Using Machine Learning for Road Performance Modelling and Influential Factors Investigation

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***Abstract*—Healthy road networks are essential to facilitate economic and social development. Sustaining the integrity of road pavement necessitates having reliable performance models. Such performance models can facilitate evaluating the effect of different physical, environmental, and operational factors on road pavement performance. Hence, this research adopts multiple Machine Learning (ML) algorithms to model the impact of these factors on a composite Pavement Condition Rating (PCR). The PCR is developed using three indicators, namely cracking, rutting, and the International Roughness Index (IRI). This study investigates the implementation of some widely acknowledged ML algorithms, including Artificial Neural Networks, Support Vector Machines, and Bagged Regression Trees to model road pavement performance. Thus, the models are developed and tested using a data set of 302 road sections managed by the Nebraska Department of Roads (NDOR). Also, the deterioration factors are ranked based on their influence on the PCR. Based on the developed models, annual daily traffic (ADT), base layer thickness, and age affect the pavement condition most.**

***Keywords*—performance modeling, pavement, machine learning, influential factors investigation**

I. INTRODUCTION

Keeping road pavements in good condition is essential to facilitate economic and social development. However, this mission is increasingly challenging. For example, according to ASCE's 2021 Report Card for America's Infra-structure, about 42% of the roads in the United States of America (USA) are in poor or mediocre condition [1]. Maintaining the integrity of road pavement is challenging due to the gigantic volume of road networks, the progressive deterioration, as well as budget limitations [2]. Nowadays, road networks are magnificent in size. In the United States of America (USA) alone, the size of the existing public roads exceeds 4 million miles. With these vast road networks, it is difficult to cap the degradation of road pavements due to the accelerated growth in traffic volume and climate change. Recently, climate change has exacerbated the environmental impact as extreme environmental events become more frequent [3]. Moreover, budgetary constraints induced new challenges for highway agencies. These constraints force them to defer some maintenance activities and necessitate a balance between current and future needs. This makes it essential for highway agencies to do more with fewer funds. In some instances, budget constraints imply deferring the maintenance of some roads and forcing decision-makers to prioritize the treatment of some roads over others [1]. Thus, it is essential to manage road pavement assets effectively and professionally.

Increasingly, highway agencies around the world are managing roads more systematically by adopting Pavement Management Systems (PMS). According to AASHTO, PMS comprises a set of tools and processes to assist decision-makers in systematically monitoring, evaluating, analyzing, and planning to preserve road pavements in a serviceable condition over time [4]. Pavement performance modelling is one of the main pillars of PMS [5].

Thus, modeling road performance is vital for decision-makers' estimation of the future condition of roads [2]. The combined effect of environmental and traffic-related factors, as well as age, causes several types of destresses that deteriorate the pavement condition [6]. Pavement performance models are used to investigate the degradation process and anticipate future pavement conditions. In addition, they primarily link pavement performance with the key influential factors, including material, design, and environment variables [7]. Commonly, pavement performance models can be categorized into three fundamental types: empirical, mechanistic, and mechanistic-empirical [8]. In comparison with other models, empirical models are the most commonly used models in pavement management. Empirical models mainly rely on observed data to link different influential factors to pavement performance [9].

Different models have been developed to model the performance of the road pavements and predict the shifts in the distresses, individual condition indices, and composite condition indices [4]. Tabatabaee *et al.* [10] utilized recurrent neural networks and support vector classifiers to model pavement performance. Wang *et al.* [11] estimated pavement fatigue failure time using survival analysis. Zhang & Damnjanović [12] and Han *et al.* [13]

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integrated the method of moments with reliability theory to model pavement deterioration. Later, pavement deterioration modeling employed machine learning models. Thus, Gajewski & Sadowski [14] integrated artificial neural networks (ANN) with the finite element method to model crack propagation in pavement asphalt layers. Similarly, Kirbaş & Karaşahin [15] created ANN performance models to model the deterioration of asphalt road sections. More recently, with the availability of big data and effective computers, deep learning models have become more common for pavement performance modeling. For example, Choi and Do [16] used LSTM to develop a pavement deterioration model. The developed models predict the upcoming year's pavement condition for different sections based on the historical data collected in the past years.

Pavement performance is often complex and dynamic. Thus, the models are required to be renovated frequently to include any possible changes [8]. Therefore, developing reliable and updated performance modeling facilitates better maintenance planning to optimize the construction material selection, treatment type, and treatment time. [2,4]. Thus, it is useful to model the relationship between a performance index with different factors that might affect the performance of road pavements, including age, physical factors (asphalt and base layer thickness), environmental factors (air and pavement temperature), and operational factors (ADT). This study aims to develop multiple pavement performance models considering pavement age as well as multiple physical, environmental, and operational factors to predict the PCR values of road pavement. PCR is calculated based on three asphalt condition criteria: IRI, rutting, and cracking. Finally, the importance of the used factors is assessed using the developed pavement performance models.

II. Methodology

The present research study intends to develop reliable road performance models using ML. In this regard, a set of deterioration factors with a potential impact on road performance are identified. This includes age, environmental factors (air temperature and pavement temperature), physical factors (base layer depth and surface layer depth), and operational factors (average daily traffic). Subsequently, road performance models are developed to establish a relationship between PCR values and age, physical, environmental, and operational factors. PCR is developed using an integrated approach based on AHP-MAUT-Monte Carlo simulation. It is developed based on questionnaire data collected by Tabara [17]. The developed index of PCR is a composite pavement index of 10 points scale. The lowest PCR value of zero indicates the worst performance, whereas the highest PCR value of ten indicates the best performance. The framework of models development is depicted in Fig. 1. Thus, the first step comprises building a database of PCR values and six factors of age, air temperature, pavement temperature, asphalt layer thickness, base layer thickness, and ADT for 302 road pavement sections. Data on the six deterioration factors as well as IRI, cracking, and rutting values used for the calculation of PCR are collected for 302 road pavement sections managed by NDOR.

To develop the performance models, the established database is split into two parts using a division ratio of 80:20. The bigger division of 242 sections is used for model development. However, the data from the remaining 60 sections are used to validate the models. Finally, the developed models are established and subsequently used to analyze the influence of the six factors on pavement performance.

A set of widely recognized ML algorithms is exploited to predict the performance condition of roads based on the six investigated factors. As shown in Fig. 2, three types of algorithms of tree-based, regression-based, and neural network based are used. These algorithms include three regression-tree-based algorithms (Regression Tree (RT), Bagged Regression Trees (BaRG), and Boosted Regression Tree (BoRT)), two artificial neural network-based algorithms (ANN, and Long Short-Term Memory (LSTM)), as well as Gaussian Process Regression (GPR), and Support Vector Machine (SVM). Their performances are analyzed by capitalizing on the evaluation indicators of mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared percentage error (RMSPE). The ANN model is selected to optimize the hyperparameters of layers and node numbers. In addition, the importance of the input-related deterioration factors is evaluated by comparing their relative importance weights in the developed models.

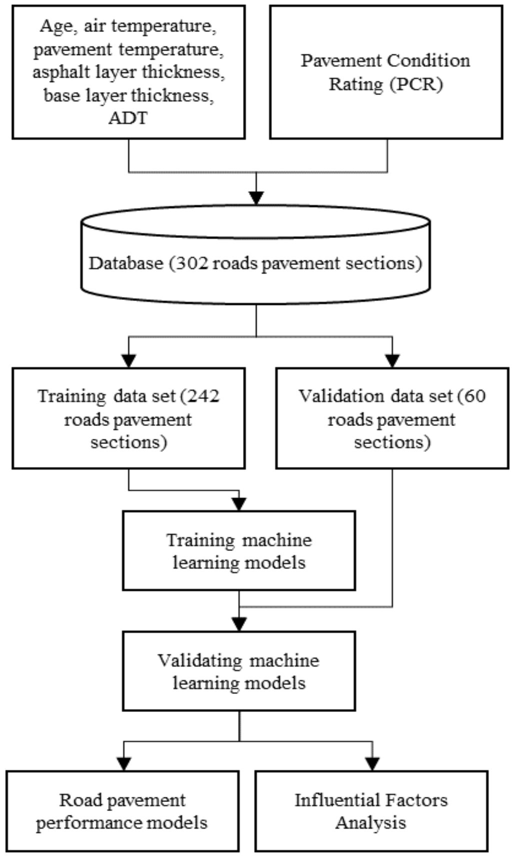

Figure 1. Research methodology.

III. Results and Analysis

Establishing relationships between the calculated PCR and factors that describe the roads' physical, environmental, and operational aspects is useful in different ways. First, it is helpful to understand the effect of various factors on roads condition. Second, it facilitates forecasting roads condition over time to establish reliable deterioration models. Finally, it is helpful to improve material selection and essential for strategic planning.

Data collected from 302 road pavement sections are used for modeling and validating the performance model. The collected data constitute six factors: two environmental factors of air temperature and pavement temperature, two physical factors of surface layer thickness and base layer thickness, as well as the age and the operational factor of ADT. Various algorithms are explored to develop reliable pavement performance models. The model development process is performed in the MATLAB environment. The model development process constitutes two stages of modeling and validation. Thus, the collected data are divided into two groups of modeling and validation. 80% of the data are used for modeling, whereas the remaining 20% of the data are used for validation. Cross-validation of five folds is adopted to develop the models in order to avoid overfitting. The performance of the developed models is evaluated using three performance metrics, namely Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Means Square Percentage Error (RMSPE). The performance of the models is measured against the two data sets of modeling and validation.

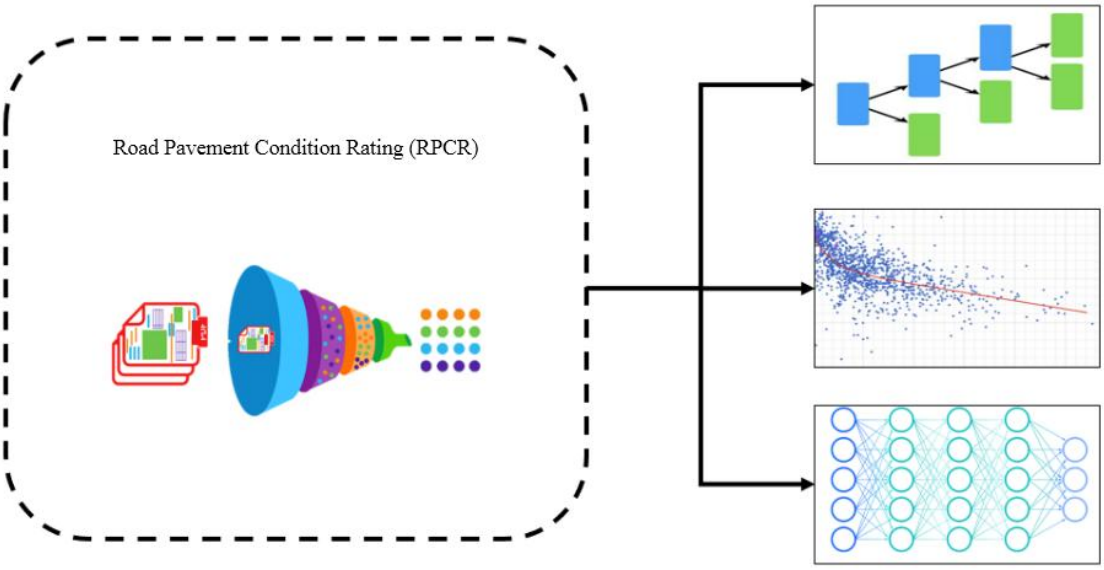

Figure 2. Road performance modeling.

Table I presents the measured performance of the developed models against the modeling data set. Among the regression tree-based models, RT performs the best. The MAE, MAPE, and RMSPE values are measured as 0.686, 12.86%, and 21.85%, respectively. LSTM performs significantly better compared to the ANN, achieving MAE, MAPE, and RMSPE of 0.591, 11.26%, and 16.49%, respectively. SVM achieves the lowest MAE and MAPE of 0.484 and 11.24%, respectively. Overall, SVM and LSTM show the best performance when tested against the modeling data set.

TABLE I. Performance of the Developed ML Models Against the Modeling Data Set.

Model	MAE	MAPE	RMSPE
RT	0.686	12.86%	21.85%
BaRG	0.869	16.78%	24.27%
BoRT	0.809	15.70%	23.46%
ANN	1.013	18.34%	25.51%
LSTM	0.591	11.26%	16.49%
GPR	0.732	13.89%	22.21%
SVM	0.484	11.24%	29.24%

Table II presents the performance metrics values for the different models against the validation data set. The obtained results indicate that the BaRG, BoRT, and ANN models perform best on the three metrics when tested against the validation data set. The three models achieve the least performance loss when tested on the validation data set compared to the modeling data set. On the contrary, the performance of the LSTM and SVM significantly decreases when tested against the validation data set compared to the modeling data set. For example, the MAE measured for the LSTM increases from 0.591 to 1.301 when tested against the modeling data set and the validation data set, respectively.

TABLE II. Performance of the Pavement Performance Modeling Against the Validation Data Set.

Model	MAE	MAPE	RMSPE
RT	1.436	22.23%	30.05%
BaRG	1.096	17.72%	25.61%
BoRT	1.094	17.62%	25.71%
ANN	1.079	17.88%	25.71%
LSTM	1.301	22.78%	32.15%
GPR	1.160	18.37%	25.93%
SVM	1.275	20.49%	27.53%

Since the ANN model yields the lowest MAE value, it is selected to conduct further investigations. Manual tuning of some hyperparameters of ANN is carried out to boost its prediction performance. The optimization process is addressed on the basis of the number and size of hidden layers. In this regard, different typologies of ANN are proposed, studied, and evaluated (see Table III). Fig. 3 demonstrates the inputs and outputs of the ANN model. In this context, it is derived that ANN of architecture [6, 3] has the lowest prediction error. The MAE, MAPE, and RMSPE are 1.05, 17%, and 24%, respectively. This architecture of ANN encompasses two hidden layers. The first layer is composed of six neurons, and the second hidden layer is composed of three neurons. It can also be noticed that increasing the number and size of hidden layers doesn't guarantee amplifying the learning capacity of ANN. Also, compared to the ANN model developed using the default hyperparameters values, optimizing the ANN's topology does not significantly improve the model's accuracy in this study.

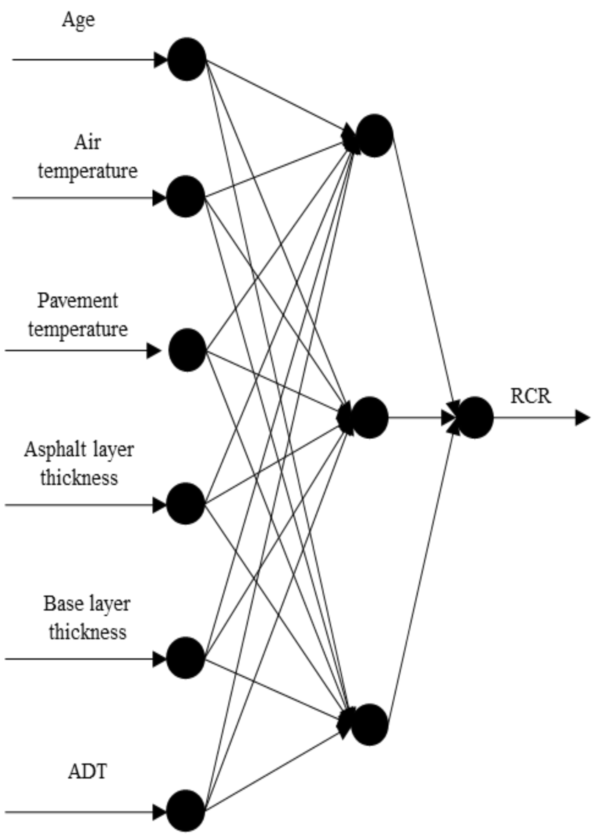

Figure 3. Configuration of the best-performing ANN model.

TABLE III. PERFORMANCE OF THE DIFFERENT ANN MODELS.

Model architecture	MAE	MAPE	RMSPE
1	1.19	19%	27%
3	1.13	18%	26%
6	1.27	21%	28%
12	1.81	29%	36%
[3,1]	1.08	18%	22%
[3,3]	1.09	18%	25%
[6,1]	1.14	18%	25%
[6,3]	1.05	17%	24%
[6,6]	1.26	21%	30%
[12,1]	1.22	19%	27%
[12,3]	1.12	18%	25%
[12,6]	1.12	19%	27%
[12,12]	1.13	19%	27%
[3,3,1]	1.27	23%	31%
[3,3,3]	1.23	20%	28%
[6,3,1]	1.22	20%	27%
[6,6,1]	1.22	20%	28%
[6,6,6]	1.11	18%	26%
[12,6,1]	1.09	18%	26%
[12,6,3]	1.55	24%	33%
[12,12,12]	1.24	20%	27%
[3,3,3,3]	1.30	21%	28%
[6,6,6,6]	1.13	18%	26%
[12,12,12,12]	1.28	20%	27%

The performance of the ANN model with the optimized architecture is compared against the training and validation data sets. Fig. 4 compares the actual and predicted PCR values for the (a) training data set and the (b) validation data set. Fig. 5 demonstrates the error histogram of the optimized ANN. Figs. 4 and 5 indicate that the ANN model achieves a promising accuracy. It is interpreted that more than 60% of the PCR values are predicted with an absolute error of less than 1 in both modeling and validation data sets. In addition, a low proportion of the modeling and validation data sets (approximately 14% and 18%, respectively) has a prediction error larger than 2. This evinces the high learning ability of the ANN model.

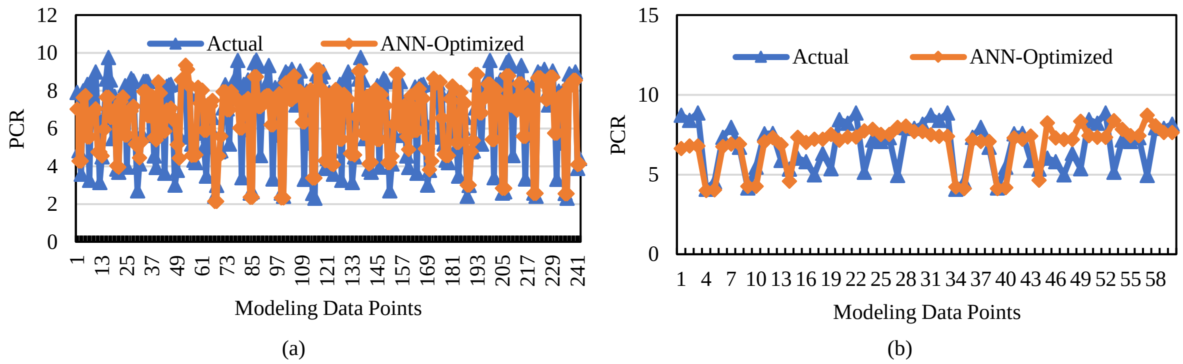

Figure 4. Comparison between actual and predicted PCR using the optimized ANN model for (a) training data set and (b) validation data set.

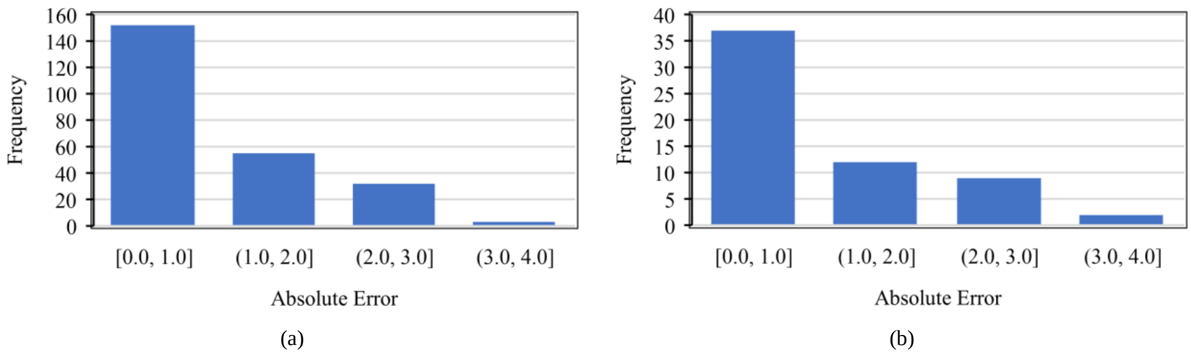

Figure 5. Histogram of the absolute error of the optimized ANN model tested on (a) training data set and (b) validation data set.

The importance of the factors used for the models' development is evaluated to understand their significance on pavement performance. Thus, the factors' importance is normalized to allow for the comparison of their significance in the different models. As shown in Table IV, ADT appears to be of paramount importance in five out of six models. The relative importance of ADT is between 16.70% and 40.00%. For the SVM model, pavement age arose to have a significantly high relative importance with a value of more than 50%. Also, the average relative importance of the different factors is calculated. As presented in Table IV, ADT, base layer thickness, and age appear to have the highest average relative importance among the six factors used. In contrast, surface layer thickness, pavement temperature, and air temperature appear to have a relatively lower impact on pavement performance.

TABLE IV. NORMALIZED IMPORTANCE OF THE DIFFERENT FACTORS.

Model	Air temperature	Pavement temperature	Pavement age	Surface layer thickness	Base layer thickness	ADT
RT	1.40%	2.70%	8.70%	16.50%	30.70%	40.00%
BaRG	15.90%	12.50%	13.40%	10.80%	21.10%	26.30%
BoRT	22.60%	8.90%	12.50%	0.00%	22.60%	33.30%
ANN	11.22%	7.32%	20.66%	7.82%	24.64%	28.32%
GPR	16.20%	12.50%	15.20%	11.80%	18.90%	25.30%
NCA	0.00%	0.00%	53.50%	0.00%	29.90%	16.70%
Average	11.22%	7.32%	20.66%	7.82%	24.64%	28.32%

IV. CONCLUSIONS

Multiple machine-learning algorithms are utilized to model road pavement performance. The collected data from the 302 sections along with the calculated PCR values, are used for the models' development and validation. Models' validation results indicate that BaRG, BoRT, and ANN models perform the best among the tested seven models. Optimizing the number of layers and nodes in the ANN model yields the best architecture with two layers of six and three neurons. Also, it is concluded that Annual Daily Traffic (ADT), base layer thickness, and age have the greatest impact on the pavement condition. The developed models can facilitate cost-effective maintenance intervention policies for municipalities and transportation agencies by utilizing the relationships between the different factors and road performance.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Ali Fares, Eslam Mohammed Abdelkader, and Nour Faris analyzed the data; Ali Fares wrote the paper; Eslam Mohammed Abdelkader, and Nour Faris revised and edited the paper; Tarek Zayed supervised the research; all authors approved the final version.

REFERENCES

[1] ASCE. (2021). 2021 Report card for America's infrastructure. [Online]. Available: https://infrastructurereportcard.org/wp-content/uploads/2017/01/Roads-2021.pdf.

[2] Colorado Department of Transportation, Risk-Based Asset Management Plan, 2019. [Online]. Available: https://www.tam-portal.com/collections/tamps/.

[3] Z. Liu, R. Balieu, N. Kringos, "Integrating sustainability into pavement maintenance effectiveness evaluation: A systematic review," *Transp. Res. Part D Transp. Environ*., vol. 104, 2022, 103187. https://doi.org/10.1016/j.trd.2022.103187.

[4] American Association of State Highway and Transportation Officials (AASHTO), Pavement Management Guide, Second Edi, Washington, DC, 2012.

[5] Vermont Agency of Transportation, Fact Book and Annual Report, 2020.

[6] M. Hoffmann and V. Donev, "Introduction of a new continuous

time and state space stochastic process in condition prediction," *Int. J. Pavement Eng*., vol. 19, pp. 339–354, 2018. https://doi.org/10.1080/10298436.2016.1162304.

[7] M. J. Khattak, C. Landry, J. Veazey, and Z. Zhang, "Rigid and composite pavement index-based performance models for network pavement management system in the state of Louisiana," *Int. J. Pavement Eng.*, vol. 14, 2013, pp. 612–628. https://doi.org/10.1080/10298436.2012.715643.

[8] A. Hu, Q. Bai, L. Chen, S. Meng, Q. Li, and Z. Xu, "A review on empirical methods of pavement performance modeling," *Constr. Build. Mater.*, vol. 342, 2022, 127968. https://doi.org/10.1016/j.conbuildmat.2022.127968.

[9] X. Shu, Z. Wang, and I. A. Basheer, "Large-scale evaluation of pavement performance models utilizing automated pavement condition survey data," *Int. J. Transp. Sci. Technol.*, vol. 11, pp. 678–689, 2021. https://doi.org/10.1016/j.ijtst.2021.09.003.

[10] N. Tabatabaee, M. Ziyadi, and Y. Shafahi, "Two-stage support vector classifier and recurrent neural network predictor for pavement performance modeling," *J. Infrastruct. Syst.*, vol. 19, pp. 266–274, 2013. https://doi.org/10.1061/(asce)is.1943-555x.0000132.

[11] Y. Wang, K. C. Mahboub, and D. E. Hancher, "Survival analysis of fatigue cracking for flexible pavements based on long-term pavement performance data," *J. Transp. Eng.*, vol. 131, pp. 608–616, 2005. https://doi.org/10.1061/(ASCE)0733-947X(2005)131:8(608).

[12] Z. Zhang and I. Damnjanović, "Applying method of moments to model reliability of pavements infrastructure," *J. Transp. Eng.*, vol. 132, pp. 416–424, 2006. https://doi.org/10.1061/(ASCE)0733-947X(2006)132:5(416).

[13] Z. Han, J. D. Porras-Alvarado, C. Stone, and Z. Zhang, "Incorporating uncertainties into determination of flexible pavement preventive maintenance interval," *Transp. A Transp. Sci.*, vol. 15, pp. 34–54, 2019. https://doi.org/10.1080/23249935.2018.1433730.

[14] J. Gajewski, T. Sadowski, "Sensitivity analysis of crack propagation in pavement bituminous layered structures using a hybrid system integrating artificial neural networks and finite element method," *Comput. Mater. Sci.*, vol. 82, pp. 114–117, 2014. https://doi.org/10.1016/j.commatsci.2013.09.025.

[15] U. Kirbaş and M. Karaşahin, "Performance models for hot mix asphalt pavements in urban roads," *Constr. Build. Mater.*, vol. 116, pp. 281–288, 2016. https://doi.org/10.1016/j.conbuildmat.2016.04.118.

[16] S. Choi and M. Do, "Development of the road pavement deterioration model based on the deep learning method," *Electron*, vol. 9, 2020, https://doi.org/10.3390/electronics9010003.

[17] W. E. Tabara, "Flexible pavement condition-rating model for maintenance and rehabilitation selection," Concordia University, 2010.