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# Deep Learning for Structural Health Monitoring of Pavements for Improving Road Maintenance and Management

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**ABSTRACT**

Durable and secure roadway networks underpin sustainable mobility systems and urban growth. In recent years, Artificial Intelligence models have increasingly been employed to estimate the structural condition of roads and pavements. Such approaches enable agencies to organise maintenance schedules more effectively and to channel resources based on evidence-driven priorities. When combined with continuous sensor streams and traffic information, these systems support anticipatory and financially efficient road management, thereby strengthening decision reliability. This investigation develops machine learning frameworks to evaluate pavement structural condition. Variables including asphalt temperature and pavement layer depth are incorporated to forecast overall pavement performance. The resulting model offers a cost-efficient, unobtrusive technique for assessing current pavement status and anticipating emerging defects, which subsequently aids maintenance planning and resource distribution. Linking this modelling approach with wider smart city and smart mobility platforms facilitates real time surveillance of pavement behaviour, enhances road safety, and reinforces transport networks that favour long-term sustainability. The study compares long short-term memory techniques with alternative machine learning methods. The outcomes reveal that the long short-term memory model demonstrates superior behaviour during both training and validation, showing high predictive precision and stronger generalisation when applied to unseen datasets. Consequently, it is identified as the most suitable predictor for the data employed in this research. The results indicate that transport authorities can utilise Artificial Intelligence-based structural health monitoring systems for continuous pavement evaluation. These agencies are also encouraged to integrate sensor outputs and traffic information within unified data environments. Furthermore, policy measures that advance predictive maintenance practices are essential, as they contribute to extended pavement longevity, reduced expenditure, and improved public safety.

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## 1. Introduction

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 [17]. 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 [39]. 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 [44]. An increasing number of machine learning approaches have been introduced to overcome these limitations and address the identified research gaps [3; 8; 9; 36; 37].

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 behaviour of the pavement system [41]. The predictive strengths of machine learning are utilised to establish proactive and efficient maintenance planning, thereby improving resource distribution and contributing to the enhancement of road safety [47]. 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 [33]. Smart mobility, which aims to optimise the movement of people and goods through advanced technological solutions, benefits substantially from 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 optimisation, and adaptive maintenance planning [28]. 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 [2]. 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.

## 2. Literature Review

Before the introduction of artificial intelligence, structural health monitoring depended heavily on conventional techniques such as manual inspections and direct testing procedures [26]. 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 [23]. 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 [53]. Ground penetrating radar was employed to understand the condition of underlying layers Bernard and Yakovenko [12], and infrared thermography located surface irregularities by capturing temperature contrasts [51]. Pavement systems were further evaluated using falling weight deflectometers, which replicated traffic-induced pressures [34]. 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 [42]. Traditional approaches are constrained by labour-intensive inspections, costly tools, and limited analytical capacity, which means that early deterioration is frequently missed or structural conditions are assessed only intermittently [24]. Artificial intelligence enhances monitoring by continually analysing 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 [21]. 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 [49].

A range of studies illustrates these benefits. For instance, research in Alnaqbi et al. [6] 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 [57]. Drawing on pavement survey data, core samples, and environmental conditions, the model offered reliable indicators of maintenance needs and supported the optimisation of repair schedules. Support vector machines have also been used to forecast the performance and residual life of rigid pavements [6]. Additional studies, for example Ali et al. [5], 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 [60]. 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 [14]. 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 [52], 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 [35]. 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 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 [38]. Although AI shows considerable capability in forecasting pavement condition and RSL, a number of research limitations remain [50]. 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 [15].

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 [10]. 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 [18]. 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 [13]. 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 [54]. 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 [19]. 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 [56].

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 explain ability seeks to mitigate these issues [58]. 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 [48]. 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.

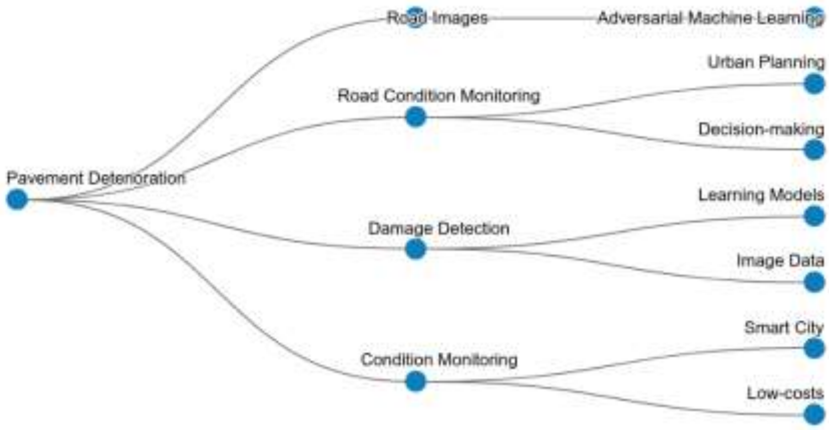



**Fig.1:** Taxonomy of ML Applications for Pavement Modelling

ML is increasingly recognised 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 [56]. Regression-based approaches have shown reliability in estimating asphalt friction performance García-Segura et al. [25], while more sophisticated ML methods such as Random Forests provide significant gains in predicting roughness progression, rutting behaviour, and fatigue-related cracking [61]. SVM and ANN models also demonstrate strong predictive capability, with ANN frequently producing superior estimations for roughness-related parameters [4].

Within DL, models including YOLOv5 and U-Net achieve notable precision for crack identification and segmentation tasks [27]. Time-series analyses benefit from architectures such as RNN and LSTM, with hybrid configurations like LSTM–FCNN consistently outperforming conventional modelling strategies [43]. Integrated systems such as SOS-LSSVR further advance predictive performance by coupling optimisation procedures with regression-based techniques [45]. These AI-enabled methods contribute to more efficient asset management by refining maintenance scheduling, prolonging pavement lifespan, and lowering overall repair expenditures [46]. Linking AI with continuous, real-time data acquisition further accelerates condition assessment and supports earlier, more targeted remedial actions [19]. Nonetheless, several constraints remain, particularly concerning labour-intensive data annotation and the limited capacity of models to adapt reliably across varied climatic, structural, and operational settings [49]. 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 [22]. These methods improve the precision of deterioration and modulus prediction, contributing to more dependable estimates of pavement reliability and overall service life [1]. 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 [11]. Deep ensemble frameworks that merge neural networks with tree-based algorithms enhance predictive quality for indicators including surface roughness and cracking [30]. Such approaches support the formulation of targeted maintenance actions and strengthen the optimisation of pavement management programmes. 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 emphasises robust modelling principles to generate accurate, actionable, and efficient predictions of pavement life, thereby reinforcing sustainable maintenance practices and long-term infrastructure resilience.

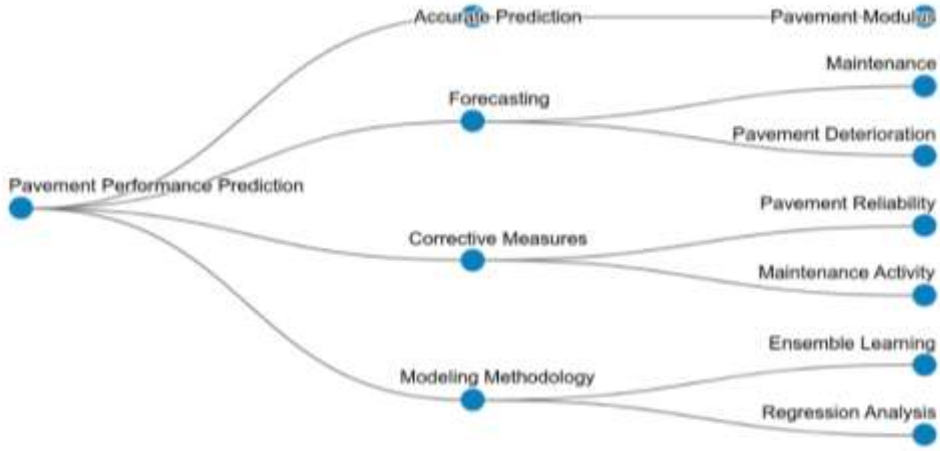



**Fig.2:** Taxonomy of DL Applications in Pavement Modelling

## 3. Materials and Methods

### *3.1 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. Asphalt surface temperature is recorded directly during field inspections, thereby incorporating environmental influences into the RSL estimation process. This data set forms the basis for developing models capable of estimating RSL without reliance on costly instruments such as the FWD and GPR, providing 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 behaviour.

### *3.2 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 optimised 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 analysing 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 normalisation, treatment of missing values, and selection of the most informative features.

#### *3.2.1 Stochastic Gradient Descent (SGD)*

SGD functions as an optimisation algorithm and is also classified as an ML technique [7]. 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 regularisation with a mixing ratio of 0.15, and a learning rate of 0.15, which was determined to provide the best performance.

#### *3.2.2 Extreme Gradient Boosting (XGBoost)*

XGBoost is an ensemble-based ML technique that constructs a robust predictive framework by combining multiple decision trees [16]. 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 emphasise 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 regularisation parameter lambda to 0.8, achieving optimal prediction performance.

#### *3.2.3 Artificial Neural Network (ANN)*

ANN is an ML technique inspired by the structure of the human nervous system [4]. 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.

### 3.2.4 ANN Integrated with Particle Swarm Optimizer (PSO)

In this stage, the previously designed ANN architecture was combined with PSO to optimise weights and biases more effectively. This approach enhances the training process by dynamically adjusting the network parameters. PSO is a population-based optimisation 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 neighbouring 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 optimised configuration.

### 3.2.5 ANN Integrated with Grey Wolf Optimizer (GWO)

In this phase, the ANN developed in the previous step was integrated with GWO to enhance the optimisation of weights and biases. The use of a supplementary optimiser during ANN training improves parameter tuning, resulting in more accurate predictions. GWO is a swarm intelligence algorithm that emulates the social hunting behaviour of grey wolves, relying on hierarchical leadership and cooperative strategies to navigate the solution space [31]. The parameters for this method were selected through a trial-and-error process, using 100 wolves and 510 iterations to achieve the optimised configuration.

### 3.2.6 Adaptive Boosting (Adaboost)

AdaBoost is an ensemble learning ML technique that combines multiple weak classifiers to generate a robust predictive model [55]. 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.

### 3.2.7 Long Short-Term Memory (LSTM)

LSTM is a specialised 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 [29]. The network configuration was established through a trial-and-error approach. The optimised LSTM model consisted of two hidden layers, each containing 50 nodes, with a learning rate set at 0.0008.

### 3.2.8 Evaluating the Models

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

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

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

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

## 4. Results

### *4.1 Statistical Specifications of Dataset*

In this step, the relationships among variables are outlined. Table 1 summarizes the statistical characteristics of the variables, including mean, sample size, standard deviation, median, minimum, maximum, variance, and skewness.

**Table 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 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.

**Table 2**
ANOVA Results

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

### *4.2 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 3**
Training Results of the Developed Models

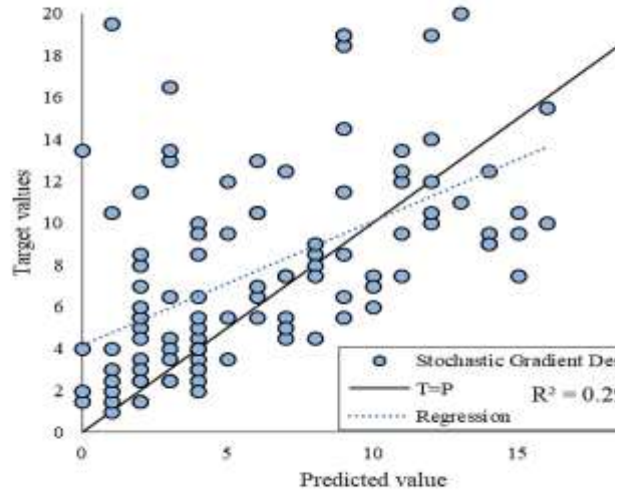
| Model | Architecture | RMSE | CC |
|---|---|---|---|
| SGD | Loss function of the epsilon intensive type of 0.31, elastic net regulation with mixing of 0.15 and learning rate optimization of 0.15 | 6.92 | 0.73 |
| XGboost | Number of trees 25, learning rate 0.3, and lambda 0.8 | 17.04 | 0.88 |
| ANN-PSO | 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 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 generalisation 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 generalisation capability of the LSTM model, which is therefore recommended as the optimal choice for this analysis.

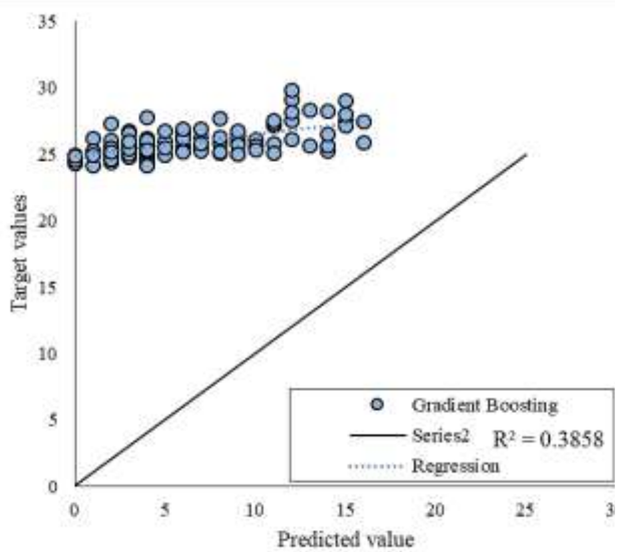
**Table 4**
Testing Results of the Developed Models

| 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 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.


Target values
Predicted value
Stochastic Gradient De
T=P
Regression
R² = 0.2

(a)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Predicted value
Gradient Boosting
Series2
Regression
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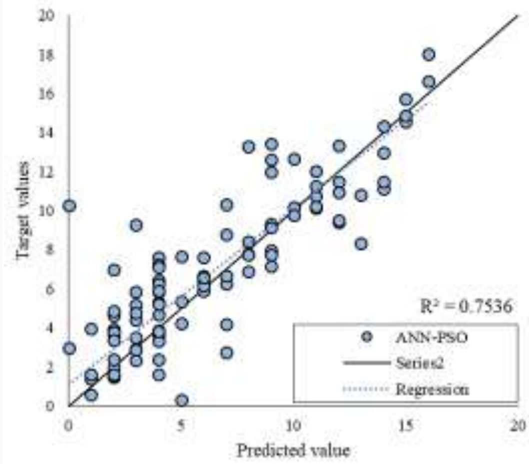
(b)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Predicted value
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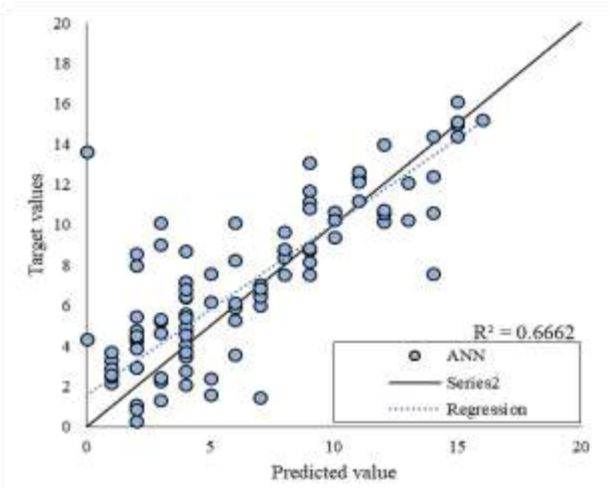
ANN-PSO
Series2
Regression

(c)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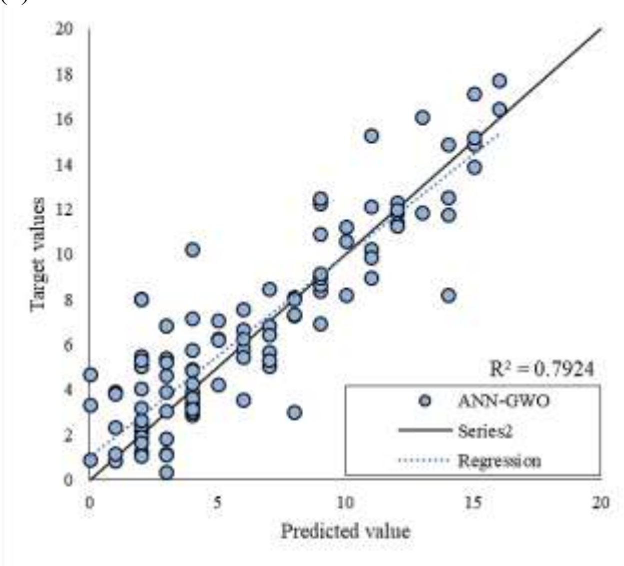
Series2
Regression

(d)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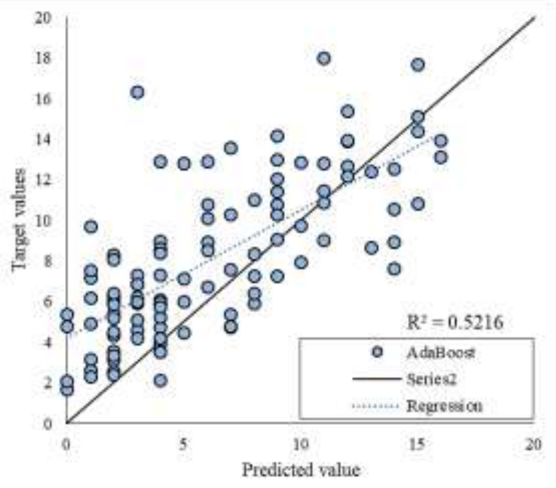
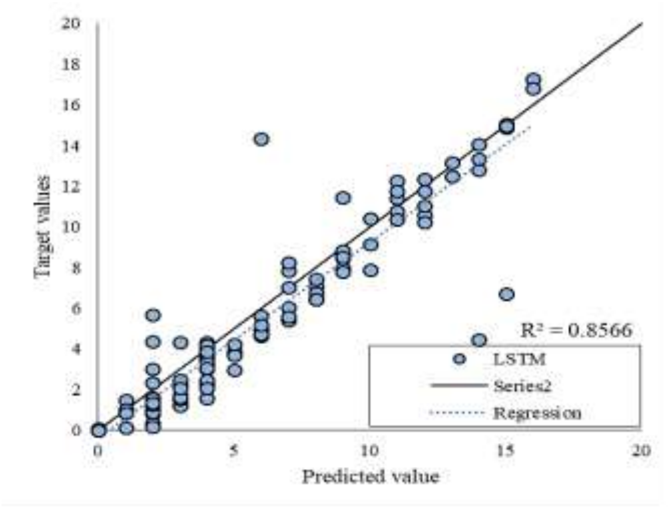
Predicted value
R² = 0.7924
ANN-GWO
Series2
Regression

(e)


Target values
Predicted value
R² = 0.5216
AdaBoost
Series2
Regression

(f)




g)

**Fig.3:** The Plot Diagram of the Testing Phase. a) Stochastic Gradient Descent, b) Gradient Boosting, c) ANN-PSO, d) ANN, e) ANN-GWO, f) AdaBoost, and g) LSTM

Figure 4 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.

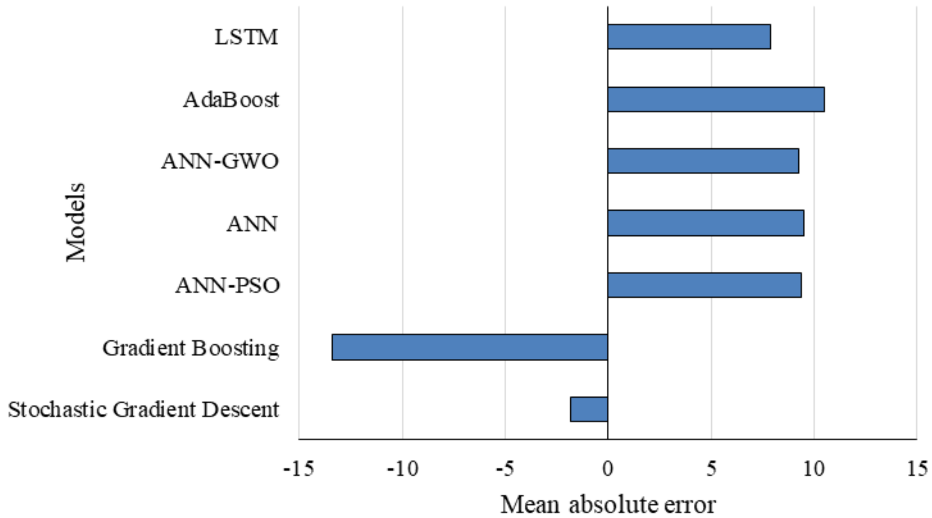



**Fig.4:** Square Relative Error of Testing Phase

## 5. 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 generalisation to unseen data. Visual analyses in

Figures 3 and 4 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 optimisation-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; generalisation to real-world conditions and accurate representation of underlying system behaviour 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.

## 6. 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, optimising 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.

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**References**

[1] Ahmad, F., Alasskar, A., Samui, P., & Asteris, P. G. (2025). Machine learning-based graphical user interface for predicting high-performance concrete compressive strength: comparative analysis of gradient boosting machine, random forest, and deep neural network models. *Frontiers of Structural and Civil Engineering*, *19*(7), 1075-1090. https://doi.org/10.1007/s11709-025-1201-8

[2] Akhayeva, Z., Zakirova, A., & ZHMUD, V. (2024). Optimization of water resources management using big data and machine learning in smart cities. *Eurasian Journal of Mathematical and Computer Applications*, *12*(2), 4-15. https://doi.org/10.32523/2306-6172-2024-12-2-4-15

[3] Alaloul, W. S., Altaf, M., Musarat, M. A., Faisal Javed, M., & Mosavi, A. (2021). Systematic review of life cycle assessment and life cycle cost analysis for pavement and a case study. *Sustainability*, *13*(8), 4377. https://doi.org/10.3390/su13084377

[4] Alatoom, Y. I., & Al-Suleiman, T. I. (2022). Development of pavement roughness models using Artificial Neural Network (ANN). *International Journal of Pavement Engineering*, *23*(13), 4622-4637. https://doi.org/10.1080/10298436.2021.1968396

[5] Ali, A. A., Milad, A., Hussein, A., Yusoff, N. I. M., & Heneash, U. (2023). Predicting pavement condition index based on the utilization of machine learning techniques: A case study. *Journal of Road Engineering*, *3*(3), 266-278. https://doi.org/10.1016/j.jreng.2023.04.002

[6] Alnaqbi, A., Al-Khateeb, G., & Zeiada, W. (2024). A hybrid approach of support vector regression with genetic algorithm optimization for predicting spalling in continuously reinforced concrete pavement. *Journal of Building Pathology and Rehabilitation*, *9*(2), 146. https://doi.org/10.1007/s41024-024-00499-z

[7] Amari, S.-i. (1993). Backpropagation and stochastic gradient descent method. *Neurocomputing*, *5*(4-5), 185-196. https://doi.org/10.1016/0925-2312(93)90006-O

[8] Sengun, E., Kim, S., & Ceylan, H. (2024). A comparative study on structural design of plain and roller-compacted concrete for heavy-duty pavements. Road Materials and Pavement Design, 25(2), 392-422. https://doi.org/10.1080/14680629.2023.2209194

[9] Azodinia, M., Mudabbir, M., Ardabili, S., Varkonyi-Koczy, A., Iskakov, K., & Mosavi, A. (2025). Service Life Modeling of Pavement with Ensemble Learning. 2025 IEEE 12th International Conference on Computational Cybernetics and Cyber-Medical Systems (ICCC),

[10] Baduge, S. K., Thilakarathna, S., Perera, J. S., Ruwanpathirana, G. P., Doyle, L., Duckett, M., Lee, J., Saenda, J., & Mendis, P. (2023). Assessment of crack severity of asphalt pavements using deep learning algorithms and geospatial system. *Construction and Building Materials*, *401*, 132684. https://doi.org/10.1016/j.conbuildmat.2023.132684

[11] Benkhalfallah, M. S., Kouah, S., & Harous, S. (2025). Predicting the Energy Consumption in Chillers: A Comparative Study of Supervised Machine Learning Regression Models. *Energies*, *18*(14), 3672. https://doi.org/10.3390/en18143672

[12] Bernard, A., & Yakovenko, S. (2025). Application of machine learning methods to channel flow modelling. *Eurasian Journal of Mathematical and Computer Applications*, *13*(2), 4-12. https://ejmca.enu.kz/assets/files/13-2-1.pdf

[13] Cano-Ortiz, S., Pascual-Muñoz, P., & Castro-Fresno, D. (2022). Machine learning algorithms for monitoring pavement performance. *Automation in Construction*, *139*, 104309. https://doi.org/10.1016/j.autcon.2022.104309

[14] Cao, Q., Al-Qadi, I. L., & Abufares, L. (2022). Pavement moisture content prediction: A deep residual neural network approach for analyzing ground penetrating radar. *IEEE Transactions on Geoscience and Remote Sensing*, *60*, 1-11. https://doi.org/10.1109/TGRS.2022.3224159

[15] Chen, K., Torbaghan, M. E., Thom, N., Garcia-Hernández, A., Faramarzi, A., & Chapman, D. (2024). A Machine Learning based approach to predict road rutting considering uncertainty. *Case Studies in Construction Materials*, *20*, e03186. https://doi.org/10.1016/j.cscm.2024.e03186

[16] Chen, T., He, T., Benesty, M., Khotilovich, V., Tang, Y., Cho, H., Chen, K., Mitchell, R., Cano, I., & Zhou, T. (2015). Xgboost: extreme gradient boosting. *R package version 0.4-2*, *1*(4), 1-4. https://cran.ms.unimelb.edu.au/web/packages/xgboost/vignettes/xgboost.pdf

[17] Di Graziano, A., Marchetta, V., & Cafiso, S. (2020). Structural health monitoring of asphalt pavements using smart sensor networks: A comprehensive review. *Journal of Traffic and Transportation Engineering (English Edition)*, *7*(5), 639-651. https://doi.org/10.1016/j.jtte.2020.08.001

[18] Doroudi, R., Lavassani, S. H. H., & Shahrouzi, M. (2024). Optimal tuning of three deep learning methods with signal processing and anomaly detection for multi-class damage detection of a large-scale bridge. *Structural Health Monitoring*, *23*(5), 3227-3252. https://doi.org/10.1177/14759217231216694

[19] Ebika, I. M., Idoko, D. O., Efe, F., Enyejo, L., Otakwu, A., Odeh, I. I., & Headquarters, A.-V. (2024). Utilizing machine learning for predictive maintenance of climate-resilient highways through integration of advanced asphalt binders and permeable pavement systems with IoT technology. *International Journal of Innovative Science and Research Technology*, *9*(11). https://doi.org/10.38124/ijisrt/IJISRT24NOV074

[20] Elghaish, F., Matarneh, S., Abdellatef, E., Rahimian, F., Hosseini, M. R., & Farouk Kineber, A. (2025). Multi-layers deep learning model with feature selection for automated detection and classification of highway pavement cracks. *Smart and Sustainable Built Environment*, *14*(2), 511-535. https://doi.org/10.1108/SASBE-09-2023-0251

[21] Elghaish, F., Matarneh, S. T., Talebi, S., Abu-Samra, S., Salimi, G., & Rausch, C. (2022). Deep learning for detecting distresses in buildings and pavements: a critical gap analysis. *Construction Innovation*, *22*(3), 554-579. https://doi.org/10.1108/CI-09-2021-0171

[22] Engqvist Stöhr, H., & Hennings, E. (2025). Deep Learning for Pavement Distress Forecasting: A Hybrid-LSTM Approach and Application Evaluation for Efficient Pavement Maintenance Forecasting. In. https://www.diva-portal.org/smash/record.jsf?pid=diva2:1977793

[23] Fawad, M., Salamak, M., Poprawa, G., Koris, K., Jasinski, M., Lazinski, P., Piotrowski, D., Hasnain, M., & Gerges, M. (2023). Automation of structural health monitoring (SHM) system of a bridge using BIMification approach and BIM-based finite element model development. *Scientific Reports*, *13*(1), 13215. https://doi.org/10.1038/s41598-023-40355-7

[24] Flah, M., Nunez, I., Ben Chaabene, W., & Nehdi, M. L. (2021). Machine Learning Algorithms in Civil Structural Health Monitoring: A Systematic Review. *Archives of computational methods in engineering*, *28*(4). https://doi.org/10.1007/s11831-020-09471-9

[25] García-Segura, T., Montalbán-Domingo, L., Llopis-Castelló, D., Sanz-Benlloch, A., & Pellicer, E. (2023). Integration of deep learning techniques and sustainability-based concepts into an urban pavement management system. *Expert Systems with Applications*, *231*, 120851. https://doi.org/10.1016/j.eswa.2023.120851

[26] Gharehbaghi, V. R., Noroozinejad Farsangi, E., Noori, M., Yang, T., Li, S., Nguyen, A., Málaga-Chuquitaype, C., Gardoni, P., & Mirjalili, S. (2022). A critical review on structural health monitoring: Definitions, methods, and perspectives. *Archives of computational methods in engineering*, *29*(4), 2209-2235. https://doi.org/10.1007/s11831-021-09665-9

[27] Gooda, S. K., Chinthamu, N., Selvan, S. T., Rajakumareswaran, V., & Paramasivam, G. (2023). Automatic detection of road cracks using efficientnet with residual u-net-based segmentation and yolov5-based detection. *Int. J. Recent Innov. Trends Comput. Commun*, *11*(4), 84-91. https://doi.org/10.17762/ijritcc.v11i4s.6310

[28] Goumiri, S., Yahiaoui, S., & Djahel, S. (2025). Smart Mobility in Smart Cities: Emerging challenges, recent advances and future directions. *Journal of Intelligent Transportation Systems*, *29*(1), 81-117. https://doi.org/10.1080/15472450.2023.2245750

[29] Graves, A. (2012). Long short-term memory. *Supervised sequence labelling with recurrent neural networks*, 37-45. https://doi.org/10.1007/978-3-642-24797-2_4

[30] Guo, W., Zhang, J., Murtaza, M., Wang, C., & Cao, D. (2023). An ensemble learning with sequential model-based optimization approach for pavement roughness estimation using smartphone sensor data. *Construction and Building Materials*, *406*, 133293. https://doi.org/10.1016/j.conbuildmat.2023.133293

[31] Hatta, N., Zain, A. M., Sallehuddin, R., Shayfull, Z., & Yusoff, Y. (2019). Recent studies on optimisation method of Grey Wolf Optimiser (GWO): a review (2014–2017). *Artificial intelligence review*, *52*(4), 2651-2683. https://doi.org/10.1007/s10462-018-9634-2

[32] Hodson, T. O. (2022). Root mean square error (RMSE) or mean absolute error (MAE): When to use them or not. *Geoscientific Model Development Discussions*, *2022*, 1-10. https://doi.org/10.5194/gmd-15-5481-2022

[33] Jagatheesaperumal, S. K., Bibri, S. E., Ganesan, S., & Jeyaraman, P. (2023). Artificial Intelligence for road quality assessment in smart cities: a machine learning approach to acoustic data analysis. *Computational Urban Science*, *3*(1), 28. https://doi.org/10.1007/s43762-023-00104-y

[34] Jiang, X., Gabrielson, J., Huang, B., Bai, Y., Polaczyk, P., Zhang, M., Hu, W., & Xiao, R. (2022). Evaluation of inverted pavement by structural condition indicators from falling weight deflectometer. *Construction and Building Materials*, *319*, 125991. https://doi.org/10.1016/j.conbuildmat.2021.125991

[35] Kang, J., Tavassoti, P., Chaudhry, M. N. A. R., Baaj, H., & Ghafurian, M. (2025). Artificial intelligence techniques for pavement performance prediction: a systematic review. *Road Materials and Pavement Design*, *26*(3), 497-522. https://doi.org/10.1080/14680629.2024.2373222

[36] Ramadan, S., Kassem, H., ElKordi, A., & Joumblat, R. (2024). Incorporating artificial intelligence applications in flexible pavements: A comprehensive overview. *International Journal of Pavement Research and Technology*, 1-26. https://doi.org/10.1007/s42947-024-00496-y

[37] K Setyawan, A., Nainggolan, J., & Budiarto, A. (2015). Predicting the remaining service life of road using pavement condition index. Procedia Engineering, 125, 417-423. https://doi.org/10.1016/j.proeng.2015.11.108

[38] Kaur, G., & Kumar, R. (2025). Assessing Fatigue and Rutting Life of Flexible Pavements Using Soft-Computing Techniques. *Journal of Failure Analysis and Prevention*, 1-17. https://doi.org/10.1007/s11668-025-02176-w

[39] Khan, S. M., Atamturktur, S., Chowdhury, M., & Rahman, M. (2016). Integration of structural health monitoring and intelligent transportation systems for bridge condition assessment: Current status and future direction. *IEEE Transactions on Intelligent Transportation Systems*, *17*(8), 2107-2122. https://doi.org/10.1109/TITS.2016.2520499

[40] Klibanov, M. V., & Timonov, A. . (2022). Deep learning and successive iterations for an inverse problem of the variable density reconstruction by the boundary control method. . *Eurasian Journal of Mathematical and Computer Applications*, *10*(3), 37-57. https://doi.org/10.32523/2306-6172-2022-10-3-37-57

[41] Kodikara, J., Sounthararajah, A., & Chen, L. (2024). Reimagining unbound road pavement technology: Integrating testing, design, construction and performance in the post-digital era. *Transportation Geotechnics*, *47*, 101274. https://doi.org/10.1016/j.trgeo.2024.101274

[42] Kulkarni, N. N., Raisi, K., Valente, N. A., Benoit, J., Yu, T., & Sabato, A. (2023). Deep learning augmented infrared thermography for unmanned aerial vehicles structural health monitoring of roadways. *Automation in Construction*, *148*, 104784. https://doi.org/10.1016/j.autcon.2023.104784

[43] Mers, M., Yang, Z., Hsieh, Y.-A., & Tsai, Y. (2023). Recurrent neural networks for pavement performance forecasting: review and model performance comparison. *Transportation Research Record*, *2677*(1), 610-624. https://doi.org/10.1177/03611981221100521

[44] Mudabir, M., Mosavi, A., Imre, F., Moniz, N., Iskakov, K., & Mohamadreza, A. (2025). Modeling Remaining Service Life and Structural Health Monitoring of Roads with Machine Learning and Deep Learning. 2025 IEEE 23rd World Symposium on Applied Machine Intelligence and Informatics (SAMI), 9798350379365. https://doi.org/10.1109/SAMI63904.2025.10883327

[45] Ngoc-Mai, N., & Cao, M. T. (2024). Predicting Mechanical Properties of Concrete Structures Using Metaheuristic Optimization-Based Machine Learning Models. *Available at SSRN 4923416*. https://ssrn.com/abstract=4923416

[46] Noureddine, S., Zineeddine, B., Toumi, A., Betka, A., & Benharkat, A.-N. (2022). A new predictive medical approach based on data mining and Symbiotic Organisms Search algorithm. *International Journal of Computers and Applications*, *44*(5), 465-479. https://doi.org/10.1080/1206212X.2020.1809825

[47] Olugbade, S., Ojo, S., Imoize, A. L., Isabona, J., & Alaba, M. O. (2022). A review of artificial intelligence and machine learning for incident detectors in road transport systems. *Mathematical and Computational Applications*, *27*(5), 77. https://doi.org/10.3390/mca27050077

[48] Omar, I. (2023). *Machine learning (ml) approaches to model interdependencies between dynamic loads and crack propagation* Cranfield University]. https://dspace.lib.cranfield.ac.uk/handle/1826/24026

[49] Plevris, V., & Papazafeiropoulos, G. (2024). AI in structural health monitoring for infrastructure maintenance and safety. *Infrastructures*, *9*(12), 225. https://doi.org/10.3390/infrastructures9120225

[50] Qureshi, W. S., Hassan, S. I., McKeever, S., Power, D., Mulry, B., Feighan, K., & O'Sullivan, D. (2022). An exploration of recent intelligent image analysis techniques for visual pavement surface condition assessment. *Sensors*, *22*(22), 9019. https://doi.org/10.3390/s22229019

[51] Ramzan, B., Malik, M. S., Martarelli, M., Ali, H. T., Yusuf, M., & Ahmad, S. (2021). Pixel frequency based railroad surface flaw detection using active infrared thermography for structural health monitoring. *Case Studies in Thermal Engineering*, *27*, 101234. https://doi.org/10.1016/j.csite.2021.101234

[52] Roberts, R., Inzerillo, L., & Di Mino, G. (2021). Exploiting data analytics and deep learning systems to support pavement maintenance decisions. *Applied Sciences*, *11*(6), 2458. https://doi.org/10.3390/app11062458

[53] Saidin, S. S., Jamadin, A., Abdul Kudus, S., Mohd Amin, N., & Anuar, M. A. (2022). An overview: The application of vibration-based techniques in bridge structural health monitoring. *International Journal of Concrete Structures and Materials*, *16*(1), 69. https://doi.org/10.1186/s40069-022-00557-1

[54] Sedighian-Fard, M., Golroo, A., Javanmardi, M., Alahi, A., & Rasti, M. (2025). Data generation for asphalt pavement evaluation: Deep learning-based insights from generative models. *Case Studies in Construction Materials*, e05116. https://doi.org/10.1016/j.cscm.2025.e05116

[55] Taherkhani, A., Cosma, G., & McGinnity, T. M. (2020). AdaBoost-CNN: An adaptive boosting algorithm for convolutional neural networks to classify multi-class imbalanced datasets using transfer learning. *Neurocomputing*, *404*, 351-366. https://doi.org/10.1016/j.neucom.2020.03.064

[56] Tamagusko, T., Gomes Correia, M., & Ferreira, A. (2024). Machine Learning Applications in Road Pavement Management: A Review, Challenges and Future Directions. *Infrastructures*, *9*(12). http://doi.org/10.3390/infrastructures9120213

[57] Xin, J., Akiyama, M., Frangopol, D. M., Zhang, M., Pei, J., & Zhang, J. (2021). Reliability-based life-cycle cost design of asphalt pavement using artificial neural networks. *Structure and Infrastructure Engineering*, *17*(6), 872-886. https://doi.org/10.1080/15732479.2020.1815807

[58] Yao, L., Leng, Z., Jiang, J., & Ni, F. (2022). Modelling of pavement performance evolution considering uncertainty and interpretability: a machine learning based framework. *International Journal of Pavement Engineering*, *23*(14), 5211-5226. https://doi.org/10.1080/10298436.2021.2001814

[59] Zhang, H., Liu, T., Lu, J., Lin, R., Chen, C., He, Z., Cui, S., Liu, Z., Wang, X., & Liu, B. (2023). Static and ultrasonic structural health monitoring of full-size aerospace multi-function capsule using FBG strain arrays and PSFBG acoustic emission sensors. *Optical Fiber Technology*, *78*, 103316. https://doi.org/10.1016/j.yofte.2023.103316

[60] Zhao, K., Xu, S., Loney, J., Visentin, A., & Li, Z. (2024). Road pavement health monitoring system using smartphone sensing with a two-stage machine learning model. *Automation in Construction*, *167*, 105664. https://doi.org/10.1016/j.autcon.2024.105664

[61] Zhu, J., Yin, Y., Ma, T., & Wang, D. (2025). A novel maintenance decision model for asphalt pavement considering crack causes based on random forest and XGBoost. *Construction and Building Materials*, *477*, 140610. https://doi.org/10.1016/j.conbuildmat.2025.140610