MODELING OF PAVEMENT MAINTENANCE MANAGEMENT USING ARTIFICIAL NEURAL NETWORK IN KHULNA METROPOLITAN CITY

MD Ibrahim Bhuyia*[1] and Quazi Sazzad Hossain[2]

[1] *Undergraduate Student, Khulna University of Engineering and Technology, Bangladesh, e-mail: ibrahimbhuyia86@gmail.com*

[2] *Professor, Khulna University of Engineering and Technology, Bangladesh, e-mail: sazzad@ce.kuet.ac.bd*

ABSTRACT

The utilization of artificial intelligence (AI) techniques in infrastructure management has emerged as a transformative approach, facilitating predictive modeling and optimization in various sectors. In this context, pavement maintenance management represents a critical area where the application of AI holds significant promise. This study presents a comprehensive methodology for optimizing resource allocation and decision-making for pavement resurfacing projects, employing the power of artificial neural networks (ANNs). The primary objective of this study is to enhance the efficiency of pavement maintenance management, particularly focusing on the Khulna Metropolitan City road network. ANNs are employed to construct predictive models for crucial parameters of pavement maintenance history. Leveraging their capacity for pattern recognition within complex datasets, ANNs deliver precise predictions essential for informed decision-making in maintenance planning. To address the optimization challenge inherent in resource allocation. The results of applying this integrated AI-driven methodology to the Khulna Metropolitan City road network reveal its capability. Not only does it streamline a decision-making processes, but it also significantly improves the allocation of resources, ensuring cost-effectiveness and timely interventions. This approach represents a valuable contribution to pavement maintenance management in urban environments. The fusion of AI techniques offers a promising avenue for revolutionizing pavement maintenance management. The approach presented in this study demonstrates it’s potential to transform the way infrastructure assets are managed, paving the way for more sustainable and efficient urban road networks.

Keywords: *Artificial neural networks, Pavement maintenance management, Resurfacing interventions, Optimizations*

1. INTRODUCTION

As urbanization continues its rapid pace, municipalities and urban planners globally are grappling with the challenge of effectively managing and maintaining critical urban infrastructure. The road network, a lifeline for urban mobility, plays a pivotal role in facilitating seamless movement (Koc et al., 2020). The economic and social prosperity of a city is substantially affected by the condition and resilience of its roadways (Ali et al.,2023). In Khulna Metropolitan City, a rapidly expanding urban centre, management of challenges associated with deteriorating pavements becomes increasingly complex.

Deteriorating pavements result in amplified travel times (Gal et al., 2017), heightened vehicle maintenance costs, and safety concerns for commuters (Li & Yang, 2023). Effectively managing pavement maintenance is imperative for ensuring sustainable development and the well-being of a city (Li et al., 2022).

In the domain of pavement management research, a variety of studies emerges. Every one of these studies contributes technological advancements to the framework of decision-making for maintenance strategies. One noteworthy investigation focuses on automating decision-making processes in highway pavement preventive maintenance by employing deep learning techniques. (Guerrieri & Parla, 2022). This endeavour seeks to imbue the decision-making framework with heightened accuracy and efficiency, ultimately prolonging the life expectancy of highway pavements.

From orchestrating maintenance plans for airport pavements with a fusion of supervised machine learning and reinforcement learning (Marugán, 2023), to finely tuning artificial neural network models for more accurate rutting prediction, these studies together showcase the progressive sophistication in road maintenance methodologies.

In a parallel venture, Researchers explore the domain of asphalt pavements, formulating an intelligent decision-making model for preventive maintenance. This model distinctively incorporates Particle Swarm Optimization (PSO) and Gated Recurrent Units (GRU) within neural networks, providing an advanced tool for decision support in scenarios related to asphalt pavement maintenance. (Li et al., 2022).

As we explore the intricacies of pavement management in Khulna Metropolitan City, some influential studies harmoniously guide our direction. One navigates the intricate domain of airport pavements, intertwining supervised machine learning and reinforcement learning for a nuanced maintenance strategy (Barua & Zou, 2022). In parallel, a refined artificial neural network model emerges, meticulously optimizing input variables to fortify rutting prediction accuracy (Wang et al., 2022). Concurrently, recent strides in computer vision applications cast a dynamic light on pavement distress and conditions (Ayman & Fakhr, 2023).

Expanding the horizon, another facet of the current studies focuses on deploying a spectrum of machine-learning techniques for the evaluation of pavement conditions (Sholevar et al., 2022). The goal here is to comprehensively explore the potential of various algorithms in assessing and predicting the state of road pavements, addressing the intricacies of diverse urban infrastructure.

Meanwhile, the mathematical modelling approach takes centre stage in estimating the pavement quality index, particularly for flexible pavements. Genetic algorithms and artificial neural networks are harnessed to refine the modelling process, shedding light on the overall quality of flexible pavement structures (Hanandeh, 2022).

In a panoramic view of pavement performance, a study undertakes the task of continuous monitoring through a machine learning algorithm. The emphasis here is on real-time assessment, enabling adaptive decision-making based on the dynamic conditions experienced by road pavements (Cano-Ortiz et al., 2022).

These collective efforts within current studies not only underscore the multifaceted nature of pavement management but also spotlight the potential for technological interventions to redefine the landscape (Li et al., 2023). However, as this study embarks on its unique contribution, it is crucial to identify and address the existing gaps that form the groundwork for the proposed modelling of pavement maintenance management in Khulna Metropolitan City.

Moreover, while various studies concentrate on prediction models for specific distress types such as rutting, potholes, and pavement evenness, there is a lack of an overarching framework that integrates these predictions into a holistic road resurfacing strategy. This study seeks to address these gaps by formulating an ANN model that not only predicts pavement resurfacing type but also aids in decision-making for optimal maintenance strategies in the context of Khulna Metropolitan City.

2. METHODOLOGY

This research introduces the Type of Resurfacing Prediction Model, employing a neural network to categorize optimal resurfacing types based on diverse road maintenance contract parameters. By analysing temporal, contract-specific, spatial, and administrative factors, this model pioneers enhanced decision-making precision in road maintenance planning.

2.1 Resurfacing Prediction Model

The Type of Resurfacing Prediction Model is designed to categorize the required resurfacing type based on various input parameters related to road maintenance contracts and pavement conditions. The input parameters encompass a comprehensive set, including Start Date, Contract ID, Pavement Condition, Duration of Work, Contract Value, Road Chainage, Length of Work, and Respective Division. Notably, the Pavement Condition parameter encapsulates critical pavement distress data. This data, combined with the other contextual parameters, forms the foundation for predicting the most suitable resurfacing strategy for a specific road maintenance scenario.

2.1.1 Model Architecture

The neural network utilized in this study adopts a multilayer perceptron with a Backpropagation algorithm. The architecture consists of three layers:

- Input Layer: Neurons are assigned to each parameter, including Start Date, Contract ID, Pavement Condition, Duration (Days), Contract Value (Lac Taka BDT), Start Road Chainage (Km), End Road Chainage (Km), Length of Work (Km), and Respective Division.
- Hidden Layer: Intermediate layers, comprising five hidden layers, each equipped with 50 neurons, serve as the pivotal components for processing the input data.

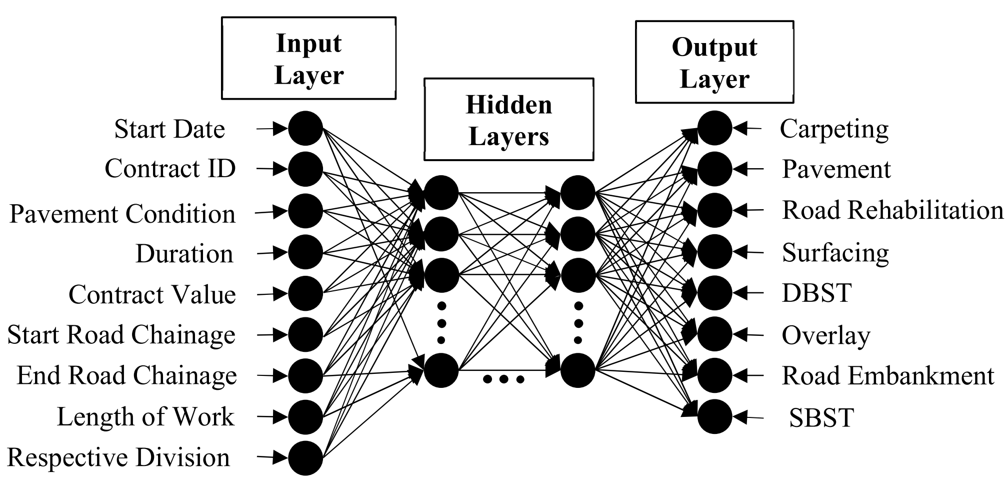


Figure 1: Architecture of the neural network

- Output Layer: One neuron representing the predicted Type of Work.

Training the neural network involves utilizing examples defined by historical data, encompassing 509 instances. Each instance features specific input parameters and the corresponding observed type of work.

2.2 Input Variables for Resurfacing Prediction

The following input variables are taken into account when training the neural network:

2.2.1 Condition Factors

Pavement Condition: This parameter serves as a critical input factor for an Artificial Neural Network model, providing essential insights into the distress and health status of the pavement. The Pavement Condition parameter incorporates a range of distress indicators. Some of them are:

2.2.1.1 Surface Distress

- Cracking: Presence and extent of surface cracks.
- Rutting: Deformation or depressions in the road surface caused by traffic.

2.2.1.2 Structural Distress

- Fatigue Cracking: Indications of structural stress and fatigue.
- Alligator Cracking: Interconnected or interlaced cracks resembling an alligator's skin.

2.2.1.3 Functional Distress

- Roughness: Unevenness or irregularities affecting the road's smoothness.
- Potholes: Depressions or cavities in the road surface.

2.2.1.4 Environmental Distress

- Weathering: The effects of weather conditions on the pavement material.
- Water Damage: Impacts from water infiltration and drainage issues.

2.2.1.5 Maintenance History

- Previous repair or maintenance activities undertaken on the pavement.

2.2.2 Temporal Factors

- Start Date: The initiation date of the road maintenance project.
- Duration (Days): The timeframe required to complete the maintenance work.

2.2.3 Contract Details

- Contract ID: A unique identifier for each road maintenance contract.
- Contract Value (Lac Taka BDT): The monetary value associated with the contract.

2.2.4 Spatial Factors

- Start Road Chainage (Km): The initial chainage points of the road section under maintenance.
- End Road Chainage (Km): The final chainage points of the road section under maintenance.
- Length of Work (Km): The distance covered by the maintenance work.

2.2.5 Administrative Factors

- Respective Division: The administrative division overseeing the maintenance project.

2.3 Output Parameter

The output parameter is the "Type of Work," representing the categorization of the required resurfacing type based on neural network predictions.

3. CASE STUDY

3.1 Resurfacing Prediction Model

The Resurfacing Prediction Model aims to forecast optimal road resurfacing types based on a comprehensive set of input parameters inherent to road maintenance contracts. This model employs a neural network architecture for predictive analytics.

3.1.1 Model Architecture

The neural network architecture follows a sequential design, comprising an input layer, five hidden layers with 150 neurons each using the ReLU activation function, and an output layer that classifies the anticipated kind of work using a Softmax activation function. The selection of this architecture resulted from trial and error, proving successful in analogous predictive modelling tasks.

3.1.2 Model Training

The model was trained using a dataset of 509 instances, encompassing key input parameters: Start Date, Contract ID, Pavement Condition, Duration (Days), Contract Value (Lac Taka BDT), Start Road Chainage (Km), End Road Chainage (Km), Length of Work (Km), and Respective Division. Twenty percent of the data was reserved for testing, while the remaining eighty percent was used for training. The representation of eight output corresponds to eight classes, spanning from class 0 to 7. The sparse categorical Crossentropy loss function and Adam optimizer were used throughout the training phase, and accuracy was used as a performance parameter.

3.1.3 Evaluation Metrics

The model assessment involved a comprehensive analysis, including training and validation metrics, MSE, R Square values, graphical representations depicting measured vs. predicted values, error histograms, auto-correlation plots, confusion metrics, a detailed classification report, precision-recall curves, ROC curves, and autocorrelation analysis. This thorough evaluation provided a nuanced understanding of the model's performance across various dimensions.

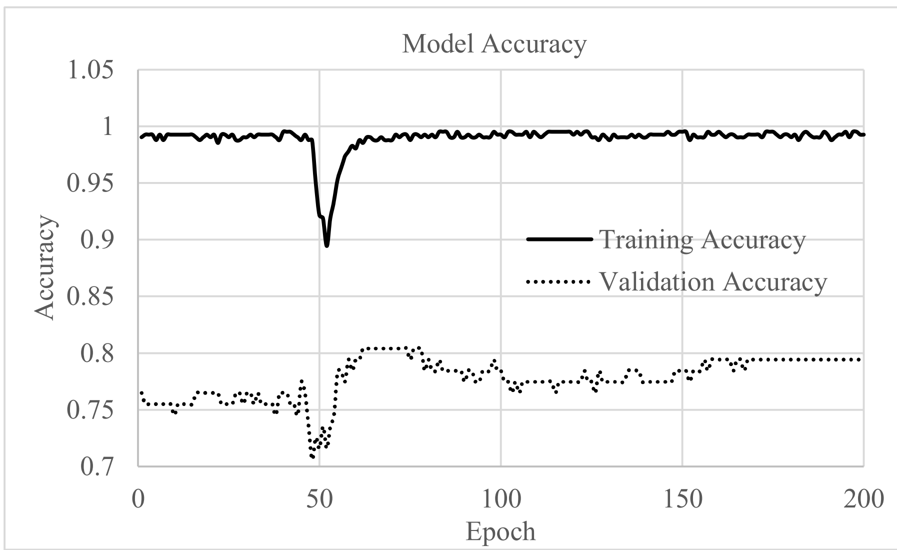
3.1.3.1 Training and Validation Loss Values

While the validation loss is computed using a different dataset that the model did not observe during training, the training loss is determined using the training dataset. The objective is to see a gradual decrease in validation loss as well as training loss, demonstrating efficient learning without overfitting.

3.1.3.2 Training and Validation Accuracy Values

Accuracy values indicate the proportion of correctly classified instances. Training accuracy is computed on the training dataset, while validation accuracy is determined on a separate dataset. Monitoring both training and validation accuracy helps assess how well the model generalizes to unseen data. Figure 2

(a)



(b)

Figure 2:(a) Model loss vs Epoch, (b) Model Accuracy vs Epoch

shows that the loss for the test set is a little bit higher than usual. The results indicate that the dataset utilized for model training and testing has certain characteristics (Terrin et al., 2003). There must be a more reliable dataset.

3.1.3.3 ***Confusion Metrics***

Confusion matrices furnish a comprehensive insight into the performance of the model in a classification task. It separates forecasts into four groups: true positives, true negatives, false positives, and false negatives. This facilitates the recognition of the model's strong points and potential weak points. Here figure 3 shows that class 0,2,4 has a higher accuracy and other classes have a little lower than expected.

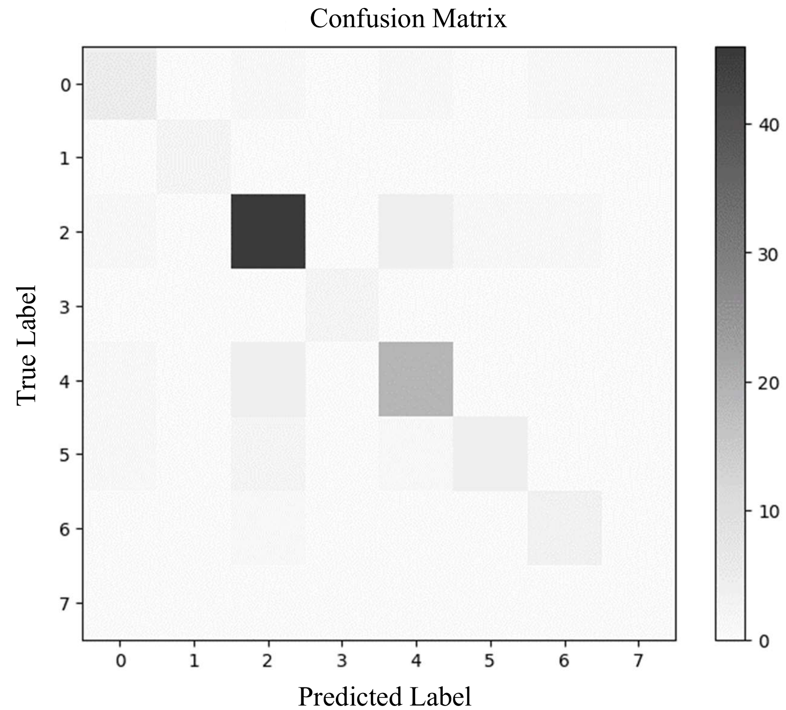


Figure 3: Confussion metrics of different output classes

3.1.3.4 ***Classification Report***

Key classification parameters, including recall, precision, and F1-score for every class, are summarized in great detail in a classification report. It provides a more detailed understanding of how well the model performs across various classes. Table 1 indicates that the model performs well for Class 2 and has excellent precision for Class 1, but it does not assist in Class 7. The model's overall performance is summed up in Table 2. The percentage of successfully identified situations is reflected in the accuracy of 77%. The weighted average and macro average precision, recall, and F1-score offer thorough insights, taking into account the evaluation's class balance and distribution.

Table 1: Classification report of different output

Class	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Precision	0.63	1	0.85	1	0.76	0.80	0.60	0
Recall	0.56	1	0.87	1	0.79	0.50	0.75	0
F1-Score	0.59	1	0.86	1	0.78	0.62	0.67	0
Support	9	2	53	2	24	4	4	0

Table 2: Aggregated metrics for the entire model

	Accuracy	**Macro avg**	**weighted avg**
Precision	0.79	0.70	0.80
Recall	0.79	0.68	0.79
F1-Score	0.79	0.69	0.79
Support	0.79	102	102

3.1.3.5 Comparison between Measured and Predicted Value

Visual comparisons between measured and predicted values provide insights into the model's accuracy. Figure 4 shows that in the learning phase, the predicted value was almost aligned with the measured value. But in the test data, the accuracy was a bit low.

Figure 4: Comparison between Measured and Predicted Value

3.1.3.6 Correlogram of Training and Testing Data

The autocorrelation plot for model validation visually represents the correlation between prediction errors at different time lags. This analysis helps identify any temporal patterns or dependencies in the model's performance. A well-distributed autocorrelation plot with minimal structure suggests that the model has effectively captured and accounted for temporal dependencies in the data, contributing to its reliability. A lower deflection for training data suggests a more stable performance over time, while a higher deflection for test data indicates increased variability in prediction errors. In Figure 5, the contrasting maximum lag values (200 for training and 100 for testing) suggest that the model exhibits more pronounced temporal dependencies in the training data. However, it faces difficulties in extending this behaviour to unseen test instances.

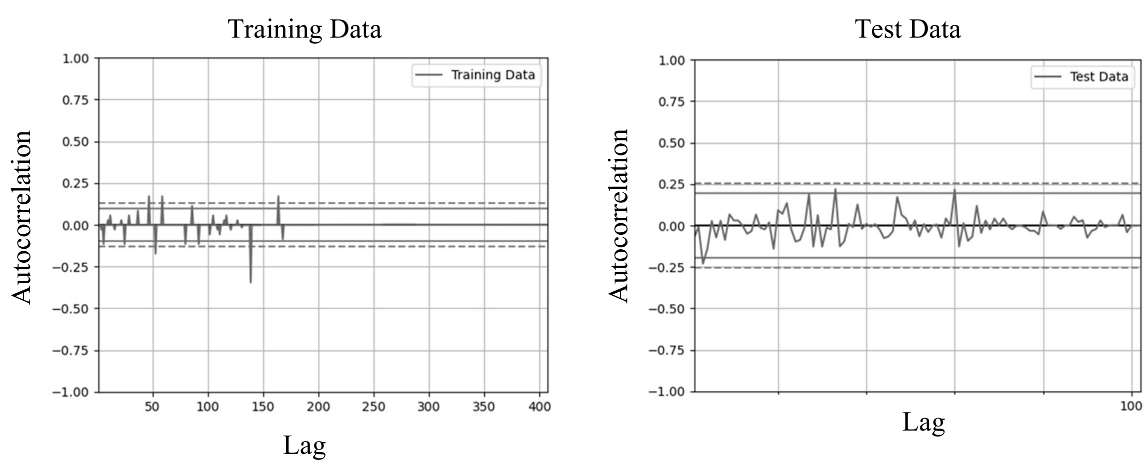


Figure 5: Comparison between Measured and Predicted Value

3.1.3.7 ***Precision-Recall Curve***

Precision-recall curves represent the trade-off between precision and recall at different classification thresholds. In figure 6 it shows that for classes 1, 3, and 6, the AUC value is 1, which indicates that for that class the learning for training was good. In classes 0, 2, 4, and 5, the AUC value is higher than 0.5 which is also good (Ramya & Ganapathy, 2023). But in class 7, the AUC value represents that the

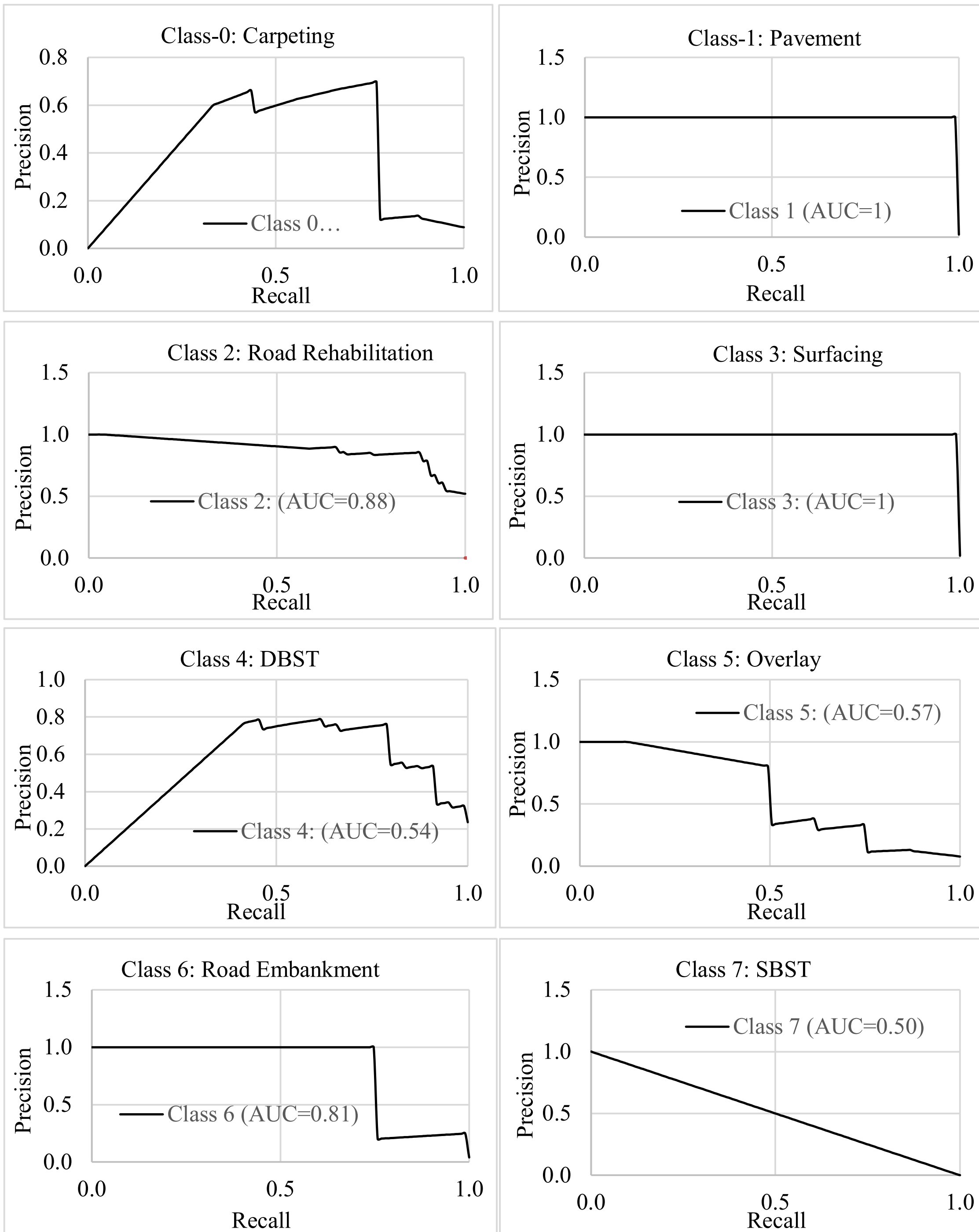


Figure 6: Precision-Recall Curves of different output classes

learning was not enough. As in the total dataset, only 49 samples have class 7 type. For this, the learning and prediction were not enough to perform a good result.

3.1.3.8 ROC Curves

Receiver Operating Characteristic (ROC) curves illustrate the model's trade-off between sensitivity and specificity at various categorization thresholds. The Area Under the Curve (AUC-ROC) summarizes the overall performance, with a higher AUC indicating improved class discrimination. The ROC curve assesses the trade-off between true positive rate and false positive rate to show how well a model can classify data across different thresholds. A higher AUC value signifies better discrimination ability. In Figure 7, Class 1 and Class 3 achieve perfect discrimination with AUCs of 1, while Classes 0, 2, and 6 exhibit strong discriminative performance with AUCs of 0.86, 0.87, and 1, respectively (Terrin et al.,

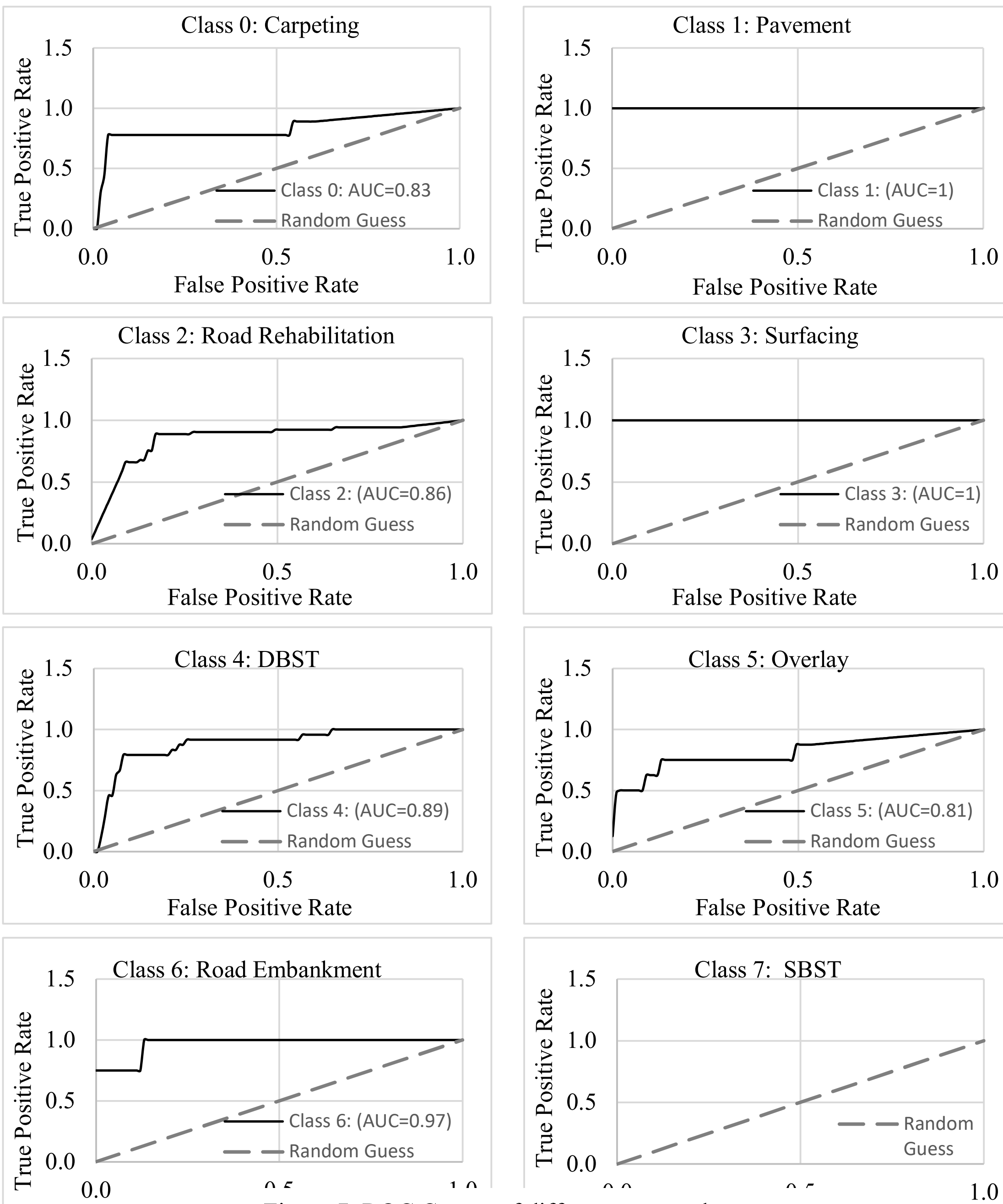


Figure 7: ROC Curves of different output classes

2003). However, Class 5 demonstrates a moderate discriminative ability with an AUC of 0.74. The "nan" AUC value for Class 7 suggests challenges in computing due to potential data scarcity or rare occurrences that need further investigation.

This meticulous training and evaluation process ensures the Resurfacing Prediction Model's proficiency in providing accurate and reliable predictions for the optimal type of road resurfacing required in diverse maintenance scenarios.

4. CONCLUSIONS

The developed neural network model, designed for predicting road resurfacing types, has exhibited commendable performance across a spectrum of evaluation metrics. Demonstrating an overall test accuracy of 77.45%, the model showcases its proficiency in accurately classifying diverse road maintenance instances. Precision, recall, and F1-score metrics for each specific road resurfacing type underscore the model's effectiveness in capturing class-specific nuances. Notably, achieving a perfect AUC for certain classes reflects the robust discriminative power of the model.

Precision, recall, and F1-score macro and weighted averages highlight balanced performance across various classes, considering both class equality and distribution. The model's ability to generalize from the training set to the test set is evident in the consistent performance metrics. Despite encountering challenges in certain classes, the model provides valuable insights into road maintenance categorization.

However, it is crucial to acknowledge the deficiency in data for Class 7, which may have impacted the model's accuracy in predicting this specific road resurfacing type. To enhance the model's effectiveness, addressing this data scarcity by obtaining more representative samples for Class 7 is imperative. Increasing the availability of data for this class will likely result in a more robust and reliable road maintenance prediction system.

ACKNOWLEDGEMENTS

I want to convey my heartfelt appreciation to Eng. Subrata Datta, Superintending Engineer, and Engr. Areena Mannan, Executive Engineer, from the Roads and Highways Department (RHD) of Bangladesh. Their invaluable support and generous provision of data significantly contributed to the success of this research endeavour. Their dedication to advancing knowledge and their willingness to share resources have been instrumental in the completion of this study. I am deeply thankful for their assistance and collaboration throughout this academic pursuit.

REFERENCES

Ali, A. A., Milad, A., Hussein, A., Yusoff, N. I. M., & Heneash, U. (2023). Predicting pavement condition index based on the utilization of machine learning techniques: A case study. *Journal of Road Engineering*, 3(3), 266-278.

Ayman, H., & Fakhr, M. W. (2023). Recent computer vision applications for pavement distress and condition assessment. *Automation in Construction*, 146, 104664.

Barua, L., & Zou, B. (2022). Planning maintenance and rehabilitation activities for airport pavements: A combined supervised machine learning and reinforcement learning approach. *International Journal of Transportation Science and Technology*, 11(2), 423-435.

Cano-Ortiz, S., Pascual-Munoz, P., & Castro-Fresno, D. (2022). Machine learning algorithms for monitoring pavement performance. *Automation in Construction*, 139, 104309.

Gal, A., Mandelbaum, A., Schnitzler, F., Senderovich, A., & Weidlich, M. (2017). Traveling time prediction in scheduled transportation with journey segments. *Information Systems*, 64, 266-280.

Guerrieri, M., & Parla, G. (2022). Flexible and stone pavements distress detection and measurement by deep learning and low-cost detection devices. *Engineering Failure Analysis*, 141, 106714.

Hanandeh, S. (2022). Introducing mathematical modeling to estimate pavement quality index of flexible pavements based on genetic algorithm and artificial neural networks. *Case Studies in Construction Materials*, 16, e00991.

Koc, E., Cetiner, B., Rose, A., Soibelman, L., Taciroglu, E., & Wei, D. (2020). CRAFT: Comprehensive resilience assessment framework for transportation systems in urban areas. *Advanced Engineering Informatics*, 46, 101159.

Li, J., Yin, G., Wang, X., & Yan, W. (2022). Automated decision making in highway pavement preventive maintenance based on deep learning. *Automation in Construction*, 135, 104111.

Li, J., Zhang, Z., Wang, X., & Yan, W. (2022). Intelligent decision-making model in preventive maintenance of asphalt pavement based on PSO-GRU neural network. *Advanced Engineering Informatics*, 51, 101525.

Li, P., Hu, G., Xia, H., & Guo, R. (2023). Efficient method based on recurrent neural networks for pavement evenness detection. *Measurement*, 212, 112676.

Li, Q., & Yang, W. (2023). An effective vehicle road scene recognition based on improved deep learning. *Measurement: Sensors*, 30, 100916.

Marugán, A. P. (2023). Applications of Reinforcement Learning for maintenance of engineering systems: A review. *Advances in Engineering Software*, 183, 103487.

Ramya, V., & Ganapathy, K. (2023). Evaluation of vehicle quality performance using ANN in comparison with decision tree using accuracy, recall and precision. *In AIP Conference Proceedings* (Vol. 2822, No. 1). AIP Publishing.

Terrin, N., Schmid, C. H., Griffith, J. L., D'Agostino Sr, R. B., & Selker, H. P. (2003). External validity of predictive models: a comparison of logistic regression, classification trees, and neural networks. *Journal of clinical epidemiology*, 56(8), 721-729.

Sholevar, N., Golroo, A., & Esfahani, S. R. (2022). Machine learning techniques for pavement condition evaluation. *Automation in Construction*, 136, 104190.

Wang, C., Xu, S., Liu, J., Yang, J., & Liu, C. (2022). Building an improved artificial neural network model based on deeply optimizing the input variables to enhance rutting prediction. *Construction and Building Materials*, 348, 128658.