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Predicting Pavement Roughness Using Deep Learning Algorithms

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Abstract

Transportation agencies should measure pavement performance to appropriately strategize road preservation, maintenance, and rehabilitation activities. The international roughness index (IRI), which is a means to quantify pavement roughness, is a primary performance indicator. Many attempts have been made to correlate pavement roughness to other pavement performance parameters. Most existing correlations, however, are based on traditional statistical regression, which requires a hypothesis for the data. In this study, a novel approach was developed to predict asphalt concrete (AC) pavement IRI, utilizing datasets extracted from the Long-Term Pavement Performance (LTPP) database. IRI prediction is categorized by two models: (i) IRI progression over the pavement's service life without maintenance/rehabilitation and (ii) the drop in IRI after maintenance. The first model utilizes the recurrent neural network algorithm, which deals with time-series data. Therefore, historical traffic data, environmental information, and distress (rutting, fatigue cracking, and transverse cracking) measurements were extracted from the LTPP database. A long short-term memory network was used to solve the vanishing gradient problem. Finally, an optimal model was achieved by setting the sequence length to 2 years. The second model utilizes an artificial neural network algorithm to correlate the impacting factors to the IRI value after maintenance. The impacting factors include maintenance activities; initial (new construction), milled, and overlaid AC thicknesses; as well as IRI value before maintenance activities. Combining the two models allows for the prediction of IRI values over AC pavement's service life.

In 2018, more than 8.8 million lane-miles of roadways existed in the United States, and 94.1% of paved roadways were asphalt concrete (AC) pavements (*1*). There were around 3.2 trillion of vehicle miles traveled, consuming more than 187 billion gallons of fuel in 2018 (*1*). However, less than 6% of state and local direct general expenditures were spent on highways and roads. Thus, it is important to optimize the national road performance and services, considering the limited available funds. The American Association of State Highway and Transportation Officials (AASHTO) promoted the use of a pavement management system (PMS) to assist decision makers in finding optimum strategies for providing, evaluating, and maintaining pavements in a serviceable condition over a period of time (*2*). Each network-level PMS typically consists of a database that comprises inventory, condition assessment, and performance data. This is supported by a feedback mechanism that provides prioritization of maintenance and rehabilitation alternatives. Therefore, pavement performance models have been developed to predict the future performance of the pavement network and to identify the needs of future maintenance and rehabilitation activities. Such models have been implemented to guide the selection of maintenance and rehabilitation alternatives, which are usually supported by life-cycle cost analysis and occasionally by life-cycle assessment.

A change in pavement surface roughness over time is an important indicator of pavement performance. Pavement roughness, as defined by ASTM Standard E867, is "the deviations of a pavement surface from a true surface with characteristic dimensions that affect vehicle dynamics, ride quality, dynamic loads and drainage" (*3*). The international roughness index (IRI) is used to indicate pavement roughness using the average rectified slope (accumulated suspension motion to distance traveled), as derived from a mathematical model of a standard quarter car passing over a measured profile at a speed of 50 mph (*4*). Predicting the progression of roughness during pavement life is important for PMS decision-making. However, various factors affect pavement surface roughness, such as traffic, climate,

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pavement structure and material type, pavement construction quality, maintenance and rehabilitation, and so forth. Thus, it is impractical to develop a single roughness prediction model that includes the aforementioned factors.

Many studies have been conducted to develop IRI prediction models. The IRI prediction model used in AASHTO is Pavement ME Design (PMED), a traditional regression statistical analysis (*5*). It is a function of traffic, material, geometry, and climate conditions derived from the Long-Term Pavement Performance (LTPP) program database (*6*). However, the relationships between IRI and these factors were not well captured using traditional statistical methods (*7*). Apart from regression analysis, Jiang and Li (*8*) applied the gray theory to predict pavement roughness, and the results showed that gray relational models provided good IRI prediction, while utilizing fewer distress parameters compared with PMED models.

With the rapid development of technological innovations in computer science, machine learning has been increasingly used in pavement engineering applications. Attoh-Okine (*9*) remarked that artificial neural network (ANN) roughness prediction models were feasible and could be the basis for developing a generic intelligent pavement deterioration process. Multivariate adaptive regression splines have been used to identify the relative significance of pavement condition, traffic, and environmental parameters (*10*). Kargah-Ostadi et al. (*11*) also developed an ANN-based pattern-recognition model to predict IRI for flexible pavement rehabilitation sections in a wet–freeze climate using the LTPP database. Although the prediction performance when using ANN was higher than that achieved when using conventional statistical analysis, Attoh-Okine (*9*) warned that prediction performance might deteriorate if prediction was based on new data, instead of the data used for learning. This is a common problem occurring in neural network algorithms: the algorithm is overfitted to the learning data.

To capture the infrastructure performance deterioration rate with time, there have been several studies utilizing Markov chain and deep learning algorithms (*12*, *13*). These approaches work well, especially for time-series data. Markov chain, however, limits the analysis of historical data by considering only information from previous states. Recurrent neural network (RNN), in contrast, can capture multiple historical states. Okuda et al. (*14*) utilized RNN to develop a prediction model for rutting depth. The RNN model provides a strong prediction model when using time-series data for road deterioration accumulated for 20 years. In this study, the RNN model is applied to predict IRI progression over pavement service life using the LTPP database.

Many IRI prediction models focus on the progression of IRI without considering the impacts of maintenance and rehabilitation activities. However, the IRI value drops significantly after maintenance, rehabilitation, and reconstruction. To simplify the analysis, the extent of the IRI drop after maintenance/rehabilitation was mostly assumed (*15*, *16*). Sometimes the IRI's change was considered as a regression function of maintenance activity and the IRI value before maintenance/rehabilitation (*17–19*). However, these models did not consider the extent of the maintenance/rehabilitation activity, and they were regionally specific. Dong (*20*) developed the IRI drop model, which considered the extent of maintenance activities and the IRI before maintenance but did not consider the impacts of different maintenance activities. Therefore, a new IRI drop model was developed using a dense ANN structure on the LTPP database. The model considers IRI value before maintenance/rehabilitation, various maintenance/rehabilitation activities, and maintenance/rehabilitation extent.

Objective

The goal of this study was to develop an IRI progression model for AC pavement over the pavement's service life using the RNN algorithm as well as a model to predict IRI's drop after maintenance/rehabilitation using the ANN algorithm. Time-series data of fatigue cracking, transverse cracking, rutting, environmental conditions, and traffic from the LTPP database were used to train and test the first model. Pavement structure, type of maintenance/rehabilitation activity, extent of maintenance/rehabilitation, and IRI value before maintenance/rehabilitation were the primary inputs to the second model to produce the drop of IRI. Therefore, an IRI prediction framework is presented here to help agencies predict the future IRI value with or without maintenance/rehabilitation.

Methodology

ANN is a multilayer, fully connected neural network. It consists of an input layer, multiple hidden layers, and an output layer. Each node in one layer is connected to nodes in the next layer. The network becomes deeper by increasing the number of hidden layers. Each given node takes the weighted sum of previous nodes and passes the sum through a nonlinear activation function. An ANN is trained by learning the weights assigned to all edges between nodes (*21*).

RNN is a class of ANNs in which nodes from a directed graph along a temporal sequence are connected (*21*). In a traditional neural network, all inputs (outputs) are independent of each other (see Figure 1). RNNs are

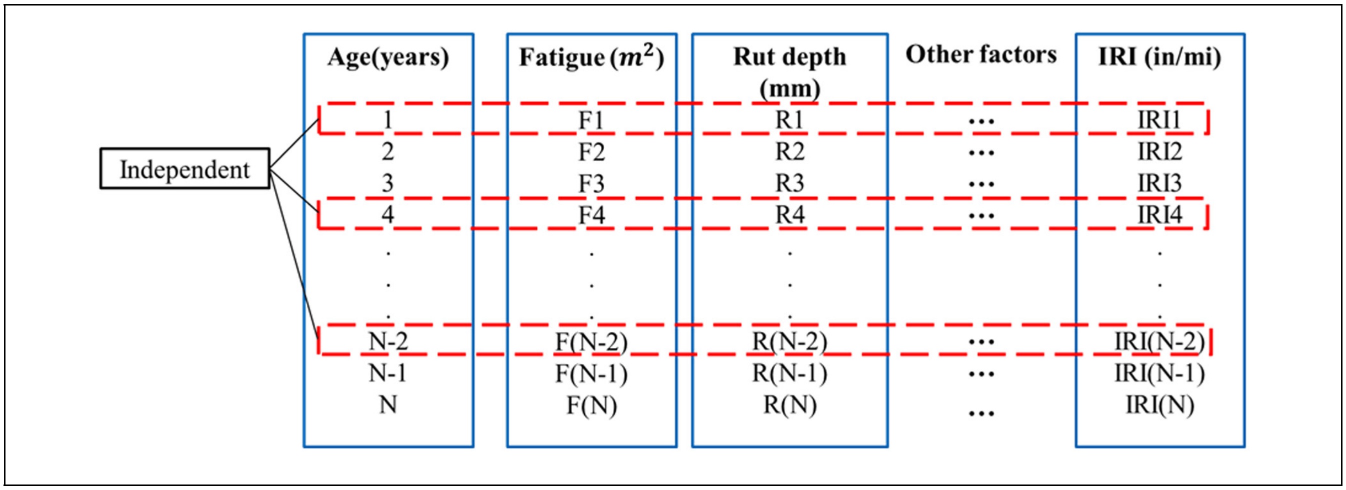

Figure 1. Relations of inputs (outputs) in the traditional neural network.
Note: IRI = International Roughness Index.

called recurrent because they perform the same task for every element of a sequence, with the output being dependent on the previous computations. Thus, RNN could handle time-series data because it memorizes the previous information in the hidden layers.

Figure 2 shows the profile of the recurrent structure of the RNN (*22*). The RNN repeatedly receives and processes the input data and previous data. RNN can consider data of different sequence lengths (SLs). Therefore, it can learn the effect of past data on subsequent data, which is analogous to predicting the next word in a sentence based on the words before it. With these characteristics, RNNs can be used to predict time-series data, such as stock prices, whose input data take the form of a time sequence.

Long short-term memory (LSTM) is an upgraded RNN that solves RNN's vanishing gradient problem and makes it effective in capturing long-term dependencies (*23*). It is already being utilized in voice recognition, language modeling, translation, and other fields, in combination with other neural networks. Figure 2 also shows the LSTM structure. It is composed of a memory movement cell that can maintain a state over time and three nonlinear gates that control data flow in and out of the cell. The memory cell (C_t) updates the state (h_t) at a specific time and decides whether information inside should be updated by using the status from the input at that moment. In addition, there are several gate types—input (i_t), forget (f_t), and output (o_t)—that control the flow of the cell.

The forget gate, f_t, decides which past information shall be removed, Equation (1). The output of the previous cell (h_{t-1}) and the current input (X_t) are applied in the sigmoid function active layer to obtain a value in the range [0,1]. This value is multiplied by the current state and the elements, and the cell chooses whether to keep or eliminate this information during the process.

$$\mathrm{f_t} = \sigma\left(W_f \times [h_{t-1}, X_t] + b_f\right) \tag{1}$$

where σ is activation function, W_f is weight of the forget gate, and b_f is the bias.

The input gate, i_t, is used to decide which information shall be stored in the cell state, as shown in Equation (2). Two stages are categorized in this process: (i) using the sigmoid function to decide the information to be updated and (ii) creating a candidate cell ($\hat{C}_t$) that could be added to the state using the hyperbolic tangent (tanh) function, Equation (3).

$$\mathrm{i_t} = \sigma(W_i \times [h_{t-1}, X_t] + b_i) \tag{2}$$

$$\hat{C}_t = tanh(W_c \times [h_{t-1}, X_t] + b_c) \tag{3}$$

where W_i and W_c are the weights of the input gate and candidate cell, respectively, and b_i and b_c represent the biases of the input gate and candidate cell, respectively.

Then the old cell state (C_{t-1}) and the candidate cell state ($\hat{C}_t$) are used to represent the updated current cell status (C_t), as shown in Equation (4). The old cell state (C_{t-1}) is multiplied by f_t, indicating to forget the information decided in forget gate, while the candidate cell state ($\hat{C}_t$) is scaled by i_t, representing the extent of updating each state value.

$$\mathrm{C_t} = f_t \times C_{t-1} + i_t \times \hat{C}_t \tag{4}$$

In the end, the output gate (o_t) decides what should be outputted. This process is broadly categorized into two stages: (i) using the sigmoid function, Equation (5), to decide which part of the cell state to output and (ii) putting the cell state through tanh (to push the values to be between −1 and 1) and multiplying it by the output of the sigmoid gate, Equation (6). Finally, output h_t is updated.

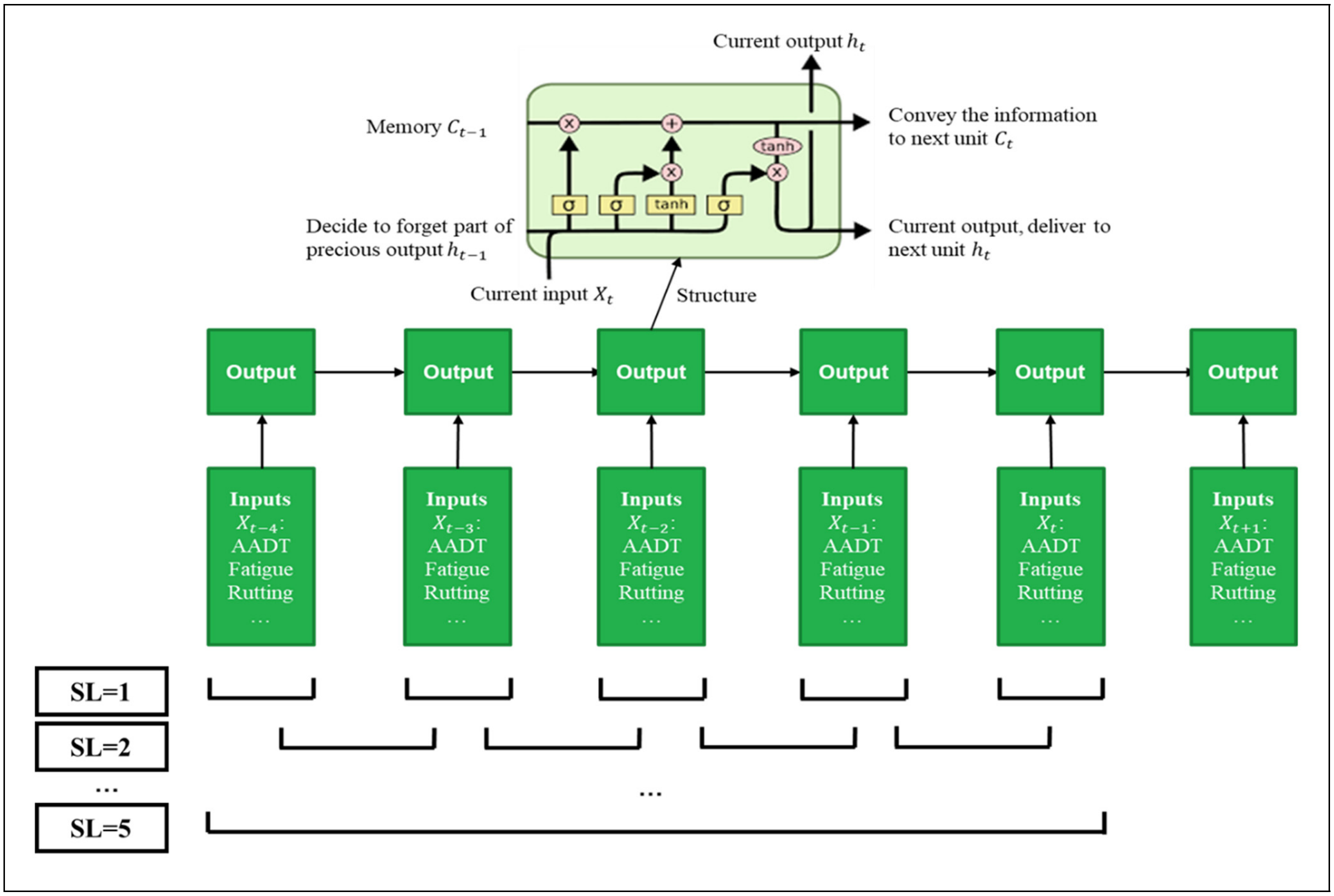

Figure 2. Structure of the recurrent neural network.

$$o_t = \sigma(W_o \times [h_{t-1}, X_t] + b_o) \quad (5)$$

$$h_t = o_t \times \tanh(C_t) \quad (6)$$

where W_o is the weight of the output gate and b_o is the bias.

LSTM calculates the final output values through the hidden variables. Unlike a standard RNN that has the form of a chain of repeating the same modules of neural networks, LSTM adjusts the information flow by adjusting appropriately using the gates during the variable calculation process of the hidden layer. Each module in LSTM has a different structure. As a result, the RNN using LSTM cells has the ability to remember information for long periods of time and handle long-term dependency problem.

Database

The LTPP program was initiated as a part of the Strategic Highway Research Project (SHRP) in 1987 and was expanded to a 20-year program under the coordination of the Federal Highway Administration. The LTPP information management system is a pavement management database documenting historical performance data for over 2,500 in-service and monitored test sections in North America. Different types of information are stored within the database in the form of seven modules: inventory, maintenance, monitoring, rehabilitation, material testing, traffic, and climate data. The datasets extracted for this study were from the LTPP data documented for the United States and Canada. From the extracted data, sections with AC over unbound granular layers were selected for analysis.

Various material, structural, and traffic parameters that affect a pavement's structural performance may be assessed through IRI observation over time. The World Bank developed a roughness prediction model through the Highway Development and Management program in which five factors contributed the most: cracking, rutting, potholes, environmental conditions, and structural deterioration (*24*). Thus, in this study, age, equivalent single axle loads (ESALs), rutting depth, fatigue cracking area, transverse cracking, evaporation, precipitation, average air temperature, and initial IRI after construction were used to relate pavement deterioration of IRI. Other possible parameters could be captured using the RNN algorithm, because RNN memorizes historical

Table 1. Descriptive Statistics of the First Set of Long-Term Pavement Performance Data

	Variable	Minimum	Maximum	Average	Median	Standard deviation	Range
Input	Data collected year	1990	2017	2001.30	2001	0.15	27
	ESALs (million)	0.01	2.9	0.27	0.13	0.42	2.89
	Rut depth (mm)	0.00	27	5.94	5.0	3.19	27
	Fatigue cracking (m^2)	0.00	563.3	31.49	2.08	69.24	563.3
	Transverse cracking (m)	0.00	415.60	26.03	3.19	49.26	415.60
	Evaporation (mm)	48.85	1010.52	798.00	837.15	314.85	961.67
	Precipitation (mm)	32.95	4501.97	1025.05	1102.96	445.76	4469.02
	Average daily temperature (°C)	−5.70	26.70	14.46	15.20	5.75	32.40
Dependent	IRI (m/km)	0.24	4.29	1.21	1.09	0.49	4.05

Note: ESAL = equivalent single axis load; IRI = International Roughness Index.

Table 2. Descriptive Statistics of the Second Set of Long-Term Pavement Performance Data

	Variable	Minimum	Maximum	Average	Median	Standard deviation	Range
Predictor	Added thickness (mm)	2.54	203.20	66.04	53.34	45.72	200.66
	Milled thickness (mm)	0.00	162.56	25.40	0.00	30.48	162.56
	IRI_Before (m/km)	0.54	4.43	1.56	1.40	0.66	3.76
Dependent	IRI_After (m/km)	0.33	3.33	0.94	0.84	0.41	3.00

Note: IRI = International Roughness Index

data behavior. This set of data has time-series information of 854 test sections, of which 683 were used to train the model and the remaining 171 were used to validate the model. Table 1 shows the description of the 854 sections.

For the IRI drop model, only flexible pavement sections were selected within the LTPP dataset. There are 1,027 sections with available IRI and maintenance/rehabilitation data in the LTPP database. However, not all sections have IRI data collected before and after maintenance/rehabilitation. Therefore, the data were filtered based on the availability of IRI data pre- and post-maintenance/rehabilitation. If a section has IRI data within 365 days before and after a maintenance/rehabilitation activity, it was selected as a training data point. Although IRI may fluctuate, especially after a maintenance/rehabilitation activity, this decision was made to increase the size of the dataset. Filtering resulted in a training dataset of 453 sections and 513 data points. Those data points had their corresponding construction activities identified with one IRI value before maintenance/rehabilitation and one IRI value after maintenance/rehabilitation. Of the 513 activities, 386 are overlay treatments, 86 are surface treatments, and 41 are both overlay and surface treatments. Table 2 describes the descriptive statistics of the data for the IRI drip model.

The extent of the maintenance/rehabilitation activity, that is, milled thickness and added thickness, was determined by comparing LTPP structures before and after the maintenance/rehabilitation activity. Added thickness is usually 25.4 to 101.6 mm (1 to 4 in.) for overlays and 2.54 to 50.8 mm (0.1 to 0.2 in.) for surface treatments, per layer of application.

As for the type of maintenance/rehabilitation activity, the LTPP dataset has 58 possible reasons for a maintenance activity. Mill and AC overlay, AC overlay, and surface treatments were selected as valid actions to improve IRI. Mill and overlay as well as overlay activities were manually given the code 1, and surface treatments were given the code 2. For example, [1,2] would refer to a section that has both an overlay and a type of surface treatment.

Models

IRI Progression Model

The hyperparameters of the RNN algorithms are generally the learning rate, number of epochs, and sequence length. The RNN algorithm was constructed to predict the IRI of pavement sections without maintenance/rehabilitation. The data of a section with maintenance/rehabilitation activity can be divided into pre- and post-maintenance/rehabilitation series data. To prepare the learning model, 80% of the data were used, and the remaining 20% were used for testing. This algorithm learned the time-series data with SL varying from one to

Table 3. Sequence Lengths (SL) and Number of Data Tuples

SL	Number of data tuples (854 sections)		
	Total	Train	Test
1	9,209	7,299	1,910
2	8,355	6,747	1,608
3	7,501	5,960	1,541
4	6,647	5,221	1,426

Table 4. Parameters of the Recurrent Neural Network Algorithm

Classification		Data
Hyperparameter	Learning rate	0.001
	Number of epochs	50
	Sequence length	1,2,3,4
	Number of LSTM layer	2
	Number of hidden states in each layer	10
Input variable	Traffic	ESALs
	Climate	Average temp, precipitation, evaporation
	Distress	Fatigue cracking, transverse cracking, rutting
Output variable		IRI

Note: ESAL = equivalent single axis load; IRI = International Roughness Index; LSTM = long short-term memory.

four years. That is, to predict the IRI value in 2020, input data from 2020 is required if SL equals one and input data from 2017–2020 are required if SL equals four. If SL is larger than four, then the model will always require a preparation of more than 4 years of historical data to predict the IRI value, which is not applicable at this time. Table 3 summarizes the number of data tuples given each sequence length.

Table 4 summarizes the parameters of the RNN algorithm. A total of 854 sections were analyzed. The number of epochs (repetitions of learning) needs to be decided: learning should be stopped when the best prediction model has been constructed. It is important to stop learning at an early state because computing resources are limited, and learning time is restricted. The optimal number of epochs can be determined by plotting the number of epochs against the loss function results. In this study, experiments showed that the best loss function could be obtained when the number of epochs was between 40 and 50, and the loss values was almost unchanged after 50 epochs. The learning rate was maintained at 0.001.

Table 5. Results of Testing Data

Classification		Sequence length			
		1	2	3	4
IRI (in/mi)	RMSE	0.25	0.22	0.30	0.28
	R^2	0.9258	0.9312	0.8744	0.9012

Note: IRI = International Roughness Index; RMSE = root mean square error.

By varying SL between one and four, the value that minimized the root-mean-square error (RMSE) was judged to select the optimal model with an optimized SL value. Table 5 summarizes the results, and Figure 3 shows the testing/validation performance of the RNN algorithm with different SL values.

The results of the model indicate that SL plays an important role in optimizing model prediction. Increasing SL does not guarantee better performance of RNN models. In this study, a SL of two achieves the lowest RMSE, which was 27% lower than that of SL three. The coefficients of determination (R^2) of the testing results can reach as high as 0.93 using SL two, which is 6.5% higher than the lowest R^2.

IRI Drop Model

The hyperparameters of the ANN algorithm include number of nodes in the input layer, number of hidden layers, number of nodes in the hidden layers, learning rate, and number of epochs. As described in the Database section, the IRI drop model aims to capture the IRI change after maintenance/rehabilitation considering several factors: pavement structure, maintenance activity, extent of maintenance, and IRI value before maintenance. Thus, the data used to train the ANN models were extracted from the LTPP database, which documents IRI value before and after maintenance/rehabilitation activity, treatment type (surface treatment or AC overlays), as well as initial, milled, and overlaid AC thicknesses.

Table 6 summarizes the parameters of the ANN algorithm. One of the key steps was to determine the number of hidden layers. Increasing the number of hidden layers could help the model learn deeper behavior; however, it can also increase the possibilities of overfitting. Only one hidden layer with eight nodes was added in this study. Based on the learning rate of 0.0001, training and testing loss becomes stable after 20 epochs. The described model was trained in Python using the Keras framework and 20% of the 513 data points as test data. Figure 4 gives the performance of the model with respect to training and testing datasets. R^2 of the testing results is 0.77.

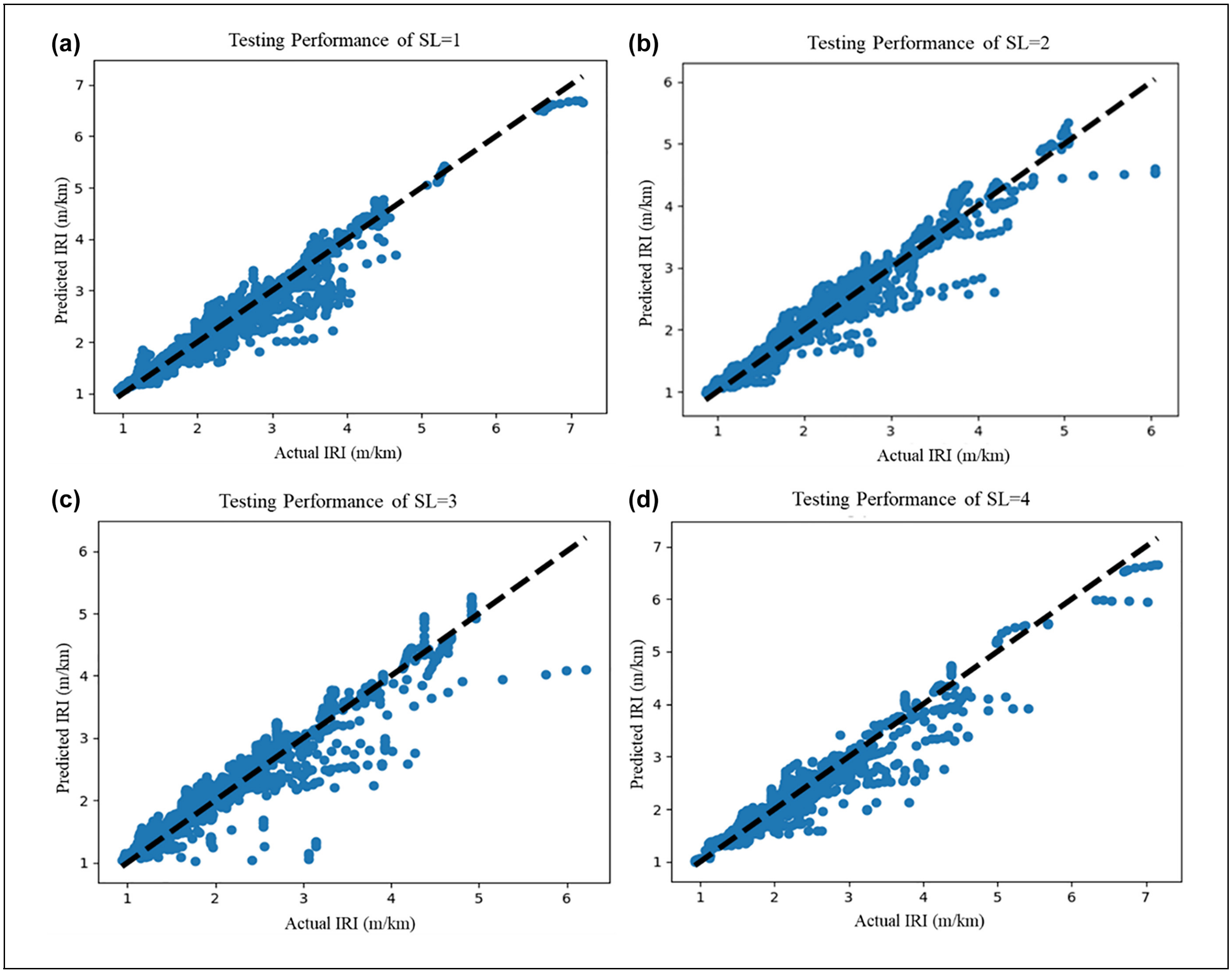

Figure 3. Testing performance of different sequence length (SL) values: (*a*) SL = 1, (*b*) SL = 2, (*c*) SL = 3, and (*d*) SL = 4.

Table 6. Parameters of the Artificial Neural Network Algorithm

Classification		Data
Hyperparameter	Learning rate	0.001
	Number of epochs	20
Input layer	Number of nodes	5
	Variables	Treatment type Initial AC thickness Milled AC thickness Overlaid AC thickness IRI before maintenance
Hidden layer	Number of layers	1
	Number of nodes	8
Output layer	Number of nodes	1
	Variable	IRI after maintenance

Note: AC = asphalt concrete; IRI = International Roughness Index.

Connection of Models

The developed models considered different aspects of IRI prediction. The IRI progression model aims to predict IRI changes of a new pavement along its service life without any interruption of maintenance/rehabilitation, whereas the IRI drop model aims to predict the IRI change caused by maintenance/rehabilitation activities. Because of limitations with the database, the IRI drop model only considered a limited number of maintenance/rehabilitation activities, including surface treatment, AC overlay, as well as milling and AC overlay. The IRI output from the IRI progression model can be used as input into the IRI drop model when a maintenance/rehabilitation activity exists. Similarly, the output of the IRI drop model may be used later as an initial IRI input to the IRI progression model for post-maintenance IRI

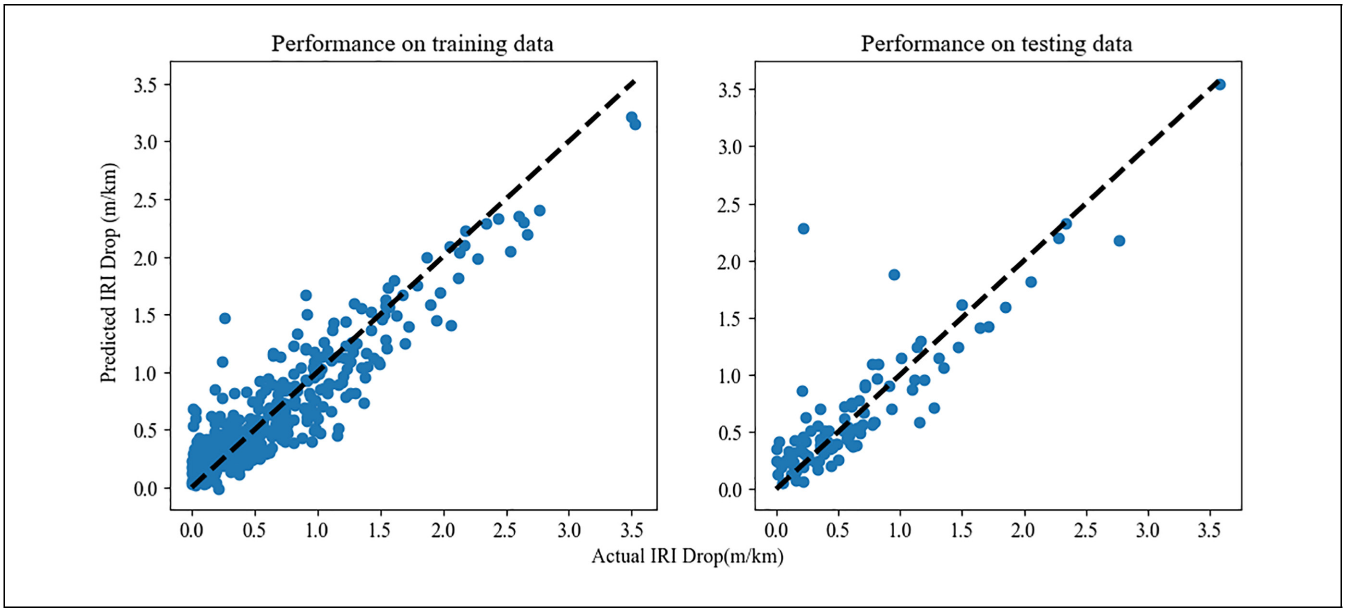

Figure 4. Training and testing performance of the artificial neural network model.

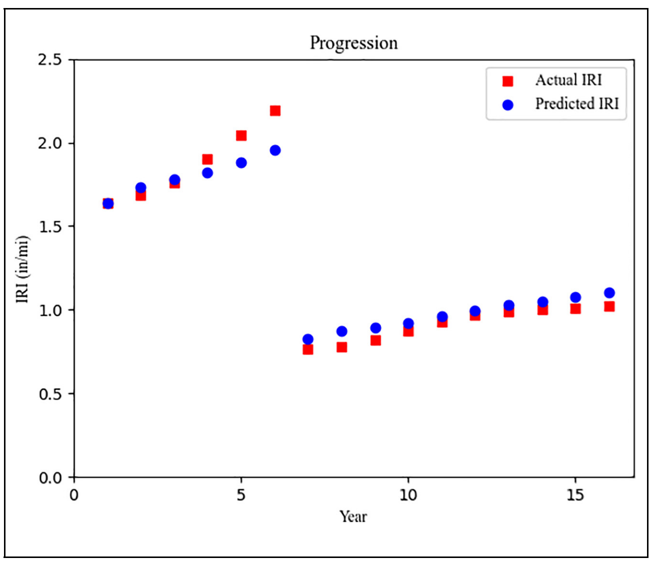

Figure 5. Actual and prediction international roughness index (IRI) of test section 1 (state ID: 10, SHRP ID: 0107).

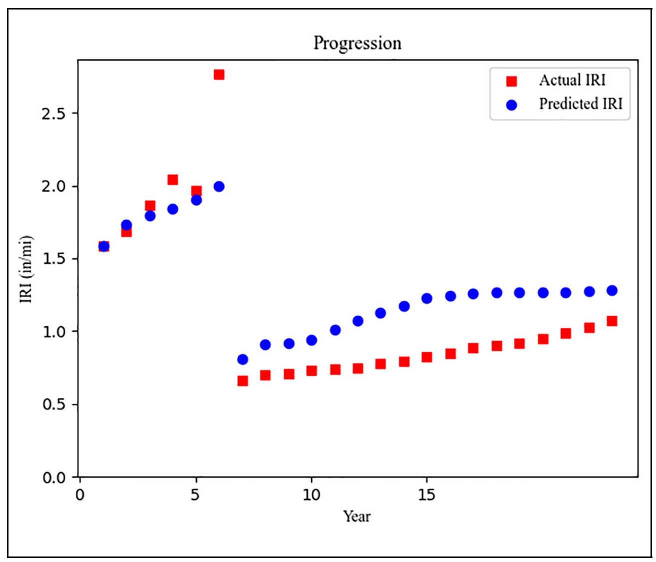

Figure 6. Actual and prediction international roughness index (IRI) of test section 2 (state ID: 12, SHRP ID: 0110).

prediction. Two sections from the LTPP database are used to demonstrate the connection success of the IRI progression and IRI drop models. Using a SL of two, the predicted and actual IRI values are shown in Figure 5 for the section 1 with state ID: 10 and SHRP ID: 0107 and Figure 6 for the section 2 with state ID: 12 and SHRP ID: 0110. Table 7 shows the first 10-year test and prediction results of IRI of these two sections.

The average difference between test data and prediction results are 0.21 and 0.098 m/km (13.3 and 6.22 in./mi) for section 1 and section 2, respectively (see Table 7). The higher average difference of section 1 is mainly from the difference in the fifth year. The test data of section 1 has a drop in the fourth year without documentation of any rehabilitation activities. IRI in the fifth year was increased by 0.81 m/km (51.3 in/mi). The inconsistent trend could be as a result of measurement errors. The prediction results of these two sections indicated the combination of IRI and drop models resulted in continuity prediction of IRI along pavement life.

Table 7. Data of Sections State ID:10, SHRP ID: 0107, State ID:12, and SHRP ID: 0110

Section	Year	1	2	3	4	5	6	7	8	9	10	Avg. diff.
State ID: 10.	Test IRI (m/km)	1.60	1.68	1.89	2.09	1.94	2.75	0.67	0.69	0.68	0.71	0.21
SHPR ID: 0107	Predicted IRI (m/km)	1.60	1.73	1.77	1.85	1.91	1.96	0.81	0.93	0.94	0.95	
State ID: 12.	Test IRI (m/km)	1.65	1.69	1.76	1.90	2.05	2.20	0.74	0.77	0.81	0.88	0.098
SHPR ID: 0110	Predicted IRI (m/km)	1.65	1.74	1.78	1.84	1.88	1.92	0.84	0.91	0.91	0.94	

Note: Avg. diff. = average difference; IRI = International Roughness Index; SHRP = Strategic Highways Research Project.

Table 8. Model Performance

Existing studies	Model	R^2	R^2 of this study
MEPDG	Traditional statistic	0.55	0.93
Attoh-Okine et al. (*9*)	ANN	0.39	
Ozbay and Laub (*4*)	General Regression NN	0.92	
Mazari and Daniel (*26*)	GEP	0.90	
Mazari and Daniel (*26*)	GEP + ANN	0.99	

Note: ANN = artificial neural network; GEP = gene expression programming; MEPDG = Mechanistic–Empirical Pavement Design Guide.

Comparing with Other Studies

Multiple methods have been tried to predict pavement roughness progression. Table 8 lists few of those studies and presents the prediction performance of those models. Mechanistic–Empirical Pavement Design Guide (MEPDG) (*25*) used a linear combination of initial IRI after construction, site factor, area of fatigue cracking, total length of transverse cracking, and average rut depth. Attoh-Okine et al. (*10*) are among the first few researchers trying to apply machine learning techniques in roughness prediction. Ozbay and Laub (*4*) and Mazari et al. (*26*) both used initial IRI, age, ESAL, as well as structure number as predictors in their studies. Ozbay and Lau (*4*) was using general regression neural network while Mazari and Daniel (*26*) applied a hybrid of gene expression programming (GEP) and ANN to predict IRI progression. Although the correlation coefficient of the models developed by Ozbay and Laub (*4*) and Mazari and Daniel (*26*) are higher than 0.93, the datasets used in their models are much smaller than those used in this study (less than 1/4 of this study). Therefore, those two models cannot be widely applied to a general case. In addition, this study also considered the IRI drop after maintenance/rehabilitation; this can help the agencies to predict IRI progression in long-term sections with or without maintenance activities.

Summary

This study was conducted based on data extracted from the LTPP program and PyTorch, an open-source deep learning framework, to introduce the concept of open innovation to the deep learning field. This study aims to predict IRI progression during the pavement's service life without interruption of maintenance/rehabilitation activities using the RNN algorithm, a new approach applied in pavements, and to predict IRI drop value after maintenance/rehabilitation activities using the ANN algorithm.

RNN was implemented using PyTorch. The algorithm was constructed to predict the pavement's IRI using the time-series as learning data. Historical data of different AC pavement sections were extracted from the LTPP database. Independent variables for the analysis were ESAL, annual average temperature, annual total precipitation, annual total evaporation, annual rutting depth, annual fatigue cracking area, and annual transverse cracking length. In the RNN model, the optimal value of SL, an important RNN hyperparameter, was determined for IRI prediction. The optimization process minimized the RMSE by optimizing the SL. Although increasing the SL value can help the model memorize more information to predict current IRI value, it does not guarantee good performance because the dataset with 854 sections may not be adequate to train a deep algorithm.

ANN was implemented using Keras. The algorithm was constructed to predict the IRI changes using 513 data points. Independent variables for the analysis were the maintenance activity type; initial, milled, and overlaid AC thicknesses; as well as IRI value before maintenance. The dependent variable is the IRI value after maintenance. Using only one hidden layer with eight nodes was able to achieve the optimal model performance with the coefficients of determination as high as 0.77.

A combination of the two developed models (IRI progression and drop models) was able to predict the AC pavement IRI deterioration along its service life, including maintenance activities. The study introduced the analysis of big data in pavements by applying the RNN algorithm. The study showed pavement IRI could be predicted with a high degree of accuracy using the RNN algorithm when SL is optimized. In addition, IRI change caused by maintenance activities could be captured using the ANN algorithm. Nevertheless, the following limitations should be considered: the RNN algorithm was not optimized by the learning rate, number of epochs, or activation function, and the IRI drop model was applied to a limited number of maintenance/rehabilitation activities.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Imad L. Al-Qadi; data collection: Qingwen Zhou and Egemen Okte; analysis and interpretation of results: Qingwen Zhou and Egemen Okte; draft manuscript preparation: Qingwen Zhou and Imad L. Al-Qadi. All authors reviewed the results and approved the final version of the manuscript.

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Data Availability Statement

All data and models that support the findings of this study are available from the corresponding author on reasonable request. The data can be requested from the corresponding author, Qingwen Zhou, via email at qingwen2@illinois.edu.

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