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An Artificial Neural Network Approach for Predicting Pavement Distress: A Case Study Toward Sustainable Road Maintenance

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Abstract. The Surface Distress Index (SDI) is a key parameter for assessing urban road conditions that is effective in sustainable infrastructure management. The current research gap focuses on high-quality roads and the absence of predictive models applicable to lower-quality infrastructure, while complex maintenance is often overlooked, especially on urban roads with diverse types of surface damage. The objective of this study is to develop a predictive model of the Surface Distress Index (SDI) based on Artificial Neural Networks (ANN) to enhance road maintenance planning in urban areas. This model was trained using five years of urban road damage data from 42 city road segments. The coefficient of determination from the research results indicates a very high prediction accuracy, with an R value of 0.99, the MAE of 0.01, and the RMSE of 0.03. This model offers a more dynamic plan to enhance the sustainable maintenance of urban infrastructure. The resulting predictive model provides adaptive solutions to existing problems, environmental changes, and supports more sustainable urban infrastructure management.

Keywords: Surface Distress Index, Pavement Deterioration, Intelligent Transportation Systems, Predictive Modeling, Sustainable Infrastructure Management

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1. Introduction

Road infrastructure is one of the most important factors in the development of mobility and the modernization of urban connectivity. Optimal road maintenance not only improves the safety and comfort of the transportation system but also influences investment and the efficiency of the transport system [1–3]. Technologically integrated road infrastructure conditions are important to meet regional needs and can promote sustainability goals, such as sustainable urban mobility [4–6]. Sustainable road maintenance must be carried out adaptively, where actual conditions, the latest knowledge, and technologies are integrated into road condition management [7–10].

With the current evolution of technology, Machine Learning (ML)-based predictive models such as Artificial Neural Networks (ANN) are increasingly used and have become the primary solution for evaluating road conditions and other industrial sectors [11–13]. In the context of road maintenance management, there are several methods for assessing road conditions, such as the Pavement Condition Index (PCI), the International Roughness Index (IRI), and the Surface Distress Index (SDI), which is specifically used for urban road maintenance. Artificial Intelligence (AI), such as Artificial Neural Networks (ANN), is now becoming a global trend and is increasingly popular in the field of civil engineering and infrastructure. This technology has demonstrated effectiveness in predicting Pavement Condition Index (PCI) values, with higher accuracy and precision compared to conventional methods [14–18]. In addition, Artificial Neural Networks (ANN) are also used to predict the International Roughness Index (IRI) with more reliable and accurate results for assessing road conditions [19–22]. The integration of Artificial Neural Networks (ANN) with road condition parameters in this predictive model contributes to more sustainable infrastructure management to support more accurate decision-making in road maintenance management [23,24].

The Surface Distress Index (SDI) is a primary metric for evaluating road conditions, particularly in urban areas with asphalt pavement. Although the use of Artificial Neural Networks (ANN) to predict road damage has been applied to most well-designed road patterns, this study aims to develop a predictive model of road conditions based on the Surface Distress Index (SDI) for urban roads that have not been fully explored previously. The International Roughness Index (IRI) and drainage conditions are also included in the development of this model. Integrating these two inputs will not only provide more accurate predictions but also enhance the model's relevance to emerging issues related to dynamic environmental changes.

Most existing models focus on high-quality national road networks. Urban road conditions with lower-quality infrastructure, climate challenges, and complex maintenance are often overlooked. Moreover, although the Surface Distress Index (SDI) has been used in certain studies, no research has specifically adopted Artificial Neural Networks (ANN) to evaluate road conditions by considering urban road infrastructure due to the combination of diverse damage levels and the integration of rapidly changing environmental conditions. Therefore, it is important to adapt and develop Artificial Neural Network (ANN) models for road conditions with varying levels of damage and to integrate other supporting technologies to enhance the effectiveness of maintenance and the overall sustainability of urban road infrastructure.

By considering the limitations of previous research variables, this study will precisely address existing gaps by developing a predictive model of the Surface Distress Index (SDI) based on Artificial Neural Networks (ANN) for urban roads that more accurately represent road conditions often overlooked in earlier studies. This research will provide an integration between road condition variables, the International Roughness Index, drainage conditions, and their effects on the prediction of urban road damage. This modeling approach aims to improve the efficiency and sustainability of road maintenance that is adaptive to environmental change challenges, which have not been extensively studied in previous research on urban road networks.

Thus, this study not only proposes a more comprehensive model for evaluating urban road conditions but also plays a significant role in the advancement of intelligent infrastructure technologies, which are increasingly becoming a global trend in sustainable civil engineering. Moreover, this research aligns with the goals of the Sustainable Development Goals (SDGs), particularly SDG 9 which focuses on sustainable infrastructure development and innovation, and SDG 11, which aims to create inclusive and sustainable cities and human settlements, an urgent challenge today, by providing more inclusive solutions for urban road maintenance [25–28].

The main objective of this study is to develop a predictive model for assessing the Surface Distress Index (SDI) on urban roads using Artificial Neural Networks (ANN). This model integrates surface distress parameters including crack length and width, crack gap, pothole, and rutting, along with the International Roughness Index (IRI) and drainage conditions to address the challenges posed by current environmental changes. The study is designed to seek solutions for improving road maintenance strategies through a more adaptive, efficient, and comprehensive planning approach to encourage a safer and more sustainable transportation system.

2. Methods

2.1. Data collection

The data used in this study include the results of field inspections on road conditions, which cover the measurement of various types of surface distress, such as crack length, crack width, crack gap, potholes, and rutting. All of these data were calculated using the Surface Distress Index (SDI), which reflects the condition value and the level of road damage. The integration of additional variables, including drainage conditions and the International Roughness Index (IRI), was also applied to improve this model, as part of the effort to address the limitations of traditional models that focus only on physical road damage parameters. Damage data were collected through visual inspection and measurement of the International Roughness Index (IRI) using the Hawkeye measurement instrument. This model was trained with primary and secondary road damage data collected over a five-year period, obtained from 42 road segments managed by the Road Maintenance Division, Public Works and Spatial Planning Office of Tegal City, Indonesia. The total damage dataset consisted of 2,467 road damage observation records.

2.2. Data Pre-processing

Data pre-processing was intended to ensure the quality and consistency of the data before it was used in model development. Accordingly, all numerical variables were normalized using min-max scaling to the [0, 1] range to achieve a consistent scale, prevent variables with large magnitudes from dominating the training process, and enable faster model convergence. In addition, missing or invalid data were imputed to ensure dataset integrity. Finally, the dataset was randomly split into three subsets: 60 percent for training, 20 percent for validation, and 20 percent for testing. This ensured that the model learned from historical data, validated it on unseen data, and evaluated its ability to generalize.

2.3. Model Development

The development of the predictive model for the Surface Distress Index (SDI) was based on key parameters of road damage by integrating surface unevenness as represented by the International Roughness Index (IRI) and drainage conditions from roadside channels. The predictive model developed in this study was divided into three main layers: the input layer, the hidden layer, and the output layer. In the input layer, data on road condition values and other related information about road damage were received. In the hidden layer, this information was processed to identify damage patterns. The output layer predicted the road condition based on the various types of data provided. The training process of the model used the backpropagation algorithm, which functioned to adjust the weights and biases in the neural network to make more accurate predictions [16]. The model learned from the training data and aimed to minimize the error between the predictions and the actual values.

The number of neurons in each layer was referred to in previous models using the formula $Nh = N_{independent} - 1, N_{independent},$ where N independent represents the number of independent variables [29]. All hidden layers and combinations of the resulting neuron numbers were tested, and the configuration that achieved the highest R^2 coefficient of determination on the validation data was selected as the optimal structure and best model. Overfitting was prevented by tuning hyperparameters and validating the model using cross-validation to ensure optimal generalization performance [30]. Dataset limitations were addressed by applying a proper composition to avoid creating a model that depends on limited data. Model interpretability was maintained to ensure that the results could be clearly understood and evaluated. Figure 1 illustrates the framework for developing the Surface Distress Index (SDI) predictive model based on Artificial Neural Networks (ANN).

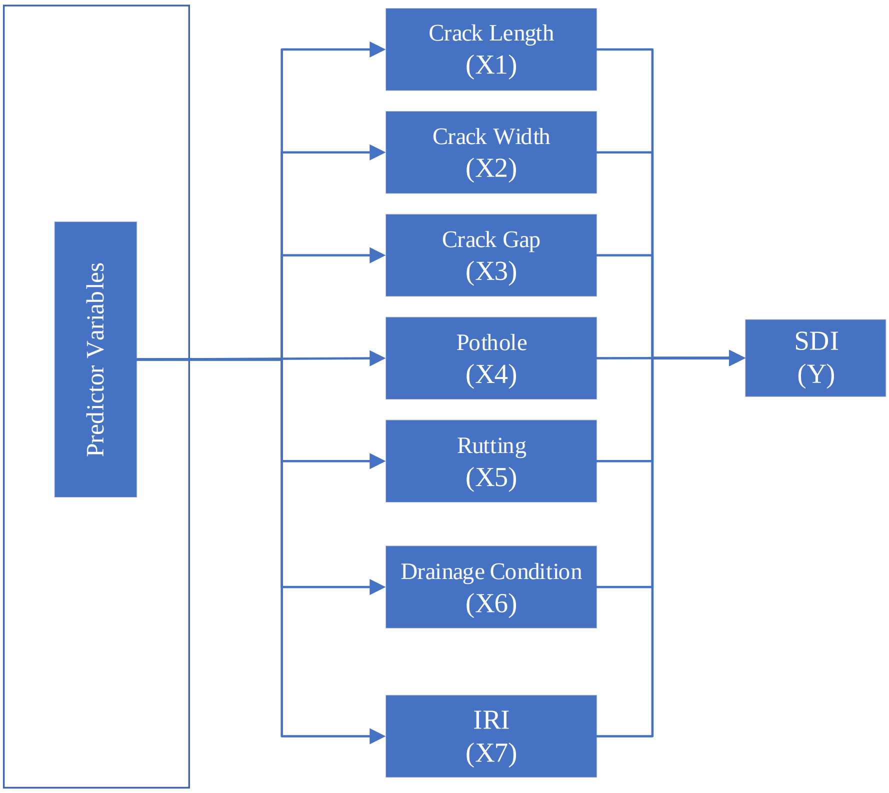

Figure 1. Network Diagram Illustration

2.4. Model Evaluation

The test data were used to measure the accuracy of the model in predicting road conditions based on the given Surface Distress Index (SDI). The model evaluation used three main metrics, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). The performance of the Artificial Neural Networks (ANN) model was assessed based on training data, testing data, validation data, and the overall dataset. This evaluation determines how well the model performs in predicting road conditions and allows comparison of the model's performance with other methods, such as linear regression, as well as with existing predictive models for road condition assessment. The evaluation was conducted in three main steps: first, on the training data to assess how well the model had learned from historical data; second, on the validation data to evaluate how well the model generalized to unseen data during training; and third, on the testing data to assess the model's performance in actual or real-world scenarios.

3. **Results and Discussion**

The road segment damage parameters used in the model development during the five-year maintenance period consisted of seven predictor variables, including crack length (X1), crack width (X2), crack gap (X3), pothole (X4), rutting (X5), drainage condition (X6), and IRI (X7), with the target variable being SDI (Y). The Surface Distress Index (SDI) predictive model was created and trained using a dataset of 2,989 road damage observations, which was divided into 1,795 for training, 597 for testing, and 597 for validation.

3.1. Descriptive Statistics and Correlogram

The correlations between variables were visualized in the form of a correlogram. A more in-depth correlation test was conducted to examine whether there were relationships between road surface damage and the influence of those values on the Surface Distress Index (SDI). The results of the correlation coefficient analysis in Figure 2 showed a strong dependency among the predictor variables. The strongest relationship was observed between the International Roughness Index (IRI) and the Surface Distress Index (SDI), with a correlation value of 0.889. The correlation between the number of potholes and the International Roughness Index (IRI) was the highest among variable pairs, with a value of 0.855. This correlation indicates that the International Roughness Index (IRI) and the number of potholes are the main factors that influence the value of the Surface Distress Index (SDI). This finding is consistent with previous studies that suggest a strong link between pavement condition and cumulative damage. The statistical significance of this relationship highlights the importance of regularly monitoring the International Roughness Index (IRI) and timely repairing pothole damage as part of an effective maintenance strategy.

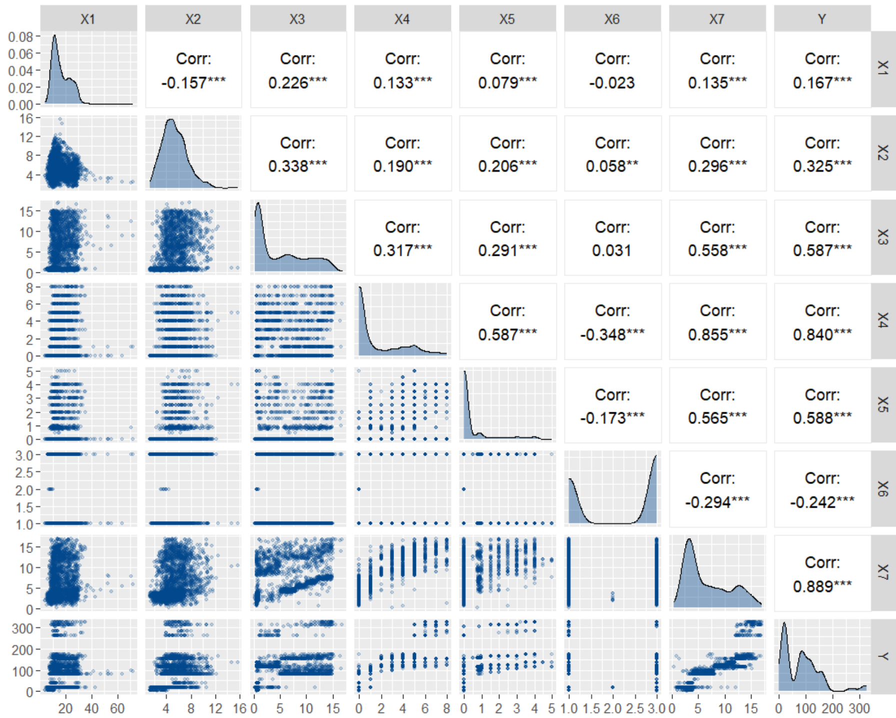

Figure 2. Correlation Coefficients between Variables

This finding aligns with the broader literature on road condition monitoring, which indicates that the International Roughness Index (IRI) and potholes are reliable indicators of surface distress. A high number of potholes is directly associated with an increase in the International Roughness Index (IRI), making it an important parameter in road condition assessment [31–33]. The number of potholes contributes significantly to the rise in the International Roughness Index (IRI) [34–37]. However, it is essential to clearly note that the strength of this correlation may vary depending on geographical location or road type. Future research should explore these adaptations to improve the model's generalizability across a wider range of road networks.

One of the concepts that can be applied from these findings to help authorities establish a more effective road maintenance strategy is using the relationship between variables such as surface unevenness measured by the International Roughness Index (IRI), potholes, and road conditions. From this, one of the practical implications of the findings is that regular monitoring and timely handling of potholes when the condition becomes too severe from the perspective of the International Roughness Index (IRI) should be a top priority when developing road maintenance strategies. Repair and monitoring of drainage conditions should be a top priority in response to dynamic climate challenges.

This concept can prevent more severe road damage from occurring and can help reduce long-term road maintenance costs.

3.2. Artificial Neural Networks Model Development

This study investigated various configurations of Artificial Neural Network (ANN) architecture in an effort to obtain the best results. The predictive model for the Surface Distress Index (SDI) was achieved by testing different neural network configurations to produce accurate prediction outcomes. The number of neurons in each hidden layer was calculated using the formula $Nh = N_{independent} - 1$, resulting in 20 artificial neural network configurations. The process of selecting the model configuration involved testing several configurations by evaluating the model's predictive performance using the R^2 value as the primary indicator. From the 20 configurations, the five with the highest R^2 values were selected for further analysis. Table 1 presents the five best ANN structure configurations from the analysis.

Table 1. Performance of Artificial Neural Network (ANN) Models

ANN Structure	Data	MAE	RMSE	R^2
4-3	Train	0.02	0.04	0.96
	Validate	0.03	0.06	0.94
	Test	0.03	0.06	0.92
	All	0.02	0.05	0.95
6	Train	0.03	0.06	0.94
	Validate	0.04	0.07	0.90
	Test	0.04	0.07	0.89
	All	0.03	0.06	0.92
6-5	Train	0.02	0.03	0.98
	Validate	0.01	0.03	0.99
	Test	0.01	0.02	0.99
	All	0.02	0.03	0.98
5-6	Train	0.02	0.03	0.98
	Validate	0.03	0.07	0.91
	Test	0.03	0.06	0.92
	All	0.02	0.05	0.96
5-5	Train	0.02	0.03	0.98
	Validate	0.02	0.05	0.95
	Test	0.02	0.05	0.95
	All	0.02	0.04	0.97

The selection and analysis of the five models allowed for a systematic approach to network model configuration. This comparison aimed to find an adequate balance between predictive capability and generalization. In the testing data, it was observed that the model with the 6-5 structure configuration was the best, achieving a coefficient of determination (R^2) of 0.99, indicating that the model had excellent capability in predicting unseen data. In the training, validation, and testing stages, the Artificial Neural Networks (ANN) model with the 6-5 neuron configuration showed consistently stable performance across all values, with very small differences in its evaluation metrics. Figure 3 presents the topology of the Artificial Neural Networks (ANN) with a 6-5 neuron configuration developed to predict road surface condition values based on the Surface Distress Index (SDI). The Artificial Neural Network architecture with the 6-5 configuration represents the most optimal structure and serves as the best model for predicting the Surface Distress Index (SDI).

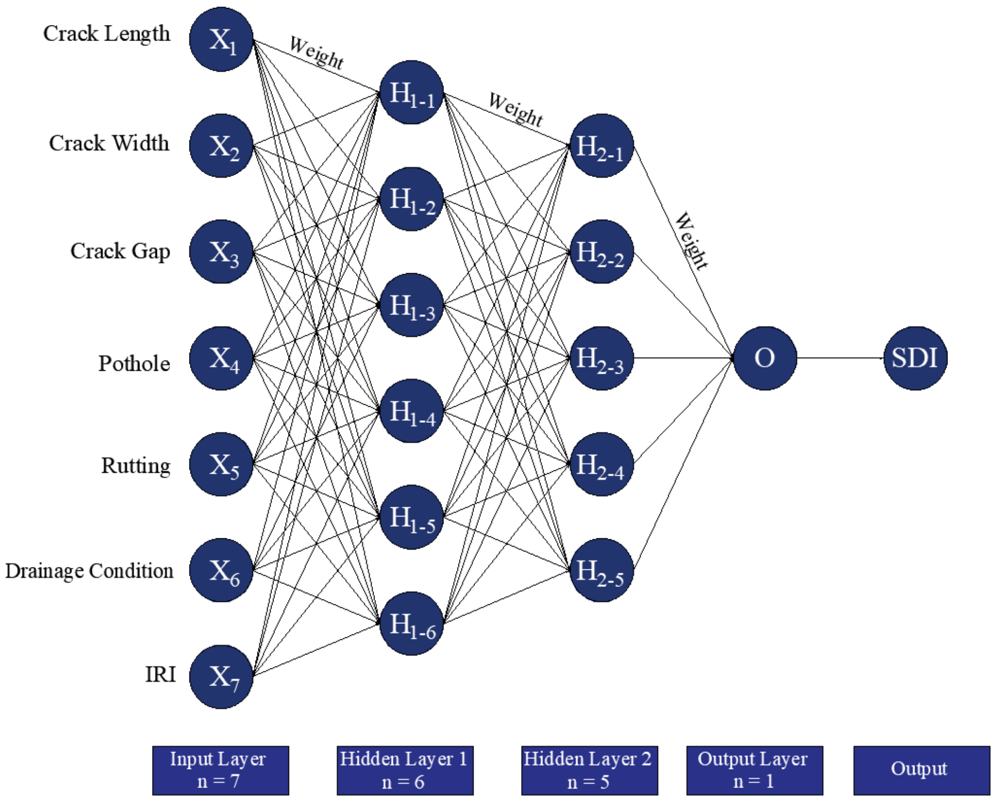

Figure 3. Topology of the Artificial Neural Networks (ANN) Model

The evaluation of the Artificial Neural Networks (ANN) topology with a 6-5 neuron configuration was conducted extensively to minimize the probability of overfitting while maintaining prediction reliability. This model demonstrated highly stable performance in all stages: Train, Validate, and Test, with very small differences in the evaluation matrices. The Surface Distress Index (SDI) predictive model showed excellent generalization capability on data that had never been seen during the training stage, with an R-squared value of 0.99 on the validation data. During the validation stage, the model's performance was evaluated using MAE, which resulted in a value of 0.01. This indicates a very small average deviation between the predictions and actual values, meaning that the accuracy and precision are very high. Additionally, the RMSE value of 0.03 also indicates a very low average error.

This predictive model provides competitive prediction accuracy, particularly when compared to previous Pavement Condition Index (PCI) and International Roughness Index (IRI) models, which reported R-squared values ranging from 0.93 to 0.99 [17,38–42]. These results prove the effectiveness of Artificial Neural Networks (ANN) in modeling nonlinear relationships between input variables and in delivering higher correlation ratios compared to linear regression models [43–45]. The Artificial Neural Networks (ANN) model is superior to existing conventional models because it is capable of delivering higher prediction accuracy when dealing with complex relationships among predictor variables [45–48].

As in previous studies, the integration of external factors such as significant environmental changes has been noted as an important consideration affecting model accuracy. The Artificial Neural Networks (ANN) model with a 6-5 configuration achieved an R-squared value of 0.99. Compared to decision tree and linear regression models that have been widely explored, this model is significantly superior, as the previously developed models tend to show weaker predictive performance on unseen data. The performance metrics in Figure 4 indicate that the model successfully explains most of the variability in the target data, and the prediction accuracy is reflected in the MSE and RMSE values.

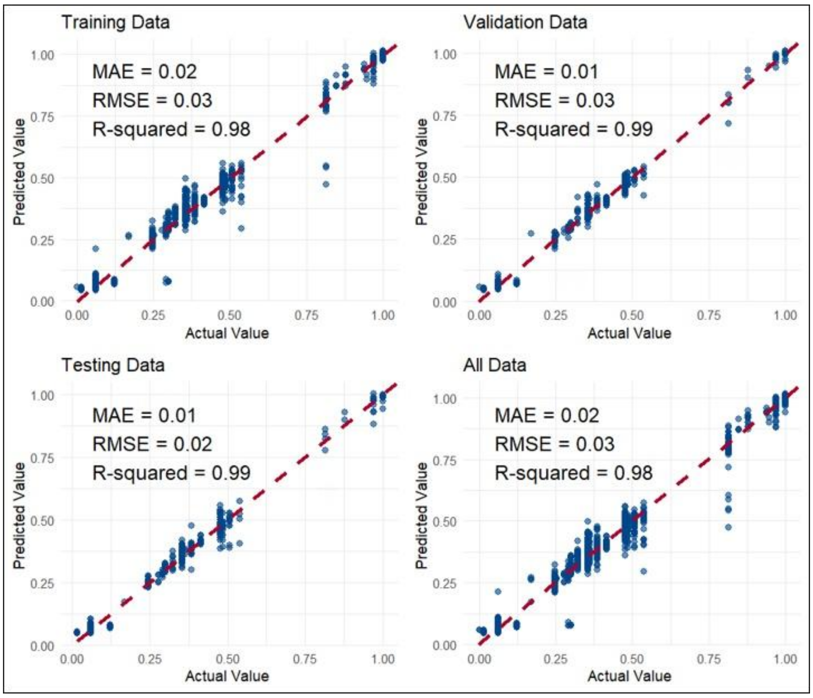

Figure 4. Performance of the Artificial Neural Networks Model

This finding reinforces that the Artificial Neural Networks (ANN) model is far better at adapting to complex, high-dimensional, and intricate data compared to traditional methods. However, although this model demonstrates more accurate and precise performance in terms of prediction accuracy, it also presents its own challenges. The model's performance may be limited when applied to road networks in other regions or countries, where road conditions, environmental factors, and maintenance practices may differ. This finding reinforces that the Artificial Neural Networks (ANN) model is far better at adapting to complex, high-dimensional, and intricate data compared to traditional methods. However, although this model demonstrates more accurate and precise performance in terms of prediction accuracy, it also presents its own challenges. The model's performance may be limited when applied to road networks in other regions or countries, where road conditions, environmental factors, and maintenance practices may differ.

The model has the ability to accurately predict road conditions, making maintenance strategies more adaptive. By prioritizing repairs based on the prediction of the Surface Distress Index (SDI), road maintenance departments can allocate resources more efficiently and in a more targeted manner, which can reduce long-term maintenance costs and extend the lifespan of roads. This approach supports the goals of sustainable urban infrastructure by providing a data-based method for managing road networks, which is in line with the Sustainable Development Goals (SDGs), particularly SDG 9 which focuses on sustainable infrastructure development and innovation, and SDG 11 in creating inclusive and sustainable cities and settlements, which is a major challenge today, by offering more inclusive solutions for urban road maintenance.

4. Conclusion

The development of a predictive model based on Artificial Neural Networks (ANN) was successfully carried out in the field of civil engineering through a road condition assessment model using the Surface Distress Index (SDI). This model, with a 6-5 neuron configuration, is capable of capturing nonlinear relationships across various types and levels of road surface distress, with a model reliability accuracy of R-squared equal to 0.99. With a very high level of model accuracy, it can be used as an alternative decision-making process in determining road repair priorities. The findings of this study indicate that integrating data-based models into road maintenance practices can help improve the quality of sustainable urban infrastructure. This strategy aligns with the goals of the Sustainable Development Goals (SDGs), which aim to facilitate the development of resilient, sustainable infrastructure and innovation in creating inclusive and sustainable cities and settlements. From a policy perspective, governments and infrastructure agencies can utilize this model to enhance long-term road maintenance planning.

By integrating this model into a prediction-based maintenance program within the policy framework, authorities and governments can ensure better resource allocation, especially in areas with limited road maintenance budgets. Meanwhile, integrating road damage data with International Roughness Index values and drainage conditions was found to be an important factor in the overall evaluation of road conditions in response to the challenges of significant climate change. As a note, innovative research on artificial intelligence (AI) based models should focus more on strategies for expanding model applications by integrating additional factors such as weather conditions, different vehicle types, traffic volume, and regional differences in road infrastructure. By integrating all factors, it will provide a more comprehensive and adaptive framework for road infrastructure management. Further studies that explore models for various types of road networks globally will have a highly effective and sustainable contribution to road maintenance in different locations.

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