**Title of TRB Paper Format Example**

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**ABSTRACT**

The Abstract should be a stand-alone summary of the contents of the paper, equaling 250 words or less. It should present the primary objectives and scope of the study, techniques, methods or approaches briefly described and a concise summary of findings and/or conclusions reached.

**Keywords:** International Roughness Index, RNN, Deep Learning, LTPP

**INTRODUCTION**

Pavement roughness is defined as the deviations of a pavement surface from a true surface with characteristic dimensions that affect vehicle dynamics, ride quality, dynamic loads and drainage(*1*). It is considered one of the most significant indicators of pavement condition as it dramatically affects the driving comfort and safety especially for high-speed-limit roads(*2*). Various factors including construction quality, maintenance, distress and traffic all affect pavement roughness. As pavements deteriorate over time due to these factors, it is essential to accurately predict their roughness condition for effective maintenance and rehabilitation planning. International Roughness Index (IRI) is widely recognized as a key indicator for pavement functional condition and ride quality, which is extensively utilized for evaluating road conditions(*3*). Therefore, predicting the IRI during pavement life becomes important for decision-making and rehabilitation planning in transportation infrastructure management.

There is a lot of research and attempts have been made on the estimation of the roughness based on pavement and traffic conditions, including Experience-based methods and machine learning-based methods. Traditionally, many researchers have tried to model IRI using regression. For example, Deng et al. (*4*) modified a feedforward network with particle swarm optimization to predict the rutting performance of asphalt pavement using material properties, structure parameter and traffic condition from collecting data from Idaho State. However, overfitting becomes the major limitation of machine learning-based approaches.

Ensemble models, which is an approach that combines predictions from multiple individual models to make a final prediction, were also popularly used in the IRI evaluation. The idea behind ensemble learning is to leverage the diversity and collective intelligence of the individual models to improve overall predictive accuracy and robustness. For example, Wang et al. (*5*) developed an Adaboost regression model to improve the performance of predicting IRI by using the inputs including pavement thickness, service age, average annual daily truck traffic (AADTT) and cracks from LTPP. The proposed model got an R2 of 0.95 and MSE of 0.0088 which is much better than linear regression. Gong et al. (*2*) used a Random Forest Regression model to estimate the IRI value of flexible pavement by considering the distress, traffic, maintenance and structure data from LTPP. It outperformed the Linear Regression model (R2 is 0.62) and got an R square more than 0.95 in both training and testing datasets. Damirchilo et al. (*6*) used XGboost to avoid overfitting of the training and handle the missing value in LTPP datasets. It obtained a R2 of 0.7 outperforming the Random Forest (RF) and Support Vector Regressor (SVR).

However, these machine learning-based methods didn’t consider the time-related characteristics of roughness. After construction, the IRI of the pavement would change with the AADT, distress, maintenance every day. In other words, IRI is a time-accumulated parameter that every previous factor would have an impact on.

RNNs are a class of neural networks specifically designed for sequential data processing, making them well-suited for time series prediction tasks. Unlike traditional feed-forward neural networks, RNNs can capture dependencies and patterns in the temporal dynamics of the data, allowing them to model the evolving behavior of pavements over time. By utilizing the historical IRI measurements and other relevant variables available in the LTPP dataset, we can train an RNN model to learn the underlying patterns and make accurate predictions of future IRI values. For example, Zhou et al. (*1*) proposed a RNN-based model to predict the IRI on the asphalt pavement based on the LTPP datasets. The loads, temperature, precipitation, evaporation, rutting and cracking are considered as input parameters for the analysis. The results showed that the presented RNN model reached a R2 of 0.93. urna.

**METHODS**

**Data Engineering**

To train the model, more than 11000 samples were collected from the long-term pavement performance (LTPP) dataset. This dataset is a comprehensive and widely used resource in the field of transportation engineering. It is a collection of data gathered from pavement sections located across the United States and Canada. The primary objective of the LTPP program is to monitor and evaluate the long-term performance of various pavement types under different conditions. In this work, initial IRI, pavement age, AADTT, maintenance type is obtained from LTPP and utilized for training.

The initial IRI is the most important parameter as it is measured immediately after construction and represents the quality of construction. Pavement age is a critical factor in understanding the long-term performance of the pavement. It helps quantify the effects of aging and deterioration processes on the roughness of the pavement. Traffic loading has a significant impact on pavement performance. A higher volume of traffic can accelerate pavement deterioration, leading to increased roughness. By incorporating AADTT as a predictor, the model can capture the influence of traffic on IRI. Cracking is one of the most common distresses observed in pavements. Including crack length as a predictor helps the model consider the extent of cracking as a factor affecting roughness. Longer cracks may result in more significant roughness development over time. Maintenance activities can greatly influence pavement condition and roughness. Different types of maintenance interventions, such as crack sealing or overlay, can have varying effects on IRI. By incorporating maintenance type as a predictor, the model can learn how different maintenance actions impact the roughness of the pavement.

75% of the data were used to train the models while the remaining 25% were used for testing. Min-max scaling would be implemented to each parameter. It is particularly useful when the features have different scales or ranges, as it helps to normalize the data and bring all features to the same scale (0 to 1). It is commonly employed in machine learning algorithms that are sensitive to the scale of the input features.

**Evaluation Metrics**

The performance of models is evaluated by Mean Square Error (MSE) and . MSE measures the average of the squared differences between the predicted results and actual values. It can provide a measure of how well the model's predictions align with the true values, with higher values indicating greater errors, as shown in **Equation 1**.

(1)

Where n is the number of total evaluated data, is the i-th data point, is the prediction of the i-th data. stands for the coefficient of determination. It measures the proportion of the total variation in the prediction that can be explained by the model. It is used to emasure the goodness of fit and can be calculated using **Equation 2**.

(2)

Where SSR is the sum of squares regression, SST stands for the sum of squares total, is the average value of the data.

In order to evaluate and compare the performance between different models statistically, each model is trained and tested three times on randomly split train and test datasets. The average value and standard deviation would be calculated based on the tests. By doing this, it can show the general accuracy of the model as well as the robustness the model can perform.

The overfitting problem would also be considered in this work. Overfitting occurs when the regression models learn the training data too well, resulting in poor generalization to unseen data. The difference between the training and testing performance are considered as an overfitting score in this work as shown in **Equation 3**. It is utilized as a metric to measure the overfitting issue in the selected approach.

(3)

Where stands for the overfitting score, is the value when model applying in the train set, is the value when model applying in the test set. It can provide a measure of the overfitting degree in the model, with higher values indicating greater overfitting problem.

**RESULTS**

*Level 3 Header*

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**Figure 1 Caption for figure**

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**RESULTS**

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**TABLE 1 Measurement Conversion**

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| --- | --- | --- |
| **When You Know** | **Multiply by** | **To Find** |
|  |  |  |
| **Length** |  |  |
| inches (in.) | 25.4 | millimeters (mm) |
| feet (ft) | 0.305 | meters (m) |
| yards (yd) | 0.914 | meters (m) |
| miles (mi) | 1.61 | kilometers (km) |
|  |  |  |
| **Area** |  |  |
| square inches (in.2) | 645.1 | millimeters squared (mm2) |
| square feet (ft2) | 0.093 | meters squared (m2) |
| square yards (yd2) | 0.836 | meters squared (m2) |
| acres | 0.405 | hectares (ha) |
| square miles (mi2) | 2.59 | kilometers squared (km2) |
|  |  |  |
| **Volume** |  |  |
| fluid ounces (fl oz) | 29.57 | milliliters (mL) |
| gallons (gal) | 3.785 | liters (L) |
| cubic feet (ft3) | 0.028 | meters cubed (m3) |
| cubic yards (yd3) | 0.765 | meters cubed (m3) |

**DISCUSSION**

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 (2)

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**CONCLUSIONS**

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**ACKNOWLEDGMENTS**

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**AUTHOR CONTRIBUTIONS**

The authors confirm contribution to the paper as follows: study conception and design: Tianjie Zhang, Yang Lu; data collection: Alex Smith; analysis and interpretation of results: Tianjie Zhang, Alex Smith; draft manuscript preparation: Tianjie Zhang, Alex Smith. All authors reviewed the results and approved the final version of the manuscript.

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