, longevity, and functional efficiency of road networks, which underpin contemporary transport systems [116]. The structural health monitoring components contribute across the early planning and design stages of road development, as well as during construction, mobility planning, transport modelling, and subsequent maintenance operations [138]. Conventional techniques for evaluating pavement condition are often limited by high operational costs, logistical constraints, and the risk of traffic interruption, which collectively weaken their suitability for wide-area infrastructure management [143]. An increasing number of machine learning approaches have been introduced to overcome these limitations and address the identified research gaps [102,107,108,135,136].

These models commonly incorporate influential variables such as asphalt surface temperature and pavement layer depth, including asphalt, base, and subbase components, each of which shapes the structural response and functional behavior of the pavement system [140]. The predictive strengths of machine learning are utilized to establish proactive and efficient maintenance planning, thereby improving resource distribution and contributing to the enhancement of road safety [146]. Incorporating structural health monitoring within broader smart city and smart mobility frameworks is presented as a strategy for urban infrastructure governance that is both adaptive and data-driven [132]. Smart mobility, which aims to optimize the movement of people and goods through advanced technological solutions, benefits substantially from a precise, real-time assessment of pavement conditions.

The proposed smart structural health monitoring concept is positioned to reinforce intelligent transport systems, as immediate pavement evaluations support smarter traffic control, route optimization, and adaptive maintenance planning [127]. This methodology ensures that the road network evolves in line with the broader objectives of smart mobility, fostering transport systems that are safe, sustainable, and operationally efficient. The smart structural health monitoring framework is therefore regarded as fundamental to improved pavement management and is established as a core component within smart city and smart mobility agendas [101]. It offers a scalable and environmentally responsible approach to infrastructure stewardship, promoting urban environments that are both resilient and responsive to the needs of current and future populations.

Before the introduction of artificial intelligence, structural health monitoring depended heavily on conventional techniques such as manual inspections and direct testing procedures [125]. These processes involved checking structures for visible forms of deterioration, including cracking and corrosion. Static and dynamic load tests were conducted to observe how structures responded to applied forces [122]. Stress variations were recorded using strain gauges, while hidden internal defects were identified through acoustic emission and ultrasonic examinations [59]. Monitoring changes in vibration patterns was a frequent approach for detecting shifts in structural stiffness, whereas radiographic methods using X rays and gamma rays supported internal diagnostic assessments [152]. Ground penetrating radar was employed to understand the condition of underlying layers Bernard and Yakovenko [111], and infrared thermography located surface irregularities by capturing temperature contrasts [150]. Pavement systems were further evaluated using falling weight deflectometers, which replicated traffic-induced pressures [133]. Although these techniques offered valuable insights, they lacked robust predictive ability. Subsurface or early-stage defects were often overlooked, and many procedures required extensive operational interruptions, making monitoring both inefficient and complex.

Artificial intelligence, including machine learning and deep learning, has altered the structural health monitoring landscape because it enables the rapid and continuous interpretation of extensive datasets in real-time [141]. Traditional approaches are constrained by labor-intensive inspections, costly tools, and limited analytical capacity, which means that early deterioration is frequently missed or structural conditions are assessed only intermittently [123]. Artificial intelligence enhances monitoring by continually analyzing data from sensors, imagery, and historical records, enabling precise and forward-looking evaluations of infrastructure conditions. Machine learning offers predictions of future degradation and maintenance requirements, while deep learning detects fine-scale damage features in drone imagery or sensor streams that conventional techniques typically fail to identify [120]. These systems progressively improve with additional data, which reduces the dependence on manual inspections, lowers maintenance expenditures, and contributes to longer service life. In pavement asset management, artificial intelligence is particularly advantageous because it permits non-intrusive, real-time monitoring of traffic effects, environmental variations, and material fatigue without stopping vehicular movement. Predicting maintenance needs ahead of time supports timely interventions, increases road safety, and strengthens the lifespan of transport networks. Such developments help cities advance towards smarter mobility systems and foster sustainable patterns of urban development [148].

A range of studies illustrates these benefits. For instance, research in Alnaqbi et al. [105] applied machine learning algorithms such as decision trees, random forests, and support vector machines to forecast the degradation of flexible pavements using historical performance information, traffic data, and climate-related variables. These models demonstrated that deterioration trends could be identified early, enabling engineers to plan rehabilitation measures and extend pavement service life. Another investigation employed artificial neural networks to estimate the remaining lifespan of asphalt pavements [156]. Drawing on pavement survey data, core samples, and environmental conditions, the model offered reliable indicators of maintenance needs and supported the optimization of repair schedules. Support vector machines have also been used to forecast the performance and residual life of rigid pavements [105]. Additional studies, for example Ali et al. [104], integrated pavement condition index data, traffic loads, and material properties, resulting in dependable performance predictions and more effective prioritization of maintenance tasks.

A separate real-time monitoring framework analyzed information from accelerometers and deflection sensors placed within the pavement structure [159]. This system captured the pavement's response to weather and vehicle loads, enabling earlier identification of structural issues and lowering disruption to traffic. Deep learning approaches, particularly convolutional neural networks, have been used to process ground penetrating radar data for pavement evaluation [113]. These methods successfully detected subsurface anomalies such as voids and cracking, which improved forecasting of pavement deterioration and informed maintenance planning. Large-scale big data platforms combined with artificial intelligence have also been developed to produce predictive pavement maintenance systems. These platforms utilize extensive datasets including traffic patterns, weather histories, and performance records [151], improving deterioration projections and enabling timely and efficient allocation of maintenance resources.

Several European countries have incorporated AI-based pavement management systems to forecast pavement deterioration and refine maintenance strategies [134]. These systems integrate sensor outputs, traffic-related loading, meteorological conditions, and historical pavement records, which enhance the ranking of repair needs, decrease unexpected disruptions, and contribute to long-term infrastructure renewal. As a result, more sustainable and resilient road networks are supported. These applications demonstrate that AI is reshaping the structural health monitoring (SHM) for pavements because performance forecasting and RSL estimation are significantly improved. In addition, ML, DL, and large-scale data analytics deliver continuous monitoring, early-stage fault detection, and optimized maintenance scheduling, all of which extend network life, reduce operational expenditure, and reinforce sustainable transport systems [137]. Although AI shows considerable capability in forecasting pavement condition and RSL, a number of research limitations remain [149]. Many existing models struggle with generalization, as they are calibrated for specific climatic, geographic, or operational contexts and cannot be reliably transferred to other settings. Predictive accuracy is also weakened by incomplete integration of relevant data sources such as detailed traffic profiles, extended weather histories, and environmental records. Furthermore, advanced AI techniques including DL and reinforcement learning are not yet fully utilized. Another constraint involves the limited representation of uncertainty. Pavement degradation is driven by unpredictable variations such as shifts in traffic load intensity or rapid weather fluctuations. These elements are often ignored in existing AI models, which highlights the need for uncertainty quantification and probabilistic modelling to strengthen predictive robustness [114].

Current AI systems also act largely as black boxes, offering limited insight into how predictions are generated. This introduces challenges for transparency and reduces confidence among engineers and decision-makers. The lack of strong linkage between AI-driven SHM and PMS further restricts the practical use of predictions for direct maintenance planning. Hybrid modelling approaches, continuous learning frameworks, and improved data acquisition strategies have been recommended to address these shortcomings. Such improvements would enhance proactive maintenance planning and support longer-lasting road infrastructure. Recent progress in AI, ML, and DL has notably advanced pavement condition assessment. DL, particularly through CNNs, demonstrates high accuracy in identifying cracking and other damage forms [20]. Tools that incorporate geotagged imagery and geospatial mapping provide spatial context by highlighting the exact locations of defects, enabling quicker and more precise repair interventions [109]. Collectively, these technologies are guiding pavement SHM towards faster, more intelligent, and more dependable systems.

ML continues to transform performance tracking and damage detection by processing large-scale datasets in real-time, surpassing manual methods in both efficiency and reliability [117]. Several developing technologies also have the potential to address existing SHM challenges. The integration of AI with big data analytics is anticipated to enhance pavement monitoring by converting extensive sensor streams into practical maintenance insights [112]. GANs are being explored to generate synthetic datasets for training ML models, helping to reduce issues related to limited real-world data, which is a common barrier in SHM applications [153]. The integration of AI and IoT further expands real-time monitoring capabilities by using inputs from sensors such as accelerometers and GPS devices to detect irregularities and assess pavement conditions with heightened accuracy [118]. Nevertheless, the practical feasibility of these technologies depends on their operational cost, data collection frequency, and implementation complexity, all of which require careful evaluation to ensure long-term sustainability [155].

Despite major advancements, several modelling challenges persist. The black box characteristics of AI methods continue to impede interpretability, responsibility, and user confidence. Ongoing research on model transparency and explainability seeks to mitigate these issues [157]. Environmental and operational variability also remains a substantial concern because AI models may yield inconsistent outcomes under changing conditions such as variable weather patterns, temperature fluctuations, or traffic volume shifts. There is a need for resilient models capable of adapting to such dynamic inputs to maintain reliable SHM performance [147]. A multidisciplinary strategy that integrates technological progress with practical implementation considerations is essential to enable AI-driven SHM systems to reach their full potential in supporting efficient and sustainable pavement maintenance.

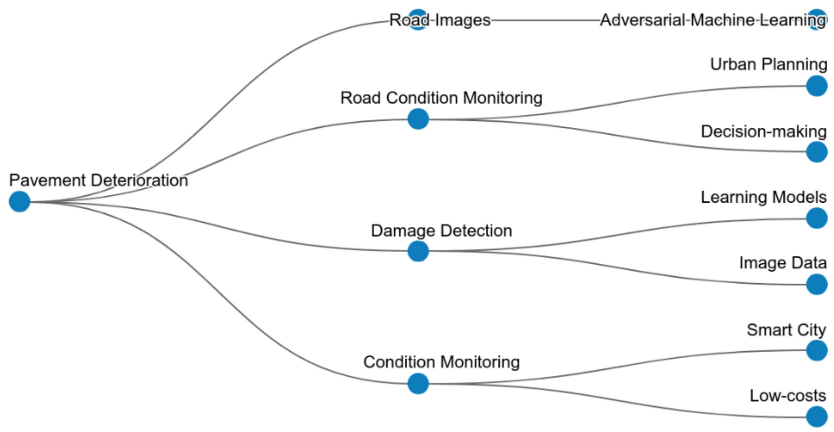


Figure T3.1. Taxonomy of ML Applications for Pavement Modelling

ML is increasingly recognized as a central component in forecasting the RSL of pavement structures, and its incorporation into PMS enhances the accuracy and operational efficiency of maintenance planning by offering analytical insights that exceed the capabilities of conventional assessment techniques [155]. Regression-based approaches have shown reliability in estimating asphalt friction performance García-Segura et al. [124], while more sophisticated ML methods such as Random Forests provide significant gains in predicting roughness progression, rutting behavior, and fatigue-related cracking [159]. SVM and ANN models also demonstrate strong predictive capability, with ANN frequently producing superior estimations for roughness-related parameters [103]. Within DL, models including YOLOv5 and U-Net achieve notable precision for crack identification and segmentation tasks [126]. Time-series analyses benefit from architectures such as RNN and LSTM, with hybrid configurations like LSTM–FCNN consistently outperforming conventional modelling strategies [142]. Integrated systems such as SOS-LSSVR further advance predictive performance by coupling optimization procedures with regression-based techniques [144]. These AI-enabled methods contribute to more efficient asset management by refining maintenance scheduling, prolonging pavement lifespan, and lowering overall repair expenditures [145]. Linking AI with continuous, real-time data acquisition further accelerates condition assessment and supports earlier, more targeted remedial actions [118]. Nonetheless, several constraints remain, particularly concerning labor-intensive data annotation and the limited capacity of models to adapt reliably across varied climatic, structural, and operational settings [148]. Continued research is required to embed AI throughout the entire pavement management cycle, extending from system design to long-term maintenance, to ensure broader adoption and deliver sustainable improvements in road infrastructure performance.

As shown in Figure 2, DL approaches play a central role in advancing pavement performance forecasting. Architectures such as RNN and LSTM demonstrate strong capability in analyzing time-series datasets to anticipate changes in pavement condition, while CNN models effectively detect and classify pavement distress patterns [121]. These methods improve the precision of deterioration and modulus prediction, contributing to more dependable estimates of pavement reliability and overall service life [100]. Ensemble learning offers further gains by integrating multiple modelling strategies. Techniques such as RFR and GBM have proven effective in forecasting deterioration trends and addressing diverse mechanisms of pavement degradation [110]. Deep ensemble frameworks that merge neural networks with tree-based algorithms enhance predictive quality for indicators including surface roughness and cracking [129]. Such approaches support the formulation of targeted maintenance actions and strengthen the optimization of pavement management programs. Despite these benefits, notable challenges remain, including restricted data availability and the inherent complexity involved in linking different model types. Approaches such as data augmentation and hybrid methods that combine regression-based modelling with physically informed representations can help mitigate these issues. Accordingly, the proposed framework emphasizes robust modelling principles to generate accurate, actionable, and efficient predictions of pavement life, thereby reinforcing sustainable maintenance practices and long-term infrastructure resilience.

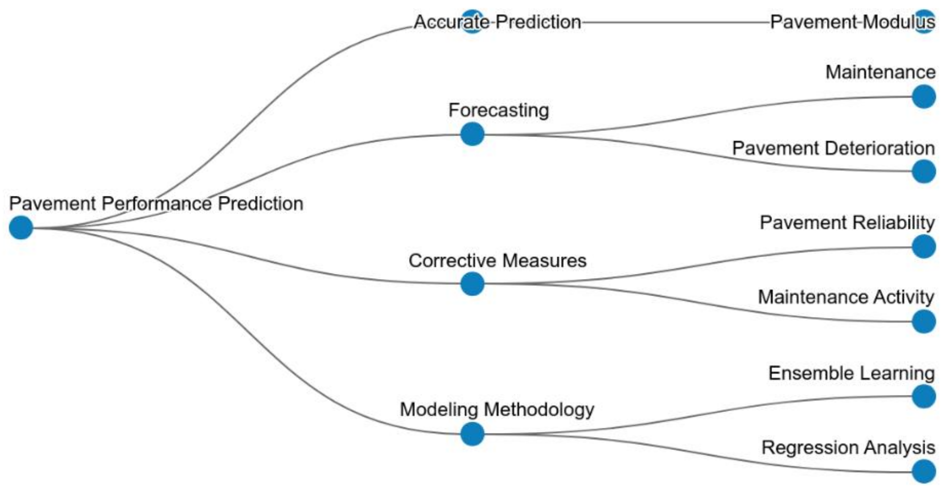


Figure T3.2 Taxonomy of DL Applications in Pavement Modelling

4.2 Materials and Methods

4.2.1 Data Description

In this study, data were compiled to estimate the RSL of pavement sections, defined as the number of years remaining before the pavement falls below an acceptable performance threshold. RSL serves as the dependent variable and is derived from surface deflection measurements collected using the FWD. The FWD generates a dynamic load that replicates traffic effects, and the resulting deflection profiles are processed through back-calculation procedures to evaluate the structural capacity of the pavement. The key inputs for determining RSL include the thickness of the AC layer, the thickness of the BS layer, and the asphalt surface temperature. Measurements of AC and BS thicknesses are obtained using GPR, a non-destructive technique capable of identifying subsurface layering characteristics. AC refers to Asphalt Concrete, which forms the surface pavement layer. AC surface temperature represents the temperature of the asphalt surface and affects pavement stiffness, rutting, and cracking behavior. AC thickness represents the thickness of the asphalt layer and influences load distribution and structural performance. BS thickness refers to the thickness of the base or subbase layer beneath the asphalt surface, which provides structural support and improves pavement durability and resistance to deformation.

Asphalt surface temperature is recorded directly during field inspections, thereby incorporating environmental influences into the RSL estimation process. This dataset forms the basis for developing models capable of estimating RSL without constant reliance on simultaneously using the costly instruments such as the FWD and GPR, which provides a more economical assessment option for regions with constrained resources. Model validation uses data obtained from detailed field investigations, including both HWD and GPR measurements, ensuring that the predictive output remains reliable and robust. The resulting model delivers a cost-efficient and non-intrusive SHM approach, drawing on ML to interpret complex interactions among input variables and the associated pavement response behavior.

4.2.2 Modelling

In this study, modelling was performed to predict SHM of pavements. AC surface temperature, AC thickness, and BS thickness were treated as independent variables, while RSL served as the dependent variable. Seven established ML techniques formed the core of the comparative analysis: Stochastic Gradient Descent (SGD), Extreme Gradient Boosting (XGboost), standalone ANN, ANN coupled with particle swarm optimizer (PSO), ANN integrated with grey wolf optimizer (GWO), AdaBoost, and LSTM. The modelling was executed using Python 3.6.5 with TensorFlow, Scikit-learn, and XGBoost libraries on a Win10 64-bit system (32 GB RAM, Intel i7-9750H), as well as MATLAB 2018 on the same hardware configuration. A 75:25 split was applied to divide the dataset into training and testing subsets, ensuring sufficient learning capacity while maintaining unbiased evaluation. Hyperparameters were optimized via a guided trial-and-error approach, using performance metrics including MAE, RMSE, and R^2 to determine the most effective configurations. In this study, model selection was guided by both literature-based reasoning and practical experience. Basic algorithms such as SGD and ANN served as benchmarks, whereas more advanced approaches, including XGBoost, AdaBoost, and hybrid ANN models augmented with PSO and GWO, were employed due to their capacity to capture complex non-linear patterns and enhance predictive accuracy. LSTM was incorporated for its ability to process sequential data, which is critical for analyzing pavement performance over time. All modelling was conducted in Python and MATLAB on high-performance systems to ensure efficient computation. The dataset underwent careful preparation, including normalization, treatment of missing values, and selection of the most informative features.

4.2.3 Stochastic Gradient Descent (SGD)

SGD functions as an optimization algorithm and is also classified as an ML technique [106]. It determines the optimal learning pathway for ML models by randomly selecting a single data point in each iteration. This approach facilitates the computation of loss gradients with respect to model parameters. In this study, the optimal configuration was identified through a trial-and-error procedure. The resulting model employed an epsilon-intensive loss function of 0.31, elastic net regularization with a mixing ratio of 0.15, and a learning rate of 0.15, which was determined to provide the best performance. The optimal configuration was obtained through a systematic trial and error tuning process in which several combinations of hyperparameters were evaluated. The investigated parameters included the epsilon intensive loss value, elastic net mixing ratio, and learning rate. For each parameter, multiple candidate values within practical ranges were tested, and model performance was measured on the validation dataset. The epsilon parameter controlled the insensitive error margin, the elastic net ratio controlled the balance between L1 and L2 regularization, and the learning rate controlled the update step size during optimization. The configuration with an epsilon value of 0.31, elastic net mixing ratio of 0.15, and learning rate of 0.15 produced the best results. Optimality was determined based on superior validation performance, such as the lowest prediction error and the highest goodness of fit metrics compared with the other tested configurations. In other words, the optimal SGD configuration was determined through a systematic hyperparameter tuning process based on iterative trial and error evaluation. The hyperparameters investigated included the epsilon insensitive loss parameter, elastic net regularization mixing ratio, and learning rate, each of which was tested across multiple candidate values to analyze their influence on model convergence, prediction stability, regularization strength, and generalization performance. The epsilon parameter controlled the insensitive error margin, the elastic net ratio controlled the balance between L1 and L2 regularization, and the learning rate controlled the gradient update magnitude during stochastic optimization. For each hyperparameter combination, the SGD model was trained and validated using identical dataset partitions, and performance was assessed using prediction error and goodness of fit metrics on the validation dataset. Configurations that produced unstable convergence, higher validation error, or weaker predictive accuracy were excluded. The configuration with an epsilon value of 0.31, elastic net mixing ratio of 0.15, and learning rate of 0.15 achieved the lowest validation error and the highest predictive performance among all tested configurations and was therefore selected as the optimal SGD setting.

4.2.4 Extreme Gradient Boosting (XGBoost)

XGBoost is an ensemble-based ML technique that constructs a robust predictive framework by combining multiple decision trees [115]. The process begins with an initial estimate, typically the mean of the target variable, and iteratively refines predictions by training successive models on the residuals of prior iterations. This approach allows XGBoost to emphasize previously misclassified instances and mitigate bias, thereby enhancing overall predictive accuracy. In this study, hyperparameters were fine-tuned using a trial-and-error approach, with the number of trees set to 25, the learning rate to 0.3, and the regularization parameter lambda to 0.8, achieving optimal prediction performance.

4.2.5 Artificial Neural Network (ANN)

ANN is an ML technique inspired by the structure of the human nervous system [103]. It is designed to emulate human learning and information processing. The network is composed of interconnected nodes, or “neurons,” organized in layers. Typically, an ANN contains three types of layers: an input layer, which receives data from the environment; one or more hidden layers, which process information through weighted connections and activation functions; and an output layer, which produces the final predictions. In this study, the ANN architecture was determined via a trial-and-error approach, resulting in a configuration of 3-18-4-1 with a ReLU activation function and SGD solver, which provided the most accurate predictions.

4.2.6 ANN Integrated with Particle Swarm Optimizer (PSO)

In this stage, the previously designed ANN architecture was combined with PSO to optimize weights and biases more effectively. This approach enhances the training process by dynamically adjusting the network parameters. PSO is a population-based optimization algorithm in which each particle represents a candidate solution and updates its position in the search space by considering both its individual experience and that of neighboring particles. This mechanism directly influences ANN performance. In this trial-and-error procedure, the existing network architecture was retrained using PSO with 150 particles and a maximum of 680 iterations, yielding the optimized configuration.

4.2.7 ANN Integrated with Grey Wolf Optimizer (GWO)

In this phase, the ANN developed in the previous step was integrated with GWO to enhance the optimization of weights and biases. The use of a supplementary optimizer during ANN training improves parameter tuning, resulting in more accurate predictions. GWO is a swarm intelligence algorithm that emulates the social hunting behavior of grey wolves, relying on hierarchical leadership and cooperative strategies to navigate the solution space [130]. The parameters for this method were selected through a trial-and-error process, using 100 wolves and 510 iterations to achieve the optimized configuration.

4.2.8 Adaptive Boosting (Adaboost)

AdaBoost is an ensemble learning ML technique that combines multiple weak classifiers to generate a robust predictive model [154]. Initially, the algorithm assigns equal weights to all training samples, which are then adjusted iteratively after each model is trained. This procedure continues until the predetermined number of classifiers is reached. The final prediction is derived as a weighted sum of all weak learners, with models demonstrating higher accuracy contributing more significantly to the output. In this study, the AdaBoost configuration was determined using a trial-and-error approach.

4.2.9 Long Short-Term Memory (LSTM)

LSTM is a specialized form of RNN and a subset of DL. This architecture regulates the flow of information to retain relevant patterns across long sequences while discarding irrelevant data during training [128]. The network configuration was established through a trial-and-error approach. The optimized LSTM model consisted of two hidden layers, each containing 50 nodes, with a learning rate set at 0.0008.

4.2.10 Evaluating the Models

In this study, two commonly applied evaluation metrics, RMSE and CC, were utilized (Eq. 1 and 2). RMSE quantifies the deviation between observed and predicted values, serving as an error-based performance indicator.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x_i})^2} \tag{1}$$

$$Correlation\ Coefficient = \frac{Cov(x,\hat{x})}{\sigma_x \sigma_{\hat{x}}} \tag{2}$$

Here, N represents the total number of samples, x_i the observed values, and $\hat{x}_i$ the predicted values, and σ_x is the standard deviation of observed values x and $\sigma_{\hat{x}}$ is the standard deviation of predicted values $\hat{x}$ [32; 40].

4.3 Results

4.3.1 Statistical Specifications of Dataset

In this step, the relationships among variables are outlined. Table T3.1. summarizes the statistical characteristics of the variables, including mean, sample size, standard deviation, median, minimum, maximum, variance, and skewness. Table T3.1. presents the statistical characteristics of the three input variables and the output variable. In1 corresponds to AC surface temperature, In2 corresponds to AC thickness, and In3 corresponds to BS thickness. The output variable (Out) represents the target response predicted by the model. The abbreviated notation was adopted in the table to improve readability and compactness; however, the full variable descriptions should be explicitly stated in the table caption or accompanying text to avoid ambiguity.

Table T3.1. The Statistical Specifications of Variables

	In1	In2	In3	Out
Mean	27.6180	170.8413	270.7913	18.0521
N	576	576	576	576
Std. Deviation	4.06419	35.25535	106.38773	15.15706
Median	27.7178	166.0000	282.0000	12.0000
Minimum	19.00	0.00	0.00	0.00
Maximum	35.90	280.00	467.00	40.00
Variance	16.518	1242.940	11318.349	229.736
Skewness	-.017	.394	-.062	.463

Table T3.2. presents the ANOVA results for the variables. The analysis indicates that the influence of the input variables on the output variable is significant at the 5% level, confirming that the modelling process can be conducted reliably. ANOVA, which stands for Analysis of Variance, is a statistical method used to determine whether the mean values of different groups differ significantly by comparing the variation between groups with the variation within groups. It tests whether an input variable has a meaningful effect on an output variable through the F statistic and the significance value (p value). In Table 2, ANOVA is applied to examine the effects of In1, In2, and In3 on the output variable. Since the significance values for In1 (0.046), In2 (0.029), and In3 (0.048) are all below 0.05, the results indicate that all three input variables have statistically significant effects on the output variable at the 5% significance level. The column "df" represents the degrees of freedom, which indicate the number of independent values used in the analysis for both between group and within group variations. The column "F" represents the F statistic, which measures the ratio between explained variance and unexplained variance. Higher F values indicate a stronger influence of the input variable on the output variable. The "Sig." column represents the p value, where values below 0.05 confirm statistically significant effects at the 5% significance level. The results indicate significance at the 5% level because the p values for In1 (0.046), In2 (0.029), and In3 (0.048) are all below the threshold value of 0.05. In ANOVA, a p value below 0.05 indicates that the relationship between the input and output variables is statistically significant and not caused by random variation. Therefore, the null hypothesis is rejected for all three input variables.

Table T3.2. ANOVA Results

		Sum of Squares	df	Mean Square	F	Sig.
	Between Groups	860.61	39	22	1.38	
In1 * Out	Within Groups	8772.044	8572.04	536	16	.046
	Total	9497.656		575		
	Between Groups	70273.5	39	1802	1.49	
In2 * Out	Within Groups	644416.757	644416.75	536	1202	.029
	Total	714690.257		575		
	Between Groups	563803.97	39	14457	1.35	
In3 * Out	Within Groups	5971966.579	5719696.7	563	10671	.048
	Total	6508050.557		575		

4.3.2 Modelling Results

This step comprises two phases: training and testing. Table 3 summarizes the network training outcomes. The LSTM model emerged as the best performer, exhibiting the lowest RMSE (2.45) and the highest CC (0.98), indicating very high predictive accuracy and strong alignment with observed data. The ANN-GWO model also demonstrated strong performance, with an RMSE of 2.82 and a CC of 0.97, approximately 15% less accurate than LSTM. Following these, the ANN-PSO and ANN models achieved RMSE values of 2.96 and 3.46, with corresponding CCs of 0.96 and 0.94. In contrast, XGBoost, despite a reasonable CC of 0.88, showed a higher RMSE (17.04), reflecting lower predictive precision. SGD exhibited the poorest performance, with an RMSE of 6.92 and a CC of 0.73, rendering it unsuitable for this task. Based on these training results, LSTM and ANN-GWO are recommended for high-accuracy prediction, although the outcomes of the testing phase must also be considered to make a final determination.

Table T3.3 Training Results of the Developed Models

Model	Architecture	RMSE	CC
SGD	Loss function of the epsilon intensive type of 0.31, elastic net regulation with mixing of 0.15 and learning rate optimization of 0.15	6.92	0.73
XGboost	Number of trees 25, learning rate 0.3, and lambda 0.8	17.04	0.88
ANN-PSO	3-18-4-1 integrated with PSO by number of particles 150 and maximum iterations 680	2.96	0.96
ANN	3-18-4-1 with activation function, ReLU and SGD solver	3.46	0.94
ANN-GWO	3-18-4-1 integrated with GWO by number of wolves 100 and number of iterations 510	2.82	0.97
AdaBoost	Number of estimators 12, Learning rate 0.3, loss function of square	5.34	0.88
LSTM	Two hidden layers, the number of nodes in each hidden layer was 50, and the learning rate was set to 0.0008	2.45	0.98

Table T.3.4 presents the testing results. Comparing these outcomes with the training phase, the LSTM model demonstrated the highest performance in both phases, with an RMSE of 3.01 and a CC of 0.92, reflecting strong predictive accuracy and robust generalization to unseen data. A reduction in accuracy is observed during testing compared to training, with the LSTM model showing an approximate 20% decrease in performance. The ANN-GWO model also performed well, achieving an RMSE of 3.55 and a CC of 0.89, although its performance declined by around 40% relative to the training phase. Other models experienced decreases exceeding 40%, indicating lower reliability. Notably, SGD and XGBoost exhibited comparatively poor results in the test phase, suggesting potential overfitting. These findings highlight the high confidence and generalization capability of the LSTM model, which is therefore recommended as the optimal choice for this analysis.

Table T3.4. Testing Results of the Developed Models

Model	Architecture	RMSE	CC
SGD	Loss function of the epsilon intensive type of 0.31, elastic net regulation with mixing of 0.15 and learning rate optimization of 0.15	9.47	0.53
XGboost	Number of trees 25, learning rate 0.3, and lambda 0.8	20.16	0.62
ANN-PSO	3-18-4-1 integrated with PSO by number of particles 150 and maximum iterations 680	3.75	0.85
ANN	3-18-4-1 with activation function, ReLU and SGD solver	4.92	0.81
ANN-GWO	3-18-4-1 integrated with GWO by number of wolves 100 and number of iterations 510	3.55	0.89
AdaBoost	Number of estimators 12, Learning rate 0.3, loss function of square	14.44	0.72
LSTM	Two hidden layers, the number of nodes in each hidden layer was 50, and the learning rate was set to 0.0008	3.01	0.92

Figure T.3.3 presents the plot diagrams of the developed models during the testing phase. As shown, the regression lines for SGD, XGBoost, and AdaBoost deviate substantially from the one-to-one line, indicating that the predicted outputs do not align well with the actual values, and thus their predictions are unreliable. In contrast, models based on ANN and DL exhibit regression lines closely aligned with the one-to-one line, demonstrating high correspondence and confirming the reliability of their results. The scatter plot illustrates the relationship between predicted and target values for the LSTM model. Each point represents a predicted value plotted against its corresponding observed target. The solid line denotes the ideal 1:1 relationship, where predictions perfectly match observations, while the dotted line represents the regression fit of predicted versus actual values. The high coefficient of determination (R^2 = 0.8566) indicates that the model explains a substantial proportion of the variance in the target values, reflecting strong predictive performance, although some deviations reveal occasional under- or over-predictions.

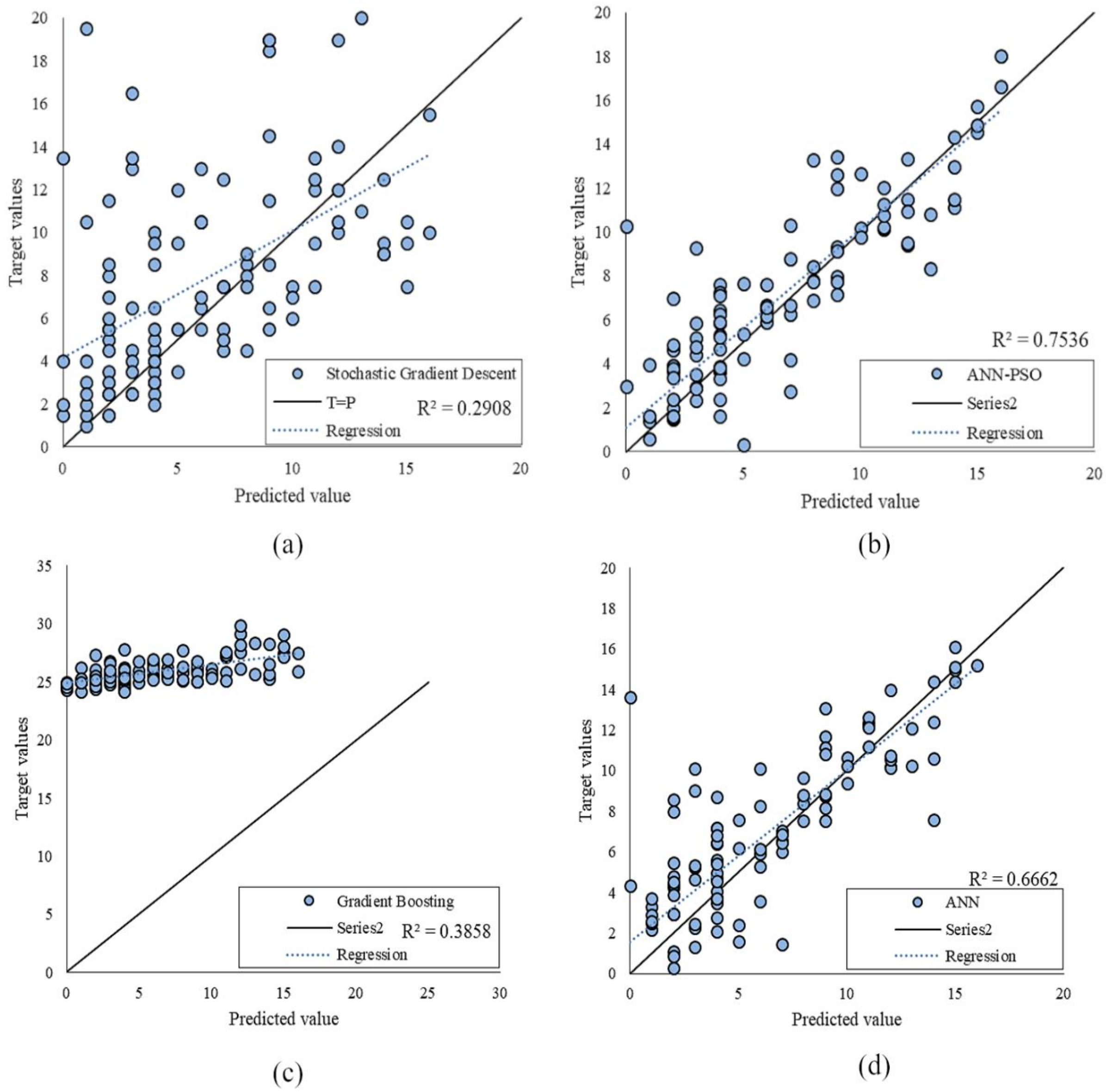
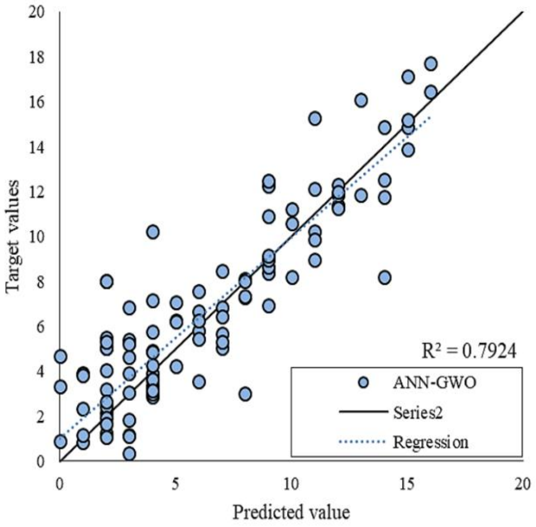
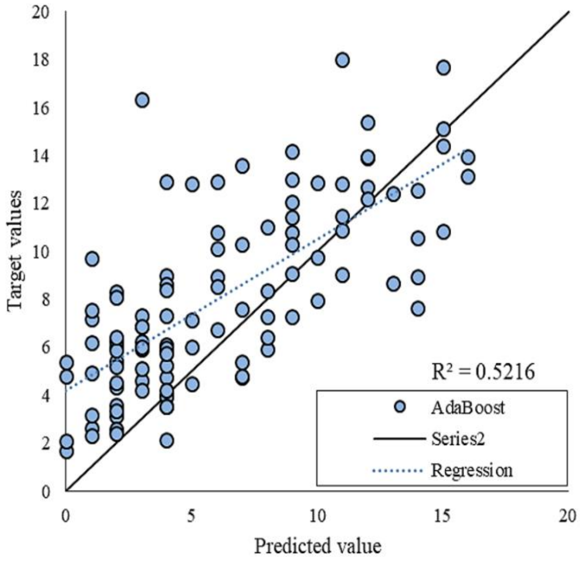


Figure T3.3. The Plot Diagram of the Testing Phase. a) Stochastic Gradient Descent, b) Gradient Boosting, c) ANN-PSO, d) ANN



(e)



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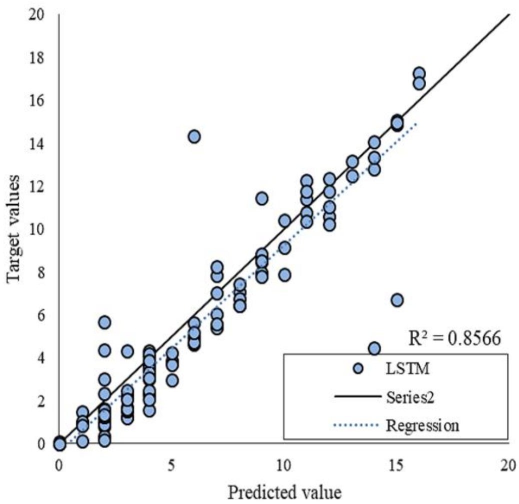

(g)

Figure T3.4. The Plot Diagram of the Testing Phase. e) ANN-GWO, f) AdaBoost, and g) LSTM

In the plots in figure T3.3 and T3.4, T = P denotes the ideal agreement line where the target value is equal to the predicted value. This diagonal reference line is included to provide a direct visual benchmark for evaluating model accuracy. Data points located close to this line indicate strong predictive performance, while larger deviations indicate higher prediction error. The label Series2 in the second figure refers to the same reference line. It was retained as the default legend entry generated by the plotting software during figure export. Although different labels appear in the two plots, both denote the identical concept of perfect agreement between predicted and target values. The distinction is only graphical and has no effect on the interpretation of the results. The reference line was included in both figures to support visual comparison between actual and predicted responses and to illustrate model reliability.

Figure T3.5 presents the relative squared error for each model during the testing phase. As indicated, XGBoost exhibits the highest negative relative error, whereas LSTM achieves the lowest positive relative error. In this context, a desirable error is minimal and positive. Negative errors suggest an inverse relationship between predicted and actual values, which is inconsistent with the objectives of this study. Moreover, analysis of MAE across the models shows that LSTM exhibits the lowest error, indicating the highest predictive accuracy and reliability. ANN-based models, including ANN-GWO and ANN-PSO, also demonstrate relatively low errors. In contrast, Gradient Boosting and SGD performed poorly, suggesting their limited suitability for pavement condition prediction tasks.

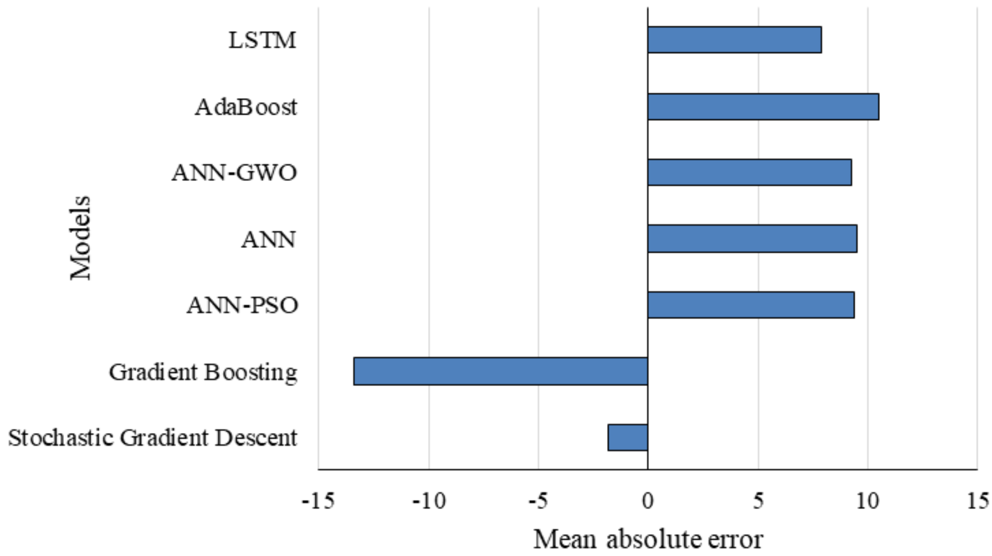

Figure T3.5. Square Relative Error of Testing Phase

4.4 Discussion

The results of this study demonstrate the superior performance of LSTM in predicting pavement SHM. With an RMSE of 3.01 and a CC of 0.92, LSTM outperformed all other evaluated models, showing both high predictive accuracy and strong generalization to unseen data. Visual analyses in Figures 3, 4, and 5 further support their ability to capture complex temporal dependencies within the dataset. The sequential architecture of LSTM is particularly suited to time-dependent data, which is critical in infrastructure monitoring where pavement conditions evolve over time. Among ANN-based models, the ANN-GWO hybrid displayed notable performance, achieving an RMSE of 3.55 and a CC of 0.89, indicating that optimization-enhanced neural networks can deliver effective predictions. However, the gap between ANN-GWO and LSTM highlights the limitations of conventional ANN models in representing long-term dependencies and nonlinear degradation processes. These findings align with previous studies reporting that DL methods surpass traditional models in time-series forecasting and SHM applications.

Other models, including ANN-PSO and standard ANN, showed moderate performance, whereas XGBoost and SGD were less effective. XGBoost, although robust for structured data, lacks the capacity to model temporal patterns, while SGD's relatively poor performance is attributable to sensitivity to data distribution and limited capability to capture nonlinear relationships without extensive tuning or feature engineering. Collectively, these results indicate that model selection should not rely solely on predictive accuracy; generalization to real-world conditions and accurate representation of underlying system behavior are equally important. LSTM addresses both aspects, making it a strong candidate for practical pavement monitoring. By learning historical patterns and predicting future deterioration, LSTM facilitates proactive maintenance and long-term infrastructure planning. These findings corroborate recent research advocating DL in transportation asset management and point toward future research directions, including the development of ensemble and hybrid learning techniques, integration of pavement and traffic datasets into unified models, and the application of explainable AI to enhance interpretability. Incorporating advanced models like LSTM into operational monitoring systems enables transportation agencies to advance toward more efficient and sustainable infrastructure management.

4.5 Conclusion

This study examines the reliability of DL for modelling SHM of pavements, using asphalt temperature and pavement thickness to predict current conditions and future deterioration. Model performance was validated with field measurements from HWD and GPR, confirming both accuracy and robustness. Among the models evaluated, LSTM demonstrated the highest performance, followed by ANN-GWO. Other methods, including ANN-PSO, ANN, XGBoost, and SGD, exhibited lower reliability and are considered less suitable for this application. High-performing models can be integrated with smart city and IoT frameworks to enable real-time, cost-effective, and non-intrusive pavement monitoring. Such integration enhances road safety, reduces maintenance expenditures, and extends pavement service life. Transportation agencies are encouraged to adopt AI-based monitoring systems and consolidate sensors, traffic, and environmental data to support informed decision-making. Policy measures are required to promote predictive maintenance strategies, optimizing budgets while improving public safety and sustainability. Future research should explore additional models, incorporate larger and more diverse datasets, and validate model performance across different regions. Further investigations should focus on explainable AI, hybrid, ensemble, and transferring learning approaches. Moreover, combining traffic prediction with pavement monitoring through spatiotemporal modelling can facilitate unified systems for urban mobility and infrastructure management, supporting resilient and sustainable cities.

5. AI-based Structural Health Monitoring of Pavements [T4]

5.1 Introduction

This study develops an artificial intelligence based structural health monitoring model that integrates nondestructive sensing technology with machine learning algorithms. The contribution lies in the combined use of Support Vector Machine, Random Forest, and Artificial Neural Network methods to estimate pavement properties such as temperature, thickness, and subsurface conditions. The use of a radiotechnical subsurface scanning device introduces a high resolution and inductive data source, which improves prediction capability. Model performance is evaluated through RMSE and correlation coefficient, where strong accuracy and generalization are observed, particularly for Support Vector Machine and Random Forest models. The novelty of this research lies in the integration of advanced sensing technology with artificial intelligence in a cost efficient and scalable manner. This combination enables automated and continuous monitoring of pavement health. The study further contributes by demonstrating how such systems can be incorporated into smart city environments, which supports safer and more efficient urban transport networks and promotes long-term infrastructure resilience.

The evolution of AI or Artificial Intelligence technologies is becoming a game changer in the domain of SHM automating the assistance of precision, decision-making, and management effectively solving infrastructural challenges. Historically, as Abdallah and Naziran describe in their works dated back to 2009, pavement inspection depended largely on manual surveys accompanied by the evaluation for many tangible features, which was vulnerable to inconsistencies, delays, and human input errors. The application of ANNs (Artificial neural networks) enabling reasoning about nondestructive testing led to efficient reinterpretation and processing of the pavement tests being done [160]. The shift in SHM from static manual techniques to intelligent autonomous adaptable systems was a remarkable achievement. Facing the persistent difficulties: estimating the material properties and forecasting the remaining service life for pavements; was a turning point in their proactive asset management strategy. In this context, deep learning has added further possibilities for assessing pavement conditions, especially for surfaced damage detection. A model developed by Baduge et al. (2023) employs deep learning not only for simple crack identification but also for measuring the crack's width and geospatially mapping damage locations to enable targeted and efficient maintenance [161]. At the same time, the merging of image-based assessments with nondestructive testing tools, as done by Keshmiry et al. (2024), has expanded the role of AI in condition evaluation to allow comprehensive assessment without using invasive techniques [164]. Meanwhile, Barbhuiya and Das (2025) showcased how AI can be applied alongside distributed sensor networks to autonomously identify internal deterioration, demonstrating a shift in emphasis from superficial diagnostics to rich, holistic, multi-sensor data monitoring strategies [162]. All these advances demonstrate that AI is not just automating processes but also augmenting the granularity and richness of information on pavements' health. Recent advancements have also focused on combining AI with real-time data to enable continuous infrastructure surveillance. Di Mucci et al. (2024) emphasized the impact of pairing AI algorithms with Internet of Things (IoT) devices for real-time bridge inspections, allowing systems to detect changes and anomalies as they occur [163]. Kumar and Kota (2024) highlighted another critical frontier: securing AI-based SHM systems against cyber threats, advocating for robust frameworks that protect both infrastructure data and privacy [165]. Additional layers of insight come from integrating AI with acoustic emission technologies, as demonstrated by Scuro et al. (2021), who showed how machine learning can detect subtle signals of material stress or crack propagation well before visible signs emerge [170]. These studies reflect a broader trend toward multidimensional monitoring solutions that offer infrastructure managers a richer and more proactive view of structural integrity. As these intelligent systems scale, the role of AI in predictive maintenance and long-term planning becomes even more pronounced. Xu and Zhang (2022) reviewed the integration of traffic and environmental datasets into machine learning models, showing how these inputs improve forecasts of pavement degradation under real-world conditions [174]. Ramadan et al. (2024) also reported improvements in the modeling and scheduling of maintenance for flexible pavements using AI, contributing to more strategic resource allocation [169]. Ngo-Kieu et al. (2023) took this further by introducing big data frameworks that streamline the interpretation of massive SHM datasets, a vital step for large-scale infrastructure networks [168]. Manoni et al. (2024) emphasized the scalability of deep learning in road condition monitoring, providing timely, location-specific insights for maintenance teams [166]. Innovations such as those by Marin-Artieda et al. (2023) demonstrate the growing alignment between AI technologies and stakeholder needs in the civil infrastructure sector, including transparency and ease of integration [167]. Xu and Guo (2025) extended this vision to lifecycle applications, positioning AI as an end-to-end solution for infrastructure management [173]. Nevertheless, challenges remain. Sun et al. (2020)

underscored the issue of generalizability in AI models, many of which struggle when applied beyond the datasets or conditions they were trained on [172]. Spencer et al. (2025) echoed the importance of comprehensive and annotated datasets, noting that without quality input, AI models cannot reach their full potential [171]. Beyond technical constraints, social acceptance of AI also matters. Marin-Artieda et al. (2023) found that stakeholder trust hinges on the interpretability of AI decisions and the perceived fairness of automated systems [167]. In terms of data infrastructure, Abu Dabous et al. (2025) called for better 3D imaging technologies and open-source data to support more adaptable SHM applications [176]. The continued surge in AI-related patents, as mapped by Desai et al. (2024), signals that the private sector sees strong potential in this space, suggesting a growing convergence of research, policy, and commercial innovation [177]. Zhang et al. (2024) further detailed how intelligent survey tools are already changing the way pavement assessments are conducted, making real-time condition mapping a feasible goal [175]. The increasing adoption of AI in SHM carries implications far beyond the engineering domain, it is a critical enabler of smarter, safer, and more sustainable cities. As global urban populations grow and transportation networks become more complex, infrastructure systems must evolve to be not only reactive but also intelligent and anticipatory. AI-based SHM supports this shift by enabling continuous, automated monitoring that enhances safety, minimizes disruption, and reduces long-term maintenance costs. Xu and Zhang (2022) noted that AI integration allows cities to align maintenance priorities with real-time usage and environmental stressors [174]. At the same time, these innovations feed directly into smart mobility initiatives, improving traffic flow and accessibility while reducing emissions and resource waste. The novelty of AI in this context lies in its ability to interpret complex, multisource data without constant human oversight, facilitating proactive infrastructure governance that resonates with the broader goals of sustainability and digital transformation.

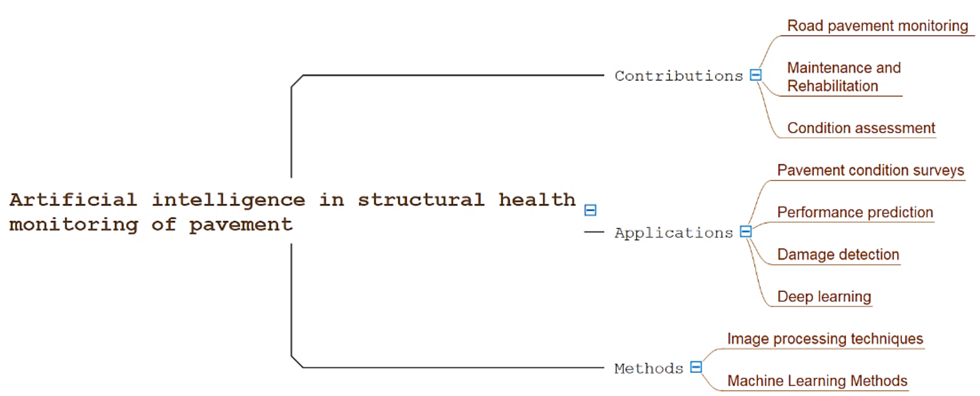

Figure T4.1. Taxonomy of AI-based Research on Structural Health Monitoring of Pavements

The taxonomy shown in Figure T.4.1 represents a scientifically valid and human-friendly view of the involvement of AI in the SHM of the roads. Table T4.1. also summarizes the applications and methodologies of ai-based research on structural health monitoring of pavements. It classifies the research domain into three primary groups: Contributions, Applications, and Methods. The Contributions domain spotlights the social and infrastructural significance of AI, concentrating precisely on the road pavement management, maintenance and rehabilitation, and condition assessment sectors, those areas that are of utmost importance for public safety and efficiency of resources. The Applications domain shows how AI is implemented in reality and also covers the crucial tasks of performance prediction and damage detection, with the help of deep learning models as the main source for increased accuracy and automation. At the same time, the Methods domain is all about the technical aspects of this study, such as image processing methods and the working of machine learning algorithms, which allow the steering of decisions by the data. Collectively, this taxonomy presents a comprehensive view of how AI technologies are indeed the facilitates for not only the assessment and maintenance of pavement infrastructure but also the innovation and development of the broader field of intelligent transportation systems.

Table T4.1. Summary of the applications and methodologies of AI-based Research on Structural Health Monitoring of Pavements

Method	Application	Contributions	Ref
Artificial Neural Networks	Pavement layer property estimation, performance curve development, remaining life estimation	Simplifies complex back calculation methods, reduces computational effort, enhances accuracy	[160]
Deep Learning	Crack detection, width calculation, geolocation-based visualization	High validation accuracy (99%), novel crack width calculation, geospatial mapping for maintenance	[161]
Machine Learning	Distress detection, performance modeling, maintenance programming	Effective in distress detection and classification, major research gap in M&R programming	[162]
Computer Vision	Automated visual inspection of bridges, damage detection	Enhances visual inspection accuracy, integrates with IoT for real-time monitoring	[163], [164]
SVM, k-Nearest Neighbor, Adaptive Boosting	Acoustic emission analysis for structural event classification	High classification accuracy in detecting structural critical events	[165]
Convolutional Neural Networks	Image analysis for damage detection	Precision in identifying structural issues, integration with non-destructive testing methods	[164]
Big Data Techniques	Data analysis for bridge SHM	Addresses data interpretation challenges, builds BD-oriented SHM framework	[166], [167]

As classified and summarized in the table, applying Artificial Intelligence for structural health monitoring of pavements represents a notable progress in the management and maintenance of transport infrastructure. Neural networks, deep and machine learning, computer vision, and big data analytics AI techniques have fostered the ability to assess pavements and detect issues at a greater pace and precision than traditional methods. These techniques enable automation of sophisticated processes such as crack detection, layer property estimation, and classification of distress, enabling continuous monitoring. This high level of automation not only reduces the need for exhaustive inspections but also improves the accuracy of the data captured. However, there is still an enormous gap between promise and reality; the integration of AI into standard engineering poses particular challenges with regard to data homogenization or standardization, model generalization, and the availability of numerous high-quality datasets. Looking ahead, there are expectations that the synergy of AI, digital twin systems, and Internet of Things devices will provide seamless automation of predictive maintenance with enhanced real-time monitoring of integrated systems. This evolution will enable infrastructure managers to shift from reactive to proactive maintenance strategies, ultimately extending pavement life, optimizing resource allocation, and reducing costs over the pavement's lifecycle.

5.2 The key challenges

The key challenges in implementing AI for structural health monitoring of pavements still remains. There are significant obstacles in the data, computational, and deployment domains when implementing AI for pavement SHM. Model performance and reliability are impacted by data-related problems, such as the challenge of gathering balanced, high-quality datasets and the time-consuming nature of precise annotation [178-180]. The intricacy of processing various sensor data and the limited transferability of AI models trained in particular contexts limit their wider applicability, which leads to computational challenges [181,182]. Technically challenging tasks on the deployment side include integrating AI systems with current infrastructure, optimizing sensor placement, and guaranteeing real-time adaptability [183-185]. Future research should concentrate on improving model generalization through adaptive learning, automating data handling, and developing edge-based sensor networks to support effective and scalable SHM systems in order to get past these obstacles [178-183].

5.3 Risks

Machine learning significantly supports pavement health monitoring by enhancing accuracy and efficiency in detecting road distress, yet its implementation is not without risks. Like a powerful yet unpredictable tool, AI demands high-quality, annotated datasets for training resources that are often scarce and costly to acquire resulting in potential model inaccuracies, especially when dealing with real-world data inconsistencies and imbalanced samples [186-188]. The story becomes more complex when considering the heavy computing requirements of these models, which may not be feasible in regions with limited infrastructure [189]. Operational hurdles emerge as embedded sensors essential to AI's functioning may deteriorate prematurely, challenging their long-term reliability [190,191], while integrating AI into traditional road systems introduces compatibility and modification challenges [189,192]. Socially, AI casts a long shadow, threatening job displacement and inducing technostress among workers uncertain about their roles in an automated future [193]. The risks deepen when advanced AI systems potentially operate beyond human oversight, raising ethical red flags around autonomy and control [194]. Moreover, failure in AI communication strategies may erode public trust, and misclassification of pavement conditions could lead to real safety hazards for road users [194-196]. Yet the narrative is not bleak, opportunities lie in advancing adaptive AI, designing robust systems, and implementing ethical and legal frameworks that balance innovation with responsibility [189-194]. Thus, the story of AI in pavement health monitoring is one of great promises intertwined with caution, urging thoughtful progression grounded in science and ethics. Despite the efforts made, many research gaps remain unaddressed. A key issue is the lack of affordable, high-resolution, non-invasive sensing systems that can be widely deployed and integrated into AI models. Moreover, few existing solutions offer seamless compatibility with smart city ecosystems or address the full complexity of real-world pavement systems. In response to these needs, our current research, i.e., AI-based Structural Health Monitoring of Pavements, introduces a methodology combining Support Vector Machine (SVM), Random Forests (RF), and ANN models with subsurface data acquired through a radiotechnical device for subsurface scanning. This inductive, non-destructive sensing approach makes it possible to estimate key variables such as temperature, pavement thickness, and subsurface conditions with high accuracy. Our findings show a strong model performance and excelling in generalization during testing. Beyond the numerical results, the contribution of this work is its real-time, automated monitoring capability, which is crucial for smart city integration. This system contributes to a scalable, cost-effective step toward AI-enhanced infrastructure management, supporting safer roads, longer pavement lifespans, and more resilient urban transportation systems.

5.4 Materials and Method

Machine learning methods of Support vector Machines, Random Forests, and Artificial Neural Networks for modeling and comparative analysis have been implemented. These methods are described as follows with the reasons they have been used in addition to our considerations on their applicability and potential in related application.

5.4.1 Support Vector Machines

SVM is a supervised machine learning technique rooted in statistical learning theory, widely used for classification and regression [197-199]. It functions by projecting data into a high-dimensional feature space and identifying an optimal hyperplane that separates classes with the largest possible margin, often using kernel functions to handle nonlinear relationships [199-201]. SVM's strength lies in its ability to manage small sample sizes, nonlinear distributions, and high-dimensional datasets while avoiding overfitting and local minima problems [197-203]. However, the method can become computationally intensive, especially with large-scale data applications [197,202]. In civil engineering, SVM has been deployed for a variety of purposes including SHM, fault diagnosis, and corrosion state prediction [204,205]. In SHM, it plays a significant role in detecting, classifying, and quantifying structural damage by utilizing vibration data and statistical features, often achieving classification accuracy as high as 94% [206-210]. It also accommodates both labeled and unlabeled data, making it suitable for real-time monitoring and adaptive learning systems [207,211]. Moreover, combining SVM with other computational methods, such as wavelet transforms, particle swarm optimization (PSO), and Bayesian optimization, further enhances its performance and reliability [210-214]. Case studies demonstrate SVM's applicability in beam health monitoring using noisy mode shape data [206], distinguishing damage in steel frame structures via PSO-SVM models [210] and assessing damage levels in historical buildings through IoT-integrated SVM systems [206].

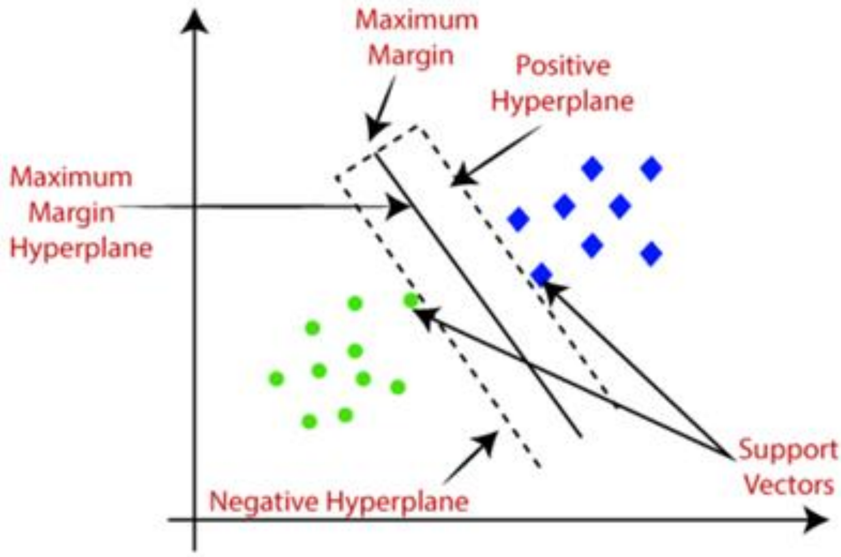

Figure T4.2. an illustration of support vector machines

SVM (as illustrated in Figure 2) classifies data by finding the best boundary which is called a hyperplane that separates two classes. This hyperplane can be a line, a plane, or a more complex surface, depending on the number of features. SVM aims to maximize the margin, which is the gap between the hyperplane and the nearest data points from each class or so-called support vectors. A wider margin improves accuracy on new, unseen data. To find the best hyperplane, SVM uses quadratic programming, ensuring that data points are correctly placed on either side. Once trained, SVM classifies new data by checking which side of the hyperplane they fall on. SVM is both simple and precise, making it highly effective for small, complex, or high-dimensional datasets.

5.4.2 Random Forests Algorithm

RF is a widely used ensemble machine learning technique known for their robustness, accuracy, and ability to handle both classification and regression problems. By combining the predictions of multiple decision trees, RF uses techniques like bootstrap aggregating (bagging) and random feature selection to reduce overfitting and improve generalization [216-219]. This makes them particularly effective in handling complex, high-dimensional data across various fields. Their adaptability and resilience to noisy or incomplete data have earned them a reputation for strong predictive performance in many machine learning tasks [220-222]. In civil engineering, particularly in SHM, RF models have been successfully applied to detect and localize damage, monitor bridge integrity, and support predictive maintenance. For instance, RF has been used to identify transverse cracks in beams using frequency shift data, and to locate damage in metallic plates with minimal sensor input [223][224]. They have also outperformed other machine learning models like SVMs in bridge damage detection and displacement prediction during tunnel construction [225][226]. RF's strength in feature selection improves SHM by refining signal data and identifying anomalies [227][228], while its use with non-destructive testing data aids in predicting structural properties for proactive maintenance planning [229]. Despite these advantages, challenges remain in computational cost and the interpretability of the models, which require careful consideration for real-world engineering use [220,230].

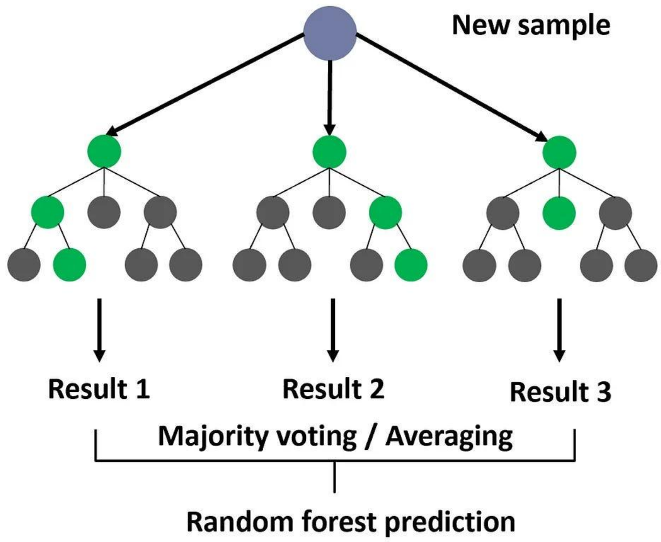

Figure T4.3. An illustration of Random forests machine learning method

RF as illustrated in Figure 3, functions by building an ensemble of decision trees during the training phase, where each tree is trained on a different subset of the data created through bootstrapping (random sampling with replacement). At each node in a tree, a random subset of features is selected, and the best split among those features is chosen to grow the tree, which introduces variability and reduces correlation between trees. During prediction, RF aggregates the outputs of all individual trees by taking a majority vote for classification tasks or averaging the results for regression to produce a final, more accurate and robust prediction [231]. This combination of bagging and random feature selection helps RF to reduce overfitting, increase generalization, and handle noise or missing data effectively, making it highly suitable for complex, high-dimensional datasets [232].

5.4.3 Artificial Neural Networks

ANNs are machine learning models inspired by the structure and learning process of biological brains. Comprised of layers of interconnected neurons, ANNs process inputs through weighted connections and activation functions that determine neuron responses [234]. During training, these weights are iteratively adjusted using algorithms such as backpropagation to minimize prediction errors [235]. This self-learning mechanism enables ANNs to identify complex patterns and make data-driven decisions, which makes them well-suited for tasks involving classification, prediction, and recognition [236]. In civil engineering, ANNs have become invaluable, particularly in SHM, where they are used to detect, localize, and quantify structural damage through analysis of vibration and sensor data [237,238,239]. Their ability to operate in real-time and maintain accuracy under varying environmental conditions significantly improves infrastructure safety and performance [240,241]. Beyond SHM, ANNs assist in structural system identification, design optimization, and construction management, while also addressing challenges in geotechnical engineering by modeling complex soil behavior [242-244]. The integration of ANNs with techniques such as–wavelet transforms, as well as advancements in deep learning like convolutional neural networks, are pushing the boundaries of what these models can achieve in engineering applications [245].

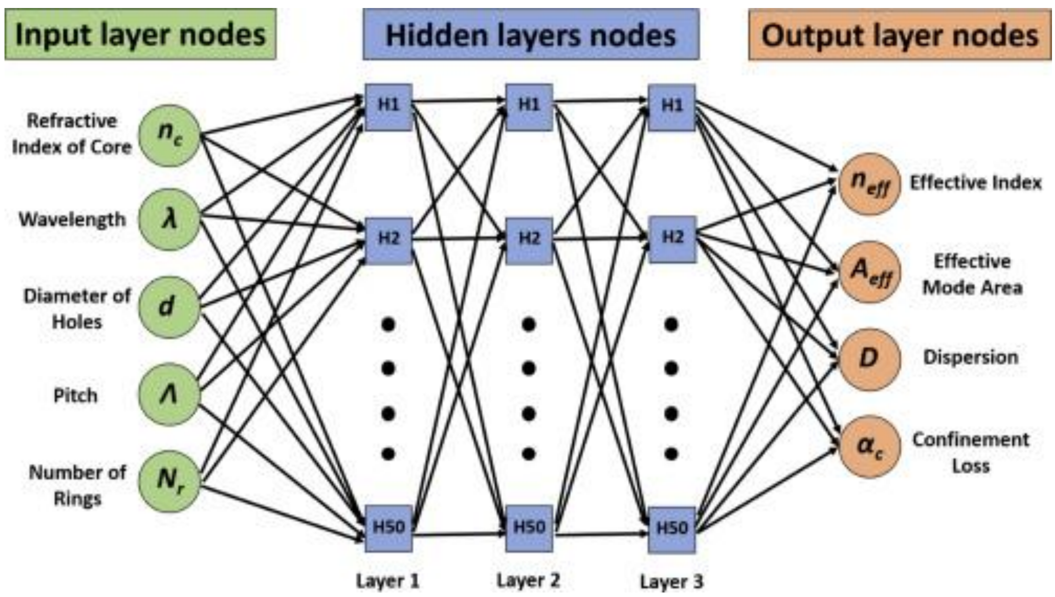

Figure T4.4. An illustration of ANNs machine learning method

As illustrated in Figure 4 the machine learning algorithm of ANNs consists of layers of interconnected neurons that compute weighted sums of inputs, add biases, and apply nonlinear activation functions to produce outputs [246]. Training involves minimizing a loss function by iteratively updating weights using backpropagation and gradient descent, which calculates gradients via the chain rule [247-249]. This process enables ANNs to model complex, nonlinear relationships by adjusting parameters to optimize input-output mappings across high-dimensional spaces. ANN makes the network by integrating weights and bias values according to Eq. 1.

$$\hat{y} = g(w_2.f(w_1x - b_1) + b_2) \tag{1}$$

For an ANN, w1x+b1 is a pretentiously worded linear combination of the input parameters into the hidden layer. The weight matrix w1 acts as to how much the j^{th} input influences the i^{th} hidden neuron as opposed to encouragement carried forward by vector b1 to the result to increase its modeling capability. This operation goes linearly to the output and gets activated via f (), e.g., ReLU, sigmoid, tanh, to nonlinearly make the network express more complex patterns. Again, the hidden layer outputs, after transformation, undergo linear combination by w2 weights of the output layer with the bias b2, leading to the final prediction y as defined in Equation (1). Expression gives the raw output g () of the network. While the output activation function varies as per the problem-at-hand; e.g., it can be softmax in multi-class classification, whereas in regression problems, there is no output activation, that is, identity function is kept.

5.5 Dataset

The dataset presented in this article was created using a radiotechnical device designed for subsurface scanning of asphalt pavement. This device uses GPR, a non-destructive technique for estimating pavement layer thickness without the need for coring or drilling [250-253]. It captures radargrams, which are visual reflections of subsurface materials, which help to assess both the thickness and condition of pavement layers [250-254]. High-frequency impulse antennas are used to collect detailed electromagnetic data critical for accurate interpretation [255]. Ground-coupled antenna measurements serve as the primary data source in this study, as they provide higher spatial resolution and more reliable layer interface detection than air-coupled systems for the pavement thicknesses encountered in the monitored sections [254,256]. The acquisition geometry is maintained consistently across all measurement campaigns, with profiles oriented longitudinally along the pavement surface and collected at a constant driving speed with a fixed trace interval. Calibration of the dielectric constant, essential for accurate depth estimation, is performed through surface reflection amplitude analysis and validated against core sample data from the monitored sections [251,256,259]. The conversion of two-way travel times to layer thickness values is conducted using the calibrated dielectric constants. A sensitivity analysis confirms that the trained models demonstrate acceptable robustness to typical seasonal dielectric variability, and asphalt surface temperature is included as a model input to partially compensate for temperature-induced changes in dielectric response. Error correction methods are also applied to address issues such as antenna height variation and signal noise, using height adjustment and signal processing techniques [254,258,260]. The dataset supports both manual analysis and automated processing using techniques such as pixel-wise detection and machine learning [252,257,258]. This approach enables continuous data collection across large areas, real-time analysis during fieldwork, and highly accurate thickness measurements, with error rates as low as 1.6 percent [253,258,259].

5.6 Feature Selection

Feature selection is a crucial step in data-driven approaches for SHM and civil engineering applications. It involves selecting the most relevant features from a dataset to improve model performance and reduce computational complexity. One effective method for feature selection is the Relief score, which evaluates the importance of features based on their ability to distinguish between different classes. Feature selection with the Relief score is a technique used to identify the most important features in a dataset by measuring how well each feature separates instances of different classes. It works by comparing nearby data points, looking at how similar or different they are depending on whether they belong to the same class or not. Features that show clear differences between classes get higher scores, making them more valuable for building accurate and efficient models.

Figure T4.5. An illustration of feature selection with the Relief score

The Relief score has shown strong potential in SHM, especially for managing high-dimensional data from numerous sensors. It helps reduce dimensionality by identifying and keeping only the most informative features, which is essential when dealing with large datasets common in SHM applications [261-263]. The main performance of the Relief score is according to the following formula (Eq. 2 and 3):

$$W[A] = W[A] + \sum_{i=1}^{m} \frac{1}{m} \left(diff\left(A, x_i, Miss(x_i)\right)^2 - \left(diff\left(A, x_i, Hit(x_i)\right)^2\right) \right) \tag{2}$$

$$diff\left(A, x_i, x_j\right) = \frac{\left|x_j^A - x_i^A\right|}{Max(A) - Min(A)} \tag{3}$$

In the Relief algorithm, $[A]$ gives weight to a feature A. Thereby, m stands for the number of random training instances taken by the algorithm. Each xi denotes the ith data sample in the dataset. The function Hit(x_i) procures the nearest neighbor of the class to which the object xi belongs. The function Miss(x_i) returns the nearest neighbor in the case that the object belongs to a different class. Diff (A, x_i, x_j) computes the difference between xi and xj on the values of a particular feature A. For numerical features, this is generally a normalized absolute difference; for categorical features, however, a binary difference is most often used (0 if equal, 1 if different). When used in combination with methods like Linear SVM Weight, it can drastically cut down the number of features, as demonstrated in a study that reduced 5,147 dimensions to just 20 [263]. This reduction not only simplifies the data but also enhances model performance, as relevant features lead to more accurate and reliable damage detection, an essential aspect in SHM for maintaining structural safety [261-264]. Additionally, combining Relief with other selection techniques has proven to further improve classification results [263-265]. In civil engineering and SHM, the Relief score supports damage detection by identifying features that are most responsive to structural changes, making it easier to diagnose issues accurately [261-264]. It has been successfully applied in systems using neural networks and support vector machines for classification tasks [261-264]. Due to its fast computational speed, Relief score-based selection is also suitable for real-time monitoring, which is critical for infrastructure like bridges and aircraft where timely detection can prevent serious failures [261-267]. Moreover, integrating Relief with machine learning models boosts their efficiency and accuracy, making it a practical and powerful tool for SHM tasks [261-265].

Feature selection using the Relief score is applied to a dataset where each sample is described by multiple features and assigned to a class, as illustrated by the transformation from the feature matrix to a vector of feature importance scores. The method operates by randomly selecting m training instances and, for each instance x_i, identifying two nearest neighbors in the feature space: a Hit from the same class and a Miss from a different class. For every feature A, a weight $W[A]$ is iteratively updated based on the difference between inter class and intra class distances, where the difference function is defined as a normalized absolute distance for numerical attributes or a binary metric for categorical ones. The update increases the weight when the feature exhibits small variation within the same class and large variation across different classes and decreases it in the opposite case. Over multiple iterations, this process estimates the discriminative power of each feature by approximating how well it separates class conditional distributions. The final output is a ranked list of features with associated scores, where higher values indicate stronger relevance for classification tasks. This ranking enables dimensionality reduction by retaining only the most informative features, which improves computational efficiency and enhances model generalization, particularly in high dimensional datasets such as those derived from GPR based structural health monitoring systems.

5.7 Results

The results of the feature selection are presented in figure 6. This bar chart presents the Relief scores for five features labeled A303, A302, A301, A118, and A117. The Relief score is a measure of a feature's ability to distinguish between different classes in the data, with higher positive scores indicating greater relevance. From the figure, all features have positive Relief scores, meaning they contribute positively to classification performance.

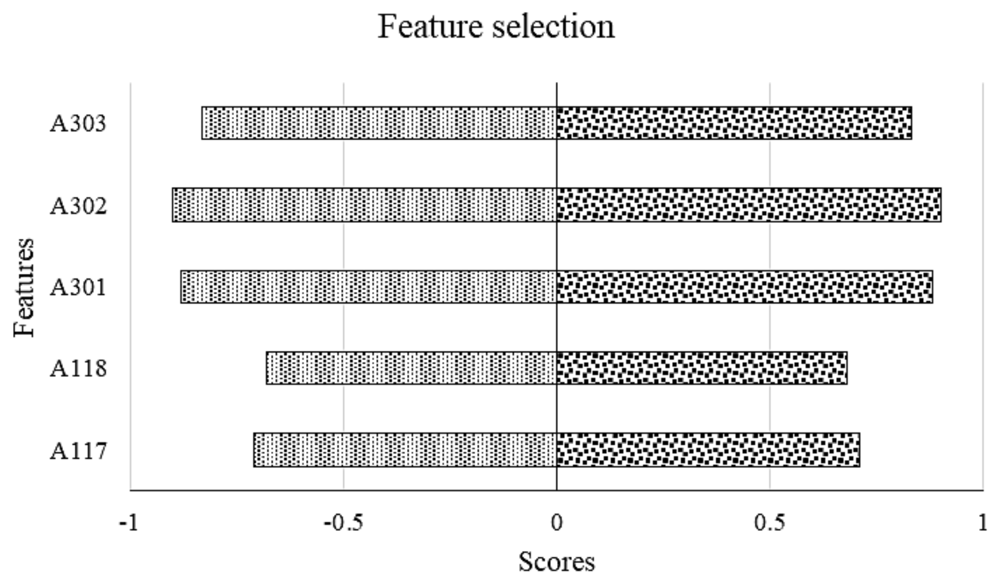

Figure T4.6. Results of the feature selection

Features A303, A302, and A301 exhibit the highest scores, suggesting they are the most informative and should be prioritized in modeling. A118 and A117, while slightly lower, still hold significant value and may contribute to improved model accuracy when included. Overall, this selection supports a well-justified reduction in dimensionality while retaining the features most critical for structural health monitoring or other classification tasks. The five features are selected through a ranking process based on Relief scores, where all candidate features are evaluated and the top ranked ones are retained due to their superior ability to separate classes. The labels A303, A302, A301, A118, and A117 represent indexed features derived from GPR signal characteristics, such as amplitude or statistical descriptors, rather than direct physical quantities. Among them, A303, A302, and A301 show the highest discriminative power, while A118 and A117 provide additional complementary information. This selection ensures an effective reduction in dimensionality while preserving the most informative attributes required for accurate and robust classification.

Consequently, the training is implemented and the results reported in Table T4.2. as follows. The training results in Table T4.2 tell an interesting story about how three different machine learning models, i.e., SVM, RF and ANN, learned from the data in their own unique ways. SVM came out as the most balanced and reliable performer, achieving the lowest error (RMSE of 0.841) while maintaining a very high correlation with actual outcomes (CC of 0.991). With its RBF kernel, SVM clearly adapted well to the patterns in the data, effectively capturing complex relationships without overfitting.

Table T4.2. Results of the training phase

Model	Structure	RMSE	CC
SVM	Regression cost= 100; Complexity bound= 1; Kernel type= RBF	0.841	0.991
RF	No. of tree= 100; No. of att.= 5	1.077	0.997
ANN	5-30-1, with logistic activation function and L-BFGS-B solver	2.715	0.935

The RF, on the other hand, showed its strength in a different way. While its error was slightly higher (RMSE of 1.077), it achieved the highest correlation coefficient (0.997), meaning it was especially good at understanding and replicating the overall trends. This makes sense given RF's ensemble approach, combining the wisdom of 100 decision trees to smooth out noise and strengthen pattern recognition. Meanwhile, the ANN struggled. Despite its more complex 5-30-1 architecture and sophisticated optimization method (L-BFGS-B), it posted the highest error (RMSE of 2.715) and the weakest correlation (CC of 0.935). This could be a result of an activation function that wasn't ideal for regression or a model that was not fully tuned to the data's specific characteristics. In a way, each model reflects a personality: the SVM is the precise strategist, the RF is the trend-savvy generalist, and the ANN is the promising but currently underprepared contender. If we had to choose a reliable performer from this cast, SVM would lead the way, followed closely by RF, while ANN may still need more training before it can shine.

The testing results are reported in TableT4.3. as follows. It reveals how each machine learning model performs when confronted with new, unseen data, a crucial step that often separates a good model from a great one. In the training phase, SVM stood out for its precision, and while it still performed admirably during testing, its RMSE increased to 1.267 and its CC slightly dropped to 0.986. This tells us that while SVM remains highly reliable, its predictive accuracy declined somewhat outside the training environment, suggesting a mild degree of overfitting or reduced generalization.

Table T4.3. Results of the testing phase

Model	Structure	RMSE	CC
SVM	Regression cost= 100; Complexity bound= 1; Kernel type= RBF	1.267	0.986
RF	No. of tree= 100; No. of att.= 5	1.162	0.992
ANN	5-30-1, with logistic activation function and L-BFGS-B solver	2.949	0.929

Interestingly, RF, which had a slightly higher training RMSE, emerges as the best performer in the testing phase. It posted the lowest RMSE of 1.162 and the highest CC of 0.992, demonstrating robust generalization and adaptability. RF's ensemble nature drawing conclusions from 100 diverse decision trees likely helped it maintain accuracy even with more complex or noisy test data. Meanwhile, the ANN continued to struggle. With an RMSE of 2.949 and a CC of 0.929, its performance further deteriorated, suggesting that it not only failed to generalize well but possibly also learned less relevant features during training. The logistic activation function, typically better suited for classification tasks, may have hindered its ability to model continuous outputs effectively in this regression setting. The broader narrative here is that RF quietly outshone its competitors when it mattered most in generalizing to real-world data. SVM, though slightly less effective in testing than in training, still proved to be a strong and reliable model. ANN, on the other hand, appears to need significant reevaluation, whether in terms of architecture, activation functions, or training strategy. In this phase of the story, RF claims the lead role with consistent and strong test performance, SVM remains a close and dependable contender, and ANN shows potential but isn't ready for deployment just yet.

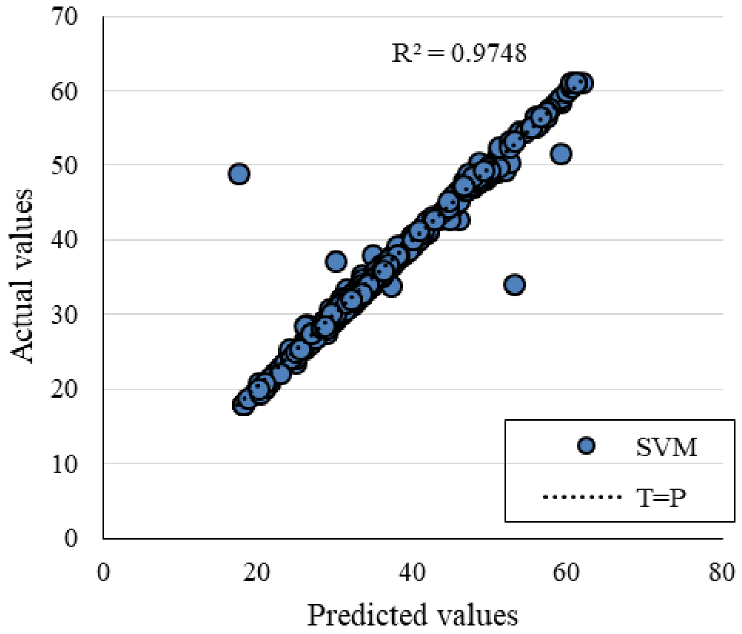

Figure T4.7. Results of the testing phase for SVM

The scatter plot of Figure T4.7. presents the results of the testing phase for SVM. It illustrates the testing performance of the SVM model, adding a visual chapter to the story already told by Table T4.3. On the x-axis, we see the predicted values, and on the y-axis, the actual values from the test set. The dotted line represents the ideal case where predicted equals actual (T = P), serving as a benchmark for perfect predictions. Most of the data points tightly cluster along this line, reinforcing the quantitative metrics we previously saw, specifically, the high coefficient of determination ($R^2 = 0.9748$) and correlation coefficient (CC = 0.986).

This visual confirms that the SVM model maintains strong predictive fidelity, with minimal dispersion around the ideal line. A few outliers are present, which explains the slight rise in RMSE (1.267) from the training phase, but they are not numerous enough to undermine the model's overall accuracy. These outliers may reflect rare or particularly complex instances that the model couldn't fully learn from the training data, a common occurrence in real-world testing. Still, the R^2 value near 1 indicates that approximately 97.5% of the variance in the actual values is explained by the SVM's predictions, which is an excellent result for a regression task.

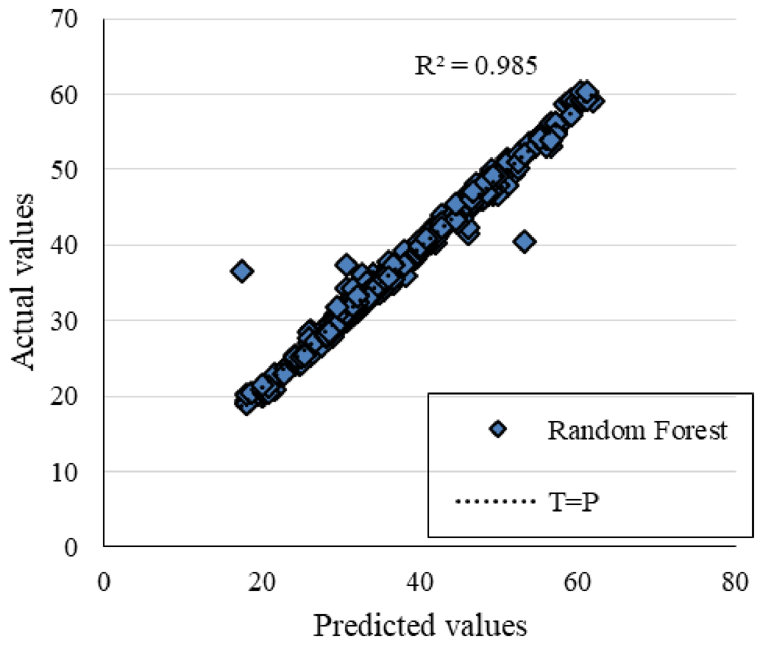

Figure T4.8. Results of the testing phase for RF

The scatter plot presented for the Random Forest model during the testing phase shows a strong alignment between the predicted and actual values, as evidenced by the data points closely following the reference line (T = P). It is reported that the model achieved an R^2 value of 0.985, indicating that 98.5% of the variance in actual values was explained by the model's predictions. This high coefficient of determination reflects excellent predictive accuracy. It is also observed that the majority of the points cluster tightly around the ideal line, suggesting a consistent and reliable model performance. Only a few outliers deviate notably from the line, implying that the model generalized well to unseen data, with minimal error in most cases. The relatively small spread and strong linear trend confirm that Random Forest maintained robustness and stability under test conditions. Overall, the plot visually supports the conclusion that the Random Forest model performed exceptionally well in predicting continuous outcomes during the testing phase.

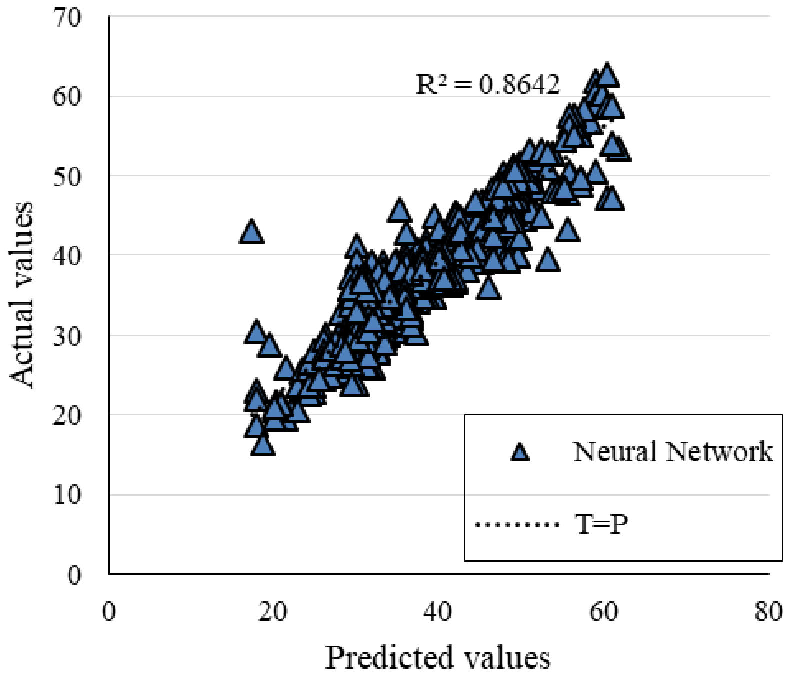

Figure T4.9. Results of the testing phase for ANNs

The scatter plot presented for the ANN model, presented in figure 9, during the testing phase illustrates a noticeably weaker performance compared to the other models in this study. It is reported that the model achieved an R^2 value of 0.8642, indicating that only about 86.4% of the variance in the actual values was explained by the network's predictions—a significant drop in explanatory power relative to both the SVM and Random Forest models. Visually, the data points appear more widely scattered around the ideal T = P line, with several noticeable deviations and a looser clustering pattern. This suggests that the model struggled to capture the true underlying relationships in the data, resulting in less accurate and less consistent predictions. It is evident from the plot that the ANN had a tendency to either underpredict or overpredict across different parts of the value range, which could be attributed to factors such as suboptimal network architecture (5-30-1), the use of a logistic activation function that may not suit regression tasks, or insufficient training leading to poor generalization. While the model still exhibits a generally positive correlation between predicted and actual values, the performance gap is clear. In the narrative of model performance, the neural network appears to be the underperformer, showing promise but lacking the robustness and precision demonstrated by the SVM and, particularly, the Random Forest. It is suggested that further tuning, architectural revisions, or even the use of alternative activation functions might be necessary for the ANN to become a more competitive and reliable option in this context.

The testing phase results paint a clear and cohesive picture of how the three machine learning models, i.e., SVM, RF and ANN, performed when faced with unseen data, each telling a distinct part of the overall story. The RF model emerged as the most accurate and consistent performer, achieving the lowest RMSE (1.162), the highest Correlation Coefficient (CC = 0.992), and a strong R^2 of 0.985, with its predictions closely hugging the ideal line and only a few minor outliers. This confirms RF's ability to generalize well, likely due to its ensemble structure that balances variance and bias effectively. The SVM also demonstrated strong performance, with a slightly higher RMSE (1.267) and slightly lower R^2 (0.9748) but still maintained a high CC (0.986) and produced a tight cluster of accurate predictions. While SVM was highly competent and reliable, it showed a slightly greater sensitivity to testing variation than RF. In contrast, the ANN lagged behind significantly, with the highest RMSE (2.949), the lowest CC (0.929), and an R^2 of only 0.8642. Its scatter plot revealed more dispersed and inconsistent predictions, suggesting that the network failed to capture complex patterns effectively, potentially due to an ill-suited architecture or activation function. Overall, while RF confidently takes the lead as the most robust and dependable model, SVM remains a close second with solid, nearly comparable results, and ANN appears to require significant improvements before it can perform competitively in this regression task.

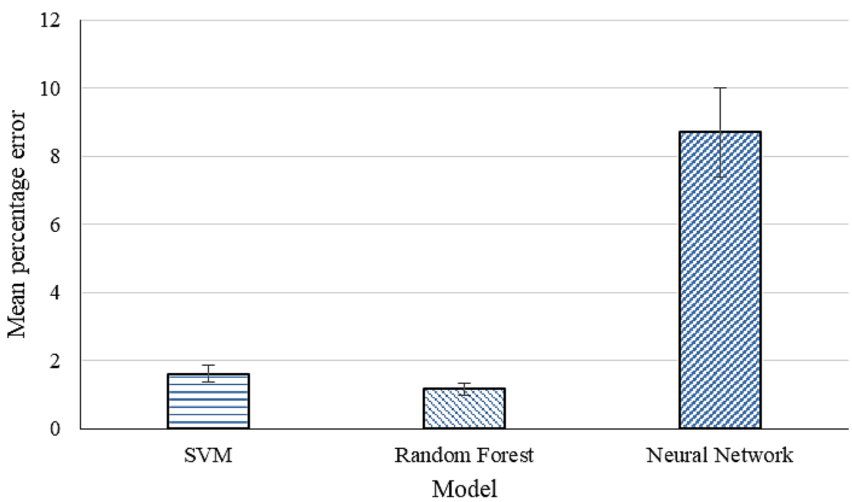

Figure T4.10. Mean percentage error values in the testing phase

The bar chart depicting the mean percentage error during the testing phase adds another important layer to the story of model performance, further validating the earlier findings. It is clearly shown that the ANN significantly underperformed, exhibiting a mean error close to 9%, the highest among the three models by a large margin, and with a visibly larger error bar indicating less stability and greater prediction variability. This reinforces earlier observations from its high RMSE and lower R^2, confirming that ANN not only struggled to deliver accurate results but also lacked consistency. In contrast, RF achieved the lowest mean percentage error, just above 1%, coupled with a small error bar, which points to both high precision and excellent generalization to unseen data. The SVM followed closely, with a slightly higher mean error than RF but still below 2%, also accompanied by a narrow error bar indicating reliability. These results affirm that while SVM remains a strong and dependable model, RF consistently delivers the most accurate and stable predictions. Meanwhile, ANN clearly falls behind, with error magnitudes that question its suitability for this regression task without significant tuning or redesign. Thus, the chart visually and quantitatively seals the conclusion: Random Forest is the most accurate and robust model, SVM performs admirably, and ANN needs reconsideration for deployment in its current form.

5.8 Computational Complexity Analysis

To evaluate the scalability of the proposed SHM framework, a computational complexity analysis was conducted for the Relief feature selection algorithm and the evaluated machine learning models, namely SVM, RF, and ANN. The computational cost mainly depends on the *number of training samples (n)*, *the number of features (d)*, *the number of trees (T)*, *the number of hidden neurons (h), and the number of optimization iterations (I)*. The Relief algorithm performs nearest-neighbor comparisons to estimate feature importance, with a complexity ranging from $O(mnd)$ to $O(n^2d)$. Although Relief requires repeated distance calculations, it effectively reduces feature dimensionality and decreases the computational burden of subsequent classifiers. This characteristic makes it suitable for high-dimensional GPR-based SHM datasets.

Among the evaluated models, RF demonstrated the best balance between computational efficiency and predictive capability due to its parallel tree-based structure, with a complexity of approximately $O(Tnd \log n)$. In contrast, SVM with the RBF kernel provides high prediction accuracy but exhibits higher computational cost, ranging from $O(n^2d)$ to $O(n^3)$. The ANN model also requires substantial computational resources because its complexity increases with the number of neurons and training iterations. Overall, the integration of Relief feature selection improves scalability by reducing the dimensionality of the dataset before model training, thereby enhancing computational efficiency and model generalization.

Table T4.4 Computational Complexity Analysis

Method	Computational Complexity	Scalability
Relief	$O(mnd)$ to $O(n^2d)$	Efficient for dimensionality reduction
SVM	$O(n^2d)$ to $O(n^3)$	High accuracy but computationally expensive
RF	$O(Tnd \log n)$	Strong scalability and parallel implementation
ANN	$O(ndhI)$	Flexible but computationally intensive

Figure T4.11 shows the relative increase in computational complexity as the dataset size grows. Relief has the lowest computational growth, while RF demonstrates moderate complexity due to its parallel tree structure. ANN requires higher computational effort because of iterative training, whereas SVM exhibits the highest complexity, especially for large datasets. Overall, RF provides a good balance between scalability and predictive performance.

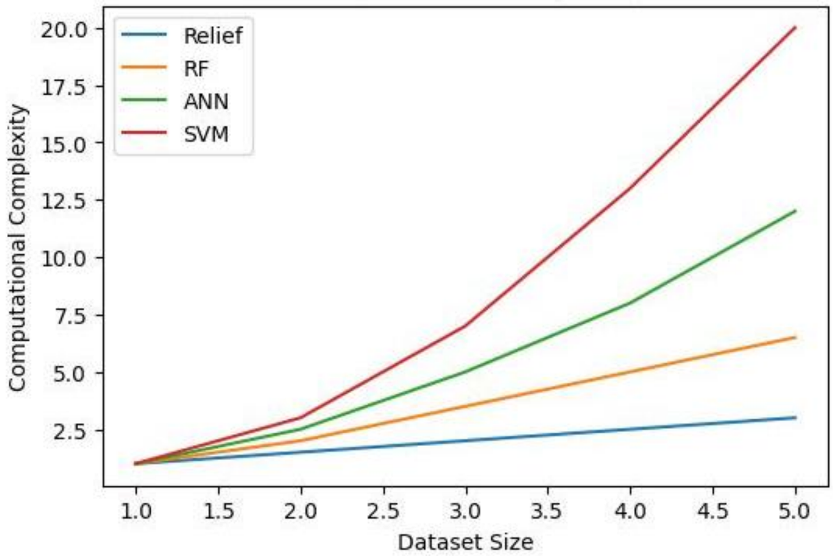

Figure. T4.11. Computational Complexity of the models

5.9 Conclusions

The current work presented a scalable AI-based SHM for pavements which utilizes machine learning techniques. The model is a multi-stage non-destructive radiotechnical subsurface sensing of pavements. The most important contribution of this work is the development of an intelligent, data-driven maintenance framework that could reliably estimate critical pavement parameters like surface temperature, layer thickness, and subsurface features using inductive signals emanating from radiotechnical devices for subsurface scanning. It was found that RF was the best performing model out of all the tested and trained models in terms of generalization, displaying the lowest Root Mean Square Error value (RMSE=1.162), highest

Correlation Coefficient (CC=0.992) during the testing phase, alongside the lowest mean percentage error. This demonstrates that RF outperforming the other models in predictive accuracy, robustness, and proves that the model was predictive. SVM was also able to produce competitive results, performing best during the training session with RF (RMSE=0.841, CC=0.991) proving itself in terms of reliability SVM with stable and reliable predictive ability. All other evaluation metrics indicate the largest prediction errors and the weakest correlation, which identifies the ANN model as the poorest performer and reveals the limitations of this application setup. This study presents a novel contribution through the integration of non-invasive and inductive sensing technologies with machine learning for structural health monitoring of asphalt pavements, which has not been widely reported in prior research. In contrast to conventional approaches that rely on intrusive sampling and visual inspection, the proposed system enables non-invasive and automated data acquisition and reduces manual effort while maintaining high spatial resolution. The implementation of Artificial Intelligence technologies into SHM procedures enables greater performance and reliability, such as precision in predictive analytics, continuous observation, and adaptability for large-scale applications which are highly useful for contemporary transport systems and smart urban environments. In addition, the proposed model supports proactive maintenance strategies, which can improve road safety, prolong pavement life, and optimize infrastructure management budgets through well-timed interventions based on precise condition predictions. The approach's scalability, made possible by the modular use of sensors and machine learning algorithms, makes it simple to adapt to different urban and regional contexts, thereby establishing the foundation for pavement monitoring networks across the country. Essentially, this work lays the groundwork for the automation and digitization of infrastructure health monitoring, which is in line with future plans for sustainable mobility systems and resilient, data-driven urban planning.

6. Deep learning for Structural Integrity Assessment of Pavements [T5]

This work presents a machine learning based method for pavement condition prediction using field data obtained from HWD and GPR tests. The contribution lies in the evaluation of deep learning models that capture temporal dependencies in pavement behavior. A comparative analysis is conducted between Gated Recurrent Unit and Long Short-Term Memory models on the dataset of the [T3]. The study establishes that the Gated Recurrent Unit model achieves higher accuracy and lower prediction error. This result indicates a better balance between computational efficiency and predictive performance. The novelty is defined by the validation of these models using real field data, which strengthens their practical relevance. The study also shows that reliable early prediction of pavement conditions supports timely maintenance decisions, reduces repair costs, and improves road safety. In addition, the findings support the adoption of intelligent systems for sustainable and resilient urban infrastructure management.

6.1 Introduction

Conventional SHM methods are costly, time intensive, and disruptive to traffic, which limits widespread application [268,269,270]. Machine learning is therefore adopted to overcome these limitations [271-275]. Pavement conditions are predicted using inputs such as asphalt temperature and pavement thickness [276]. As a result, maintenance is planned proactively, resources are used efficiently, and safety is enhanced [277]. When SHM is integrated with smart city and mobility initiatives, real-time infrastructure management is enabled, which improves traffic flow, route planning, and adaptive maintenance [278,279]. Thus, SHM contributes to sustainable road management and future ready transport networks [280]. Before the adoption of AI, SHM was based on visual inspection, load testing, strain measurement, vibration analysis, and radiographic techniques [281–284]. Tools such as GPR, infrared thermography, and FWD are applied for pavement assessment [285–287]. However, these methods are limited by slow execution, traffic disruption, and weak predictive capability. Hidden damage is rarely detected at an early stage, and large data volumes are not processed effectively. With AI, ML and DL methods enable real-time analysis of sensor data, images, and historical records [288]. Early defects are identified, deterioration is predicted, and preventive maintenance is supported [289,290]. Consequently, inspection effort is reduced, costs are lowered, and pavement service life is extended [291]. Previous studies demonstrate the effectiveness of AI techniques. Decision trees, random forests, support vector machines, and artificial neural networks are applied to predict pavement deterioration and remaining service life [292,294]. DL methods are also used to analyze GPR data for subsurface defect identification with high accuracy [297]. In addition, traffic, weather, and pavement data are combined to support resource allocation, maintenance prioritization, and long-term planning [298,299]. Despite these advances, several limitations remain. Many models are developed for specific regions, which restricts general applicability [301]. Integrated consideration of traffic, weather, and environmental factors is often absent. Prediction uncertainty is rarely addressed, although pavement performance is affected by variable traffic and extreme climate conditions [302]. Moreover, limited interpretability of AI models reduces trust among engineers and decision makers [310]. A direct link between AI and PMS is identified as a major gap, which reduces practical impact. Hybrid models, real-time learning, and improved data collection are proposed by researchers to address these limitations. Emerging tools, e.g., geotagged imaging, geospatial mapping, and Generative Adversarial Networks (GANs), are identified as new opportunities [303,304,307]. The combination of AI with big data and IoT is proposed to support continuous monitoring, in which sensors provide real-time information on traffic loads and road conditions [306,308]. However, practical issues, e.g., high costs, operational complexity, and limited adaptability to environmental changes, are reported and must be resolved [309,311]. With transparent and explainable models and a multidisciplinary approach, the full potential of AI is achieved for smarter, safer, and longer-lasting pavement management practices. Machine learning is widely applied to pavement life prediction and maintenance planning, which results in higher accuracy [312]. Simple regression models are used to estimate friction [313]. Advanced methods, e.g., Random Forests, SVM, and ANN, are applied to predict roughness, rut depth, and cracking [314,315]. Deep learning models, e.g., YOLOv5, U-Net, RNN, and LSTM, are applied to crack detection and time series prediction with improved performance [316,317]. Hybrid and ensemble approaches are adopted to increase reliability through the combination of multiple techniques [318,324,326]. As a result, costs are reduced, pavement life is extended, and proactive maintenance is supported [319,320]. Nevertheless, challenges related to data availability, annotation quality, and model adaptability are reported [321]. The application of AI across all stages of pavement management is expected to support safer and more sustainable road networks [322-328]. Among machine learning and deep learning methods, Gated Recurrent Unit (GRU) is not applied to pavement modeling. Therefore, this study aims to apply this method.

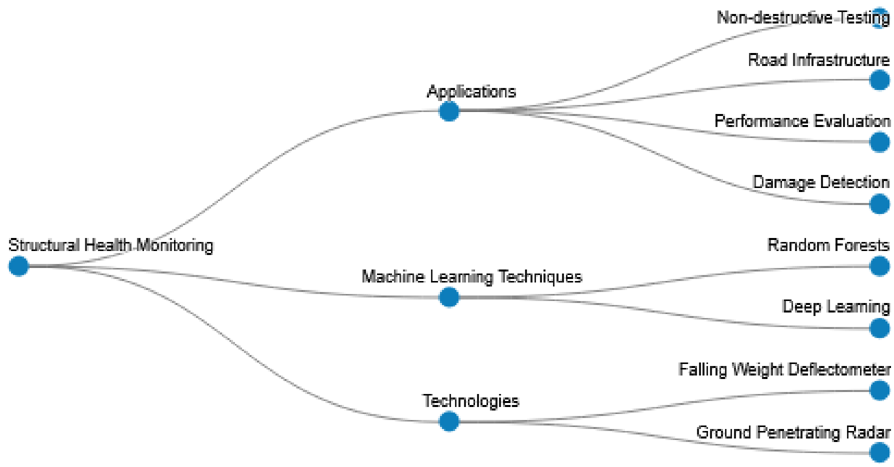

Figure T5.1. Taxonomy of the state of the art

6.2 Materials And Methods

Data are collected to model the RSL of pavements, which estimates the service duration before quality decline. RSL is calculated using surface deflection data obtained from the FWD, which simulates traffic loads and evaluates structural capacity. Key inputs include asphalt thickness, base thickness, and asphalt surface temperature, which are measured using GPR and field sensors. These measurements reflect both structural and environmental conditions. The dataset enables the development of models that predict RSL without dependence on costly tools such as FWD and GPR. Therefore, applicability is improved for regions with limited resources. To ensure accuracy, model validation is performed using field tests from HWD and GPR. As a result, a cost effective and non-intrusive approach for pavement monitoring is achieved, in which machine learning identifies patterns and enhances long-term maintenance planning. For modeling purposes, recurrent neural networks such as LSTM and GRU are applied. LSTM preserves essential information over long sequences, while GRU applies a simpler structure and faster computation with comparable accuracy. GRU is a recurrent neural network architecture that employs gating mechanisms to regulate information flow. It is a relatively new method. GRU functions similarly to the LSTM network by controlling which information is retained or discarded during training. However, unlike LSTM, GRU does not include a separate context vector or output gate, which reduces the number of parameters and simplifies the model structure. Both approaches regulate information flow, in which relevant data are retained and irrelevant data are discarded. Network parameters are optimized through iterative adjustment of hidden layers, node numbers, and learning rates. These methods capture complex relationships within pavement data. Therefore, more accurate RSL prediction is achieved.

Together, these models support proactive maintenance planning and improve the efficiency and reliability of pavement management.

6.3 Results

The training results in Table T5.1 indicate that both GRU and LSTM models performed well, achieving low RMSE and high correlation coefficients. The GRU showed a slight advantage with an RMSE of 2.29 and CC of 0.989, compared to the LSTM with an RMSE of 2.45 and CC of 0.982. This suggests that the GRU was better at capturing temporal dependencies in the data during training. Its simpler architecture, with stacked layers of fewer parameters, may also have helped reduce overfitting while maintaining accuracy. The LSTM also performed strongly, which confirms its ability to model long-term dependencies but required more complexity to achieve similar outcomes. Overall, both models proved effective, though the GRU provided a more efficient balance between accuracy and computational cost.

Table T5.1. Training results of the models

Model	Architecture	RMSE	CC
GRU	2 stacked GRU layers, each with 50 hidden units, and a learning rate of 0.0008	2.29	0.989
LSTM	Two hidden layers, the number of nodes in each hidden layer was 50, and the learning rate was set to 0.0008	2.451	0.982

Table T5.2. Testing results of the models

Model	Architecture	RMSE	CC
GRU	2 stacked GRU layers, each with 50 hidden units, and a learning rate of 0.0008	2.785	0.951
LSTM	Two hidden layers, the number of nodes in each hidden layer was 50, and the learning rate was set to 0.0008	3.016	0.925

The test results reported in Table 2 show that both models generalize well. However, performance is slightly reduced relative to the training phase, as expected. The GRU again outperforms the LSTM, as a lower RMSE of 2.79 and a higher correlation coefficient of 0.951 are achieved, compared with 3.02 and 0.925 for LSTM. This outcome indicates that temporal patterns are preserved more effectively by the GRU when unseen data are applied. As a result, stronger predictive accuracy is maintained. LSTM also produces reliable outcomes. However, higher error and lower correlation values indicate partial loss in dependency representation during testing. Overall, both models demonstrate robust performance. Nevertheless, a more favorable balance between accuracy and efficiency is provided by the GRU when new data are evaluated.

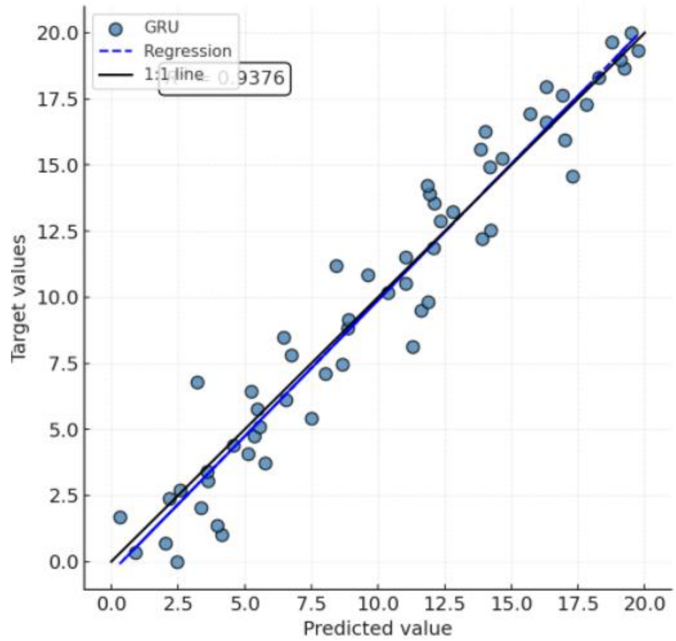

Figure T5.2. GRU results for the testing phase

6.4 Computational Complexity Analysis

To further evaluate the scalability and efficiency of the implemented deep learning models, a computational complexity analysis was conducted for both the GRU and LSTM architectures as presented in Table T5.2. and illustrated in Figure T5.3. The computational cost mainly depends on the number of input features, hidden units, sequence length, and training samples. Although both models exhibit similar asymptotic complexity, the GRU requires fewer parameters because it uses a simpler gating structure. LSTM contains additional gating mechanisms and a memory cell state, which increase the number of matrix operations and computational requirements. In contrast, GRU reduces computational cost and memory usage by employing only update and reset gates. Consequently, GRU demonstrates faster training and better computational efficiency while maintaining strong predictive performance.

Table T5.2. Computational Complexity Analysis or LSTM and GRU

Model	Main Gates	Relative Parameters	Computational Efficiency
GRU	Update gate, Reset gate	Lower	Faster training and lower memory usage
LSTM	Input gate, Forget gate, Output gate	Higher	Higher computational cost and memory usage

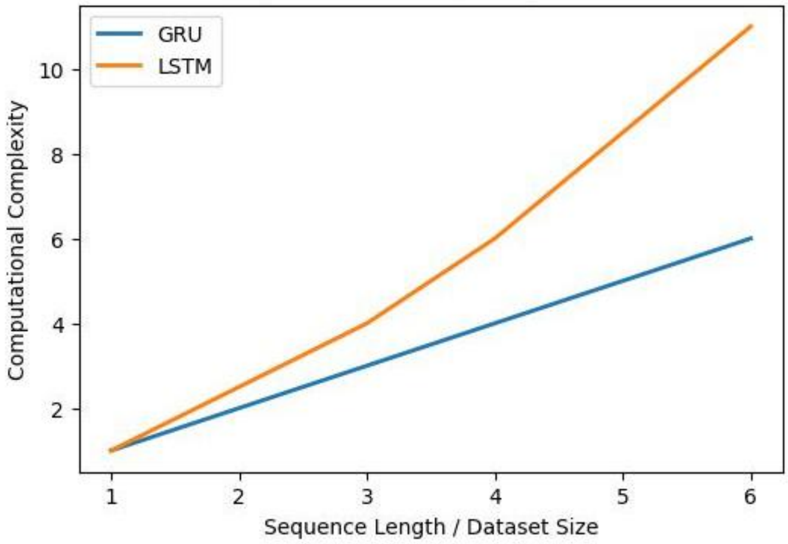

Figure T5.3. Relative Computational Complexity of GRU and LSTM

The computational complexity analysis was conducted by examining the structural differences between GRU and LSTM architectures in relation to sequence length, hidden size, input dimensionality, and dataset scale. The number of matrix multiplications and gating operations in each model was considered to estimate relative computational cost. Both models were evaluated under the same temporal learning setting used in structural health monitoring data, where long sequential dependencies are present. The figure presents a qualitative comparison in which computational cost is plotted against sequence length or dataset size. The upward trend indicates that both models increase in cost as data size grows. However, the GRU curve remains lower because fewer gating operations are involved and no separate memory cell is maintained. The LSTM curve rises more steeply due to its additional input, forget, and output gates, which increase parameter count and matrix computations. This visual representation supports the analytical result that GRU maintains lower computational demand while preserving sequential learning capability.

6.5 Conclusions

This study demonstrates that deep learning significantly enhances pavement monitoring and maintenance. The GRU model predicts the remaining service life of roads using basic measurements such as asphalt thickness, base layer depth, and surface temperature. These inputs, combined with structural and environmental data, enable the model to capture complex pavement behavior over time. Both GRU and LSTM models provide reliable performance, but the GRU consistently achieves higher accuracy with lower computational requirements. Strong predictive performance is maintained even on unseen data, which indicates effective generalization. By reducing reliance on costly and time-consuming field tests, this approach makes pavement monitoring more practical and affordable. Road agencies can use the predictions to plan repairs in advance, prevent severe damage, conserve resources, and enhance driver safety. Overall, the GRU based method provides a simple, efficient, and robust tool for proactive and sustainable road maintenance. It illustrates how artificial intelligence can support smarter infrastructure management and contribute to longer lasting, safer roads.

7. Conclusions

Table 7.1. Summary of Thesis Statements, Supporting Evidence, and Publications

Thesis Statement and Claim	Supporting Chapter and Section	Publication
T1: PRISMA-guided review of ML in pavement performance and RSL prediction (foundational literature contribution)	Chapter 2, Sections 2.1-2.5	Azodinia, Shayakhmetov & Mosavi (2025). Eurasian J. Math. Comp. App., 13(4), 41-52
T2: Cross-domain taxonomy of ML for stress evolution modeling (structured methodological synthesis)	Chapter 3, Sections 3.1-3.7	Wang, Mosavi, Felde, Azodinia et al. (2025). Acta Polytechnica Hung., 22(12), 95-114
T3: LSTM identified as most effective model for time-series pavement SHM using physical variables (independent scientific result)	Chapter 4, Sections 4.1-4.9	Azodinia et al. (2025). Decision Making: Appl. Mgmt. Eng., Vol. 8, Issue 1
T4: RF and SVM demonstrated as most accurate models for GPR-based pavement condition prediction using Relief-based feature selection (independent scientific result)	Chapter 5, Sections 5.1-5.9	Azodinia et al. (2026). Decision Making: Appl. Mgmt. Eng., Vol. 9, Issue 1
T5: LSTM achieves superior accuracy; GRU provides computationally efficient alternative for RSL prediction (independent scientific result)	Chapter 6, Sections 6.1-6.5	Azodinia, Mosavi & Besheyev (2026). J. Appl. Comp. Sci. Telecomm., 1(1), 38-42

This thesis presents an advanced artificial intelligence-based methodology for non-invasive pavement SHM, which relies on GPR data, radiotechnical subsurface sensing, and sensor-based measurements. Pavement structural condition is estimated from asphalt temperature, pavement layer thickness, and subsurface characteristics, which are obtained without physical disturbance. Validation is conducted using field measurements from GPR and HWD, through which high accuracy and reliability are demonstrated. Continuous and high-resolution data acquisition is achieved, as a result of which spatial and temporal variability in pavement condition is effectively captured. Therefore, informed, predictive, and network-level decision making for road maintenance and infrastructure management is supported.

A central innovation of this research is defined by the original integration of non-invasive inductive sensing technologies with machine learning and deep learning methods for pavement SHM. Radiotechnical subsurface signals are directly linked to artificial intelligence models for automated estimation of critical pavement parameters. Conventional practices that rely on intrusive coring, visual inspection, and manual surveys are reduced. In fact, detailed subsurface information is preserved while operational disruption is avoided. Hence, pavement evaluation is transformed into a scalable, data-driven process that supports continuous monitoring across large road networks.

Methodological novelty is further demonstrated through the comprehensive comparison of machine learning and deep learning models under identical data and validation conditions. SVM achieves strong accuracy during training phases, which confirms effective learning of complex subsurface patterns. RF demonstrates superior generalization during testing, with the lowest RMSE and highest CC, which indicates robustness under unseen conditions. ANN-based approaches exhibit weaker performance, which highlights their limitations for this application context. Deep learning models, particularly LSTM and GRU, capture temporal dependencies within sequential pavement data, through which long-term deterioration trends are represented. LSTM provides stable predictions across diverse datasets, while GRU achieves comparable or higher accuracy with reduced computational demand. Therefore, sequential deep learning models are identified as advanced solutions for pavement conditions and remaining service life estimation.

A further innovation is demonstrated by the ability to achieve reliable prediction using limited and practical input variables, e.g., asphalt thickness, base layer depth, and surface temperature. Complex pavement behavior is captured without reliance on frequent and costly field testing. As a result, proactive maintenance strategies are enabled, which allow early intervention and damage prevention. Maintenance planning is improved, budget allocation is optimized, and pavement service life is extended. Moreover, road user safety is enhanced through timely maintenance actions based on predictive indicators rather than reactive observations. From an application perspective, the proposed approaches are well suited for implementation within smart city and smart mobility environments, in which real-time monitoring and large-scale coverage are required. Integration with IoT platforms is supported, which allows continuous data exchange and coordinated infrastructure management. Sensor modularity and adaptable learning models enable transfer across regions with different traffic loads, materials, and climatic conditions. Therefore, transportation agencies are provided with practical tools for automated pavement monitoring, asset prioritization, and evidence-based policy formulation.
The discussion of the obtained results highlights important scientific and practical implications. Performance differences among models confirm that model selection must account for data characteristics, temporal structure, and deployment constraints. RF demonstrates strong

robustness for static prediction tasks, while LSTM and GRU demonstrate clear advantages for time-dependent analysis. Trade-offs between predictive accuracy and computational efficiency are observed, which influences suitability for real-time applications. In addition, the results confirm that non-invasive sensing combined with artificial intelligence can replace or substantially reduce intrusive testing, as long as reliable calibration and validation are maintained. Thus, the findings support a shift toward predictive and data-centric pavement management practices. The future research is encouraged to extend the proposed methodologies across broader datasets and geographic regions, which will improve generalization and transferability. Further investigation of explainable AI methods is required, as interpretability is essential for engineering acceptance and policy adoption. Hybrid and ensemble approaches should be explored to combine the strengths of multiple models. Transfer learning should be examined to reduce data requirements in regions with limited measurements. In addition, integration of traffic prediction, environmental variability, and spatiotemporal modeling should be pursued, which will support unified management of mobility and infrastructure assets. Consequently, this research provides a strong basis for continued advancement of artificial intelligence based, non-invasive pavement SHM with long-term impact on resilient and sustainable transportation networks. Model transferability is acknowledged as a limitation of the current study. The trained models are validated on specific pavement sections with defined layer structures and acquisition configurations. Transfer to pavements with substantially different dielectric properties or layer architectures is addressed through transfer learning, in which a small calibration dataset from the target pavement is used to fine-tune the pre-trained model. The use of physically interpretable input features, i.e., layer thickness, asphalt surface temperature, and dielectric-derived structural parameters, rather than raw GPR waveforms, provides a structural advantage for cross-domain generalization. Furthermore, model calibration is performed once at the point of deployment on a representative dataset from the target pavement section; no periodic recalibration is required under normal operating conditions, as the physically interpretable input features provide sufficient robustness against routine environmental and seasonal variability. A full retraining cycle is considered necessary when a structural change in pavement composition is recorded for a monitored section. An online learning strategy is proposed for deployment contexts, in which the model is updated incrementally as new field data become available, which reduces the need for full re-training cycles and supports continuous adaptation to pavement-specific ageing processes.

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Further publications of the candidate not used in the thesis

[P1] **Azodinia**, M., Mudabbir, M., Ardabili, S., Várkonyi Kóczy, A. R., Iskakov, K., & Mosavi, A. (2025). Service life modeling of pavement with ensemble learning. In Proceedings of the IEEE 12th International Conference on Computational Cybernetics and Cyber Medical Systems (ICCC) (pp. 167–174). IEEE.

[P2] Mosavi, A., & **Azodinia**, M. (2025). Gated recurrent unit for modeling structural integrity of pavements for enhanced road maintenance. In Proceedings of the 10th International Scientific and Practical Conference on Computer Science and Applied Mathematics (CSAM 2025) (pp. 462–469). Al Farabi Kazakh National University.

[P3] **Azodinia**, M., Iskakov, K., Turarova, M., Ardabili, S., & Mosavi, A. (2025). Machine learning for structural health monitoring of pavements. In Proceedings of the XVII Saginov Readings International Scientific and Practical Conference (pp. 11–13). Karaganda Technical University.

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