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THE USE OF ANN AND MACHINE LEARNING ALGORITHMS TO PREDICT ROAD SURFACE DETERIORATION

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ABSTRACT: Despite advancements in the application of artificial intelligence for monitoring and predicting pavement conditions, current models are not extensively utilized due to their limited adaptability and inadequate consideration of environmental variables. This study focuses on developing enhanced models for predicting the Pavement Condition Index (PCI) using artificial neural networks and the backpropagation algorithm. The aim is to improve the accuracy of the predictions. The models were trained using a dataset of 1,614 samples collected during an experiment conducted on a motorway between Kostanai and Astana. The dataset included information on asphalt pavement thickness, subgrade, traffic loads, temperature, precipitation, and deflectometer data. The architecture model with the highest performance, labeled as 9-9-1, attained peak efficiency with a value of 0.0344 after 22 training iterations. The results demonstrated a high level of accuracy, as indicated by a multiple correlation coefficient (R^2) of 0.954, a mean absolute error (MAE) of 0.125, and a root mean square error (RMSE) of 0.162. The developed models possess the capability to extrapolate information, adjust to variations, and accurately forecast the rate of roadway deterioration.

Keywords: Neural Networks, Infrastructure Optimization, Web Condition Prediction, Error Backpropagation, Asphalt Wear, Machine Learning

1. INTRODUCTION

Road network infrastructure helps sustain development and citizen comfort. Road surfaces need regular maintenance and repair under heavy transport infrastructure use. The costs of such works question the road management model's sustainability. Given these challenges, artificial intelligence (AI) has become a powerful tool for optimizing and improving road infrastructure in recent decades. AI can revolutionize road surface maintenance and management with machine learning, data analytics, and automation [1]. Machine learning algorithms can predict road surface problems' occurrence and location. Such models can determine the best time to repair or maintain, preventing damage and saving resources on overly frequent maintenance. Artificial intelligence can also recommend the best repair methods and road surface materials, improving repair quality and durability. This optimizes road network maintenance costs, extends road surface life, and reduces operating costs, which is crucial for road network infrastructure sustainability and development.

AI, sensors, and surveillance cameras can create a road surface composition monitoring system that analyzes long-term changes. Overloads and uneven loads can be identified by measuring pressure and strain distributions across road sections. Road structure condition data is created using AI and neural networks [2]. The system of monitoring road construction based on neural networks is cost-effective and practical, significantly reducing the costs of construction and maintenance of road infrastructure [3]. Systems based on neural networks have a unique ability to successfully adapt to a variety of environmental conditions [4].

Artykbaev et al. highlight that current techniques for automatically identifying pavement defects using computer vision and deep learning often have restrictions in their ability to be applied across various environmental conditions and types of defects [5]. They stress the importance of conducting additional research to create more resilient and adaptable models.

Alqawasmeh highlights the limitations of traditional empirical and mechanistic models used for predicting the lifespan of pavements [6]. These models often fail to consider different environmental factors and non-linear relationships. The author proposes the utilization of artificial neural networks to enhance the precision and adaptability of modelling. However, the scholar emphasizes the necessity for additional enhancement and optimization of these models.

This paper aims to address the current limitations in the applicability and accuracy of existing AI models for predicting road wear. It proposes the use of more flexible and powerful neural network architectures that are trained on representative data to improve the performance of these models.

The dataset has inherent limitations such as restricted geographical coverage from only one motorway, an incomplete range of variables, and uncertain data quality and collection methods. The limitations of extrinsic datasets are related to time constraints and the inability to consider long-term changes or seasonal variations. Regarding the model, there are inherent limitations associated with the use of a relatively simple ANN architecture. This architecture may not be able to fully capture complex non-linear relationships. Additionally, ANNs are considered black-box models, which means that it is difficult to interpret their inner workings. The limitations of the extrinsic model include the absence of evidence regarding its ability to generalize to unseen data from different regions, its sensitivity to biased or unrepresentative training data, and potential problems with hyperparameter tuning, which, if not addressed properly, could result in suboptimal performance.

The primary goal of this research is to create and assess an AI system for the upkeep and restoration of road surfaces. The system will utilize machine learning algorithms to examine data from diverse sources, including sensors, cameras, and weather forecasts, to forecast the degradation of the road surface and determine the most favorable moment for maintenance and repair. The system will additionally offer suggestions regarding the optimal road surface materials and repair techniques, taking into account the distinct conditions and needs of each road segment.

2. RESEARCH SIGNIFICANCE

The research demonstrates the potential of neural networks with error backpropagation algorithms, to forecast pavement deterioration and inform strategic decision-making. The authors developed models that can reliably predict pavement condition indices and the rate of deterioration. This has significant practical implications, enabling more efficient allocation of limited resources, extended pavement lifespan, and reduced disruptions to road users.

3. MATERIALS AND METHODS

The software used during the work included the MATLAB program. The data obtained for building the artificial neural network model were collected during the experiment conducted by LeaderStroy LLP on the road between Kostanay and Astana. A total of 1614 datasets representing 51 different sections along the road were used to build an artificial neural network model. The dataset that was available for analysis included various parameters such as inspection date, air temperature, asphalt pavement thickness, base course thickness, traffic volume, and precipitation and deflection data obtained using a falling weight deflectometer. These data were used as input parameters to train artificial neural networks to predict the values of the pavement condition index (Table 1).

Table 1. Dataset description

Dataset	Number of Samples
Total Dataset	1614
Training Set (70%)	1130
Validation Set (15%)	242
Testing Set (15%)	242

Mean Absolute Error (MAE) measures the difference between predicted and actual values. Coefficient of multiple correlations (R^2) is a statistical measure that indicates the proportion of the variance in the dependent variable (y) that is predictable from the independent variable (x). Root Mean Square Error (RMSE) is a measure of the difference between the predicted values and the actual values, similar to the MAE. Pavement condition index (PCI) is a numerical rating that is used to assess the overall condition of a pavement section. They were determined by the formulas (1-4):

$$MAE = (1/n) * \Sigma|yi - xi|, \quad (1),$$

where yi - actual value; xi - predicted value; n - number of data points.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(y_i - x)^2}, \quad (2),$$

where yi - actual value; xi - predicted value.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \quad (3),$$

where yi - actual value; xi - predicted value.

$$PCI = w_1*I_1 + w_2*I_2 + w_3*I_3 + ... + w_6*I_6. \quad (4),$$

where In is the different distress types; wn - weighting factor.

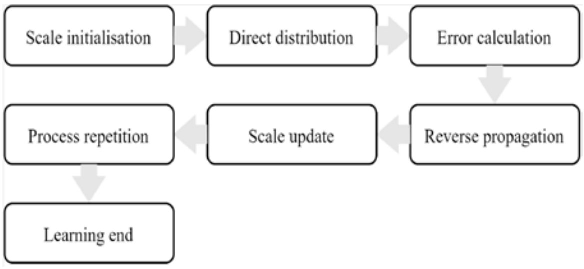

Fig.1 Error backpropagation algorithm [8]

The analysis of statistical data made it possible to identify the most significant factors affecting their efficiency and accuracy. The comparative analysis provided a basis for identifying ways to optimize the parameters of systems using artificial intelligence. The analysis method also allowed us to analyze the properties and characteristics of some materials and technologies used in road pavements. Artificial neural networks with error backpropagation algorithms were used in this study (Figure 1); they are computer models that are inspired by biological neural networks in the human brain [7].

The error backpropagation algorithm was a key component in the training of neural networks. The training process consisted of selecting optimal weights and network parameters to minimize the difference between predicted and actual data [8]. At the beginning of training, the weights of neurons in the neural network are initialized by random values or other special methods. These weights are the parameters that the model will optimize. Learning starts by passing input data through the network to obtain predictions. Each neuron in the network calculates its output using a weighted sum of the input signals, which is then passed through an activation function. This creates the predictions of the model. After direct propagation, model predictions are compared with actual data. The difference between predictions and actual data is measured using a loss function. Backpropagation is a widely used algorithm in training artificial neural networks, which involves calculating the gradient of the loss function with respect to the weights of the network by propagating the error backwards through the layers. After the gradients are calculated, the neuron weights are updated.

These steps are repeated several times to optimize the model. During each epoch, the weights are updated, and the forward and backward error propagation procedure is repeated. Training is completed when the model achieves satisfactory performance or convergence of the loss function.

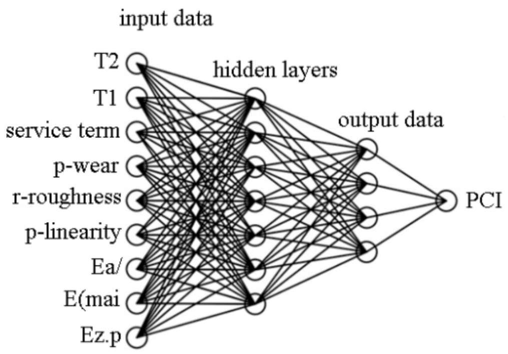

Fig.2 The architecture of the neural model used

The database for input to the neural network includes two categories of information: a set of input data and a set of output data. The measured values of several parameters including pavement durability, asphalt pavement thickness, base layer thickness, p (fatigue), p (roughness), and p (rutting) indices are used as input data. The modulus of elasticity for the pavement layers was represented as average values for each road segment. The database was randomly divided into three data sets: 70% of the information was used to train the neural network, 15% represented the training validation set, and the remaining 15% of the data was allocated to test the neural network (Figure 2).

Each of the nine input parameters is represented by an individual neuron in the input layer. Hidden layer neurons learn and represent complex input-output patterns. They do this by applying mathematical operations to previous layer input signals. The number of hidden layer neurons is usually determined by experimentation and parameter tuning. This study used neural network models with 11 hidden neurons, 7 in the first layer and 4 in the second. Sensor placement on the road surface is crucial for monitoring and predicting road surface conditions. Strain sensors, accelerators, and thermocouples are embedded or attached to the road surface. Roadway type, traffic loading, and environmental conditions determine sensor placement and spacing. For optimal data collection, sensors can be placed at joints, cracks, and stressed areas. This study uses the mistake backpropagation algorithm, a popular neural network training algorithm. The backpropagation of the mistake algorithm iteratively changes neuron weights and biases to minimize the difference between predicted and actual output values.

The study has limitations in that it did not take into account variables such as vehicle velocity, drainage state, and climatic conditions.

4. RESULTS

The performance of the trained models was evaluated using metrics such as MAE, R^2 and RMSE. MAE assesses how close or far the model predictions are from the actual values. Smaller MAE values indicate that the mean predictions of the model are closer to the real data, indicating that the model is highly accurate [9, 10]. The R^2 is also an important statistical metric used to assess the quality of models. R^2 measures how closely the model fits the data set. The closer the R^2 to 1, the greater percentage of the variance in the data is explained by the model [11]. RMSE takes the square root of the RMSE difference. This is done to convert the errors into the same units of measurement as the original data. A model with a lower RMSE value is more capable of making more precise predictions [12]. The regression and performance results graph demonstrate the data associated with the training, validation, and testing process of the neural network. The researchers in this study conducted training on several neural network models with varying architectures, specifically by altering the number of neurons in the hidden layers, ranging from 8 to 14. The validation loss was calculated for each model after every training epoch. The model, designed with a (9-9-1) architecture, attained the minimum validation loss of 0.0344 following 22 training epochs (Figure 3).

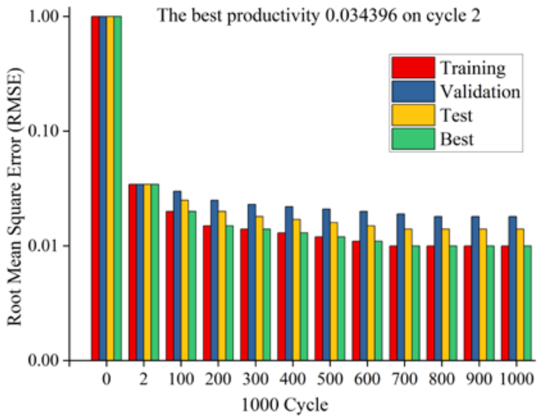

Fig.3 Regression and efficiency plots are presented for the best model

The (9-9-1) architecture refers to an artificial neural network with nine input neurons, nine neurons in the hidden layer, and one output neuron. This architecture is commonly used in regression and prediction problems, where the goal is to predict a single continuous value based on a set of input features. After that, a new dataset consisting of 37 partitions was applied. At this stage, only input data for the specified parameters are provided to the models. As a result, the developed network successfully predicted the PCI based on previous experience gained [13] (Table 2). These results also confirm the ability of the models to generalize information and adapt to different conditions and variations in the data (Table 3).

Table 2: Observed vs. Predicted PCI Values

Road Section	Observed PCI	Predicted PCI
501	4.2	4.1
713	3.8	3.7
1043	4.5	4.6
1216	3.9	4

To evaluate the ability of the developed neural network models to predict the rate of pavement deterioration, each model defined the input data for each pavement section and fixed them by excluding one variable related to service life. The models were then allowed to predict output values based on their previous experience. This experiment was conducted on sites numbered 501 and 1216, as shown in Figures 4 and 5. These graphs clearly show that as the service life increases, the value of the pavement condition index decreases, which is consistent with the real observations on the roads. This demonstrates that the models are successful in capturing the relationships between pavement parameters and their changes over time. By analyzing load and traffic flow data, it is possible to more accurately assess where road surfaces are most susceptible to deterioration [14]. Artificial neural models can automatically detect various defects and deficiencies that may occur during the construction process.

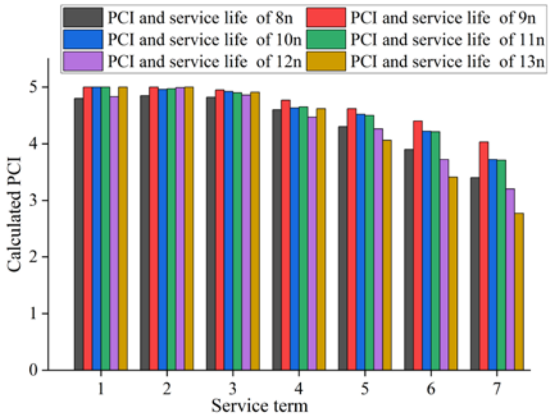

Fig.4 Deterioration of the road surface during the operational phase (Sector No. 501)

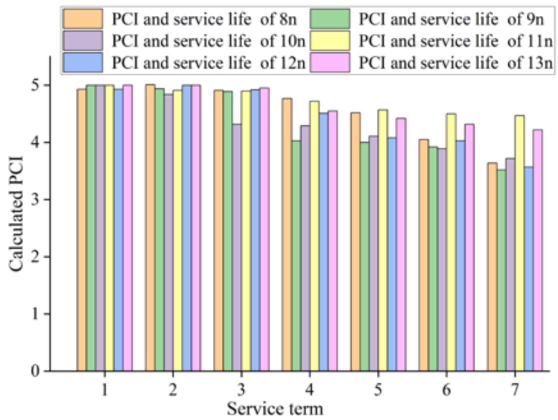

Fig.5 Deterioration of the road surface during the operational phase (Sector No. 1216)

This will not only prevent defects that could have required costly repairs but will also improve the overall reliability and durability of road surfaces. The results reveal how well ANN models predict and analyze pavement deterioration over time. The models accurately correlated longer service life with lower PCI, matching real-world observations. Even without the service life variable, the models were able to accurately predict the output PCI values using other parameters, demonstrating their ability to simulate deterioration rates. Timely prediction is essential for predicting pavement performance and strategically planning maintenance and rehabilitation interventions to prevent excessive deterioration.

Table 3. Statistical evaluation of the results of the created models

No.	Statistical parameters	PCI						
		8-n	9-n	10-n	11-n	12-n	13-n	14-n
1	MAE	0.139	0.125	0.116	0.133	0.137	0.157	0.117
2	$\boldsymbol{R^2}$	0.914	0.954	0.943	0.934	0.931	0.865	0.946
3	RMSE	0.204	0.162	0.173	0.186	0.188	0.279	0.165

Timely prediction is essential for predicting pavement performance and strategically planning maintenance and rehabilitation interventions to prevent excessive deterioration. Graphical representations of projected and observed PCI decay curves throughout operational life could demonstrate the models' accuracy in predicting deterioration rates. The PCI is a widely accepted and comprehensive indicator that reflects the overall condition of a pavement, including its surface distress, roughness, and structural adequacy, which are all critical factors that affect the pavement's quality and performance. Therefore, the PCI can be considered as a key parameter that controls the quality of the pavement.

The study emphasizes the significance of various essential input variables when evaluating road pavement conditions. The durability and age of the pavement are key factors that significantly impact the remaining service life. The thickness of pavement layers, specifically asphalt and base, directly affects the rate at which deterioration occurs. Thicker pavements generally experience slower rates of deterioration. Environmental factors such as temperature and precipitation can expedite degradation, particularly when temperatures are extreme and there is excessive moisture. Traffic load parameters such as fatigue, roughness, and rutting indices are affected by higher traffic volumes, which lead to accelerated deterioration due to repeated loading. The pavement modulus or stiffness refers to the ability of the pavement to resist deformation and cracking. Pavements with higher stiffness are more resistant to these issues.

The ability of ANN models to integrate the intricate relationship between crucial construction, environmental, and operational factors allows for precise forecasting of the overall pavement condition. Sensitivity analyses can provide a more precise quantification of the relative significance of each variable. Models based on data analysis using artificial neural networks can provide recommendations for selecting the best materials and construction methods to maximize pavement durability for specific road conditions. Neural networks can monitor data on ambient temperature, asphalt temperature and other factors affecting its condition. During construction, they can also determine the optimum temperature regimes for specific conditions to ensure that asphalt is applied and compacted according to best practices [15].

5. DISCUSSION

Social importance lies in road system development and improvement. Adapting AI methods and models to specific geographical and climatic features requires constant data updates and consideration of traffic volume, temperature extremes, precipitation, and other road conditions variables. Researchers can create more advanced and accurate artificial neural network models using machine learning and deep learning algorithms. Vyas et al. [16] showed that a pavement condition monitoring system using neural networks can lead to significant benefits for road infrastructure. This system provided impressive accuracy in detecting changes in the road surface, achieving an accuracy rate of 97%. The model obtained in the current paper was also able to achieve high accuracy and confirms that the use of neural networks in pavement monitoring has the potential to lead to significant infrastructure benefits.

Sirhan et al. [17] found that the system of monitoring of motor transport movement based on the use of artificial neural networks can accurately measure the speed of vehicles. The results obtained in the current study demonstrate the high accuracy of neural networks, which significantly improve traffic control on roads. Kumar et al. [18] found that integrating AI into road infrastructure has reduced road maintenance and repair costs, improving road surface quality and generating economic benefits. When comparing these data with the current study, it should be noted that installing and integrating such systems into road infrastructure may be costly. Implementing such systems requires detailed planning, cost estimation, and selection of the best technological solutions and equipment suppliers. System effectiveness depends on regular inspection, software updates, and maintenance.

According to Hassaballah et al. [19], the use of systems based on artificial intelligence can accurately classify and determine the mass of vehicles on the road. The data obtained confirms that pavement condition monitoring systems are becoming a key tool to ensure the control and safety of road infrastructure. To maximize their potential and ensure reliable operation, it is also essential that such systems are regularly calibrated to ensure their accuracy and reliability during operation.

Neural networks in the road condition

monitoring system have detected road surface vibrations and dynamic loads, as claimed by Olayode et al. [20]. Their integration improved road condition monitoring and deformation detection, enabling rapid pavement problem response. Their study showed that this approach reduces road deterioration, making roads safer and longer-lasting. The reviewed study focuses on road surface vibrations and stresses, while this study uses artificial intelligence and neural networks to determine pavement durability. Both research areas are crucial to road infrastructure safety and reliability, and their complementary effects can improve pavement condition management. This can improve road maintenance and repair, improving infrastructure quality and safety.

According to Mandal et al. [21], systems that use sensors with artificial intelligence are successful and determine the speed of traffic in real time. They can measure the deformations caused by the movement of wheels on the road surface. The results of the study confirmed the accuracy in determining the speed of traffic at 97%, which indicates the reliability and high efficiency of such systems in the context of road infrastructure.

This study reinforces the importance of such systems in road traffic safety and efficiency and shows that AI-based systems are valuable in today's world. Researchers and engineers can improve road system safety, reliability, and efficiency by using advanced technologies like artificial intelligence and neural networks [22-24]. Research and innovation in this area are essential to providing quality and modern road infrastructure, which improves people's quality of life and social development.

The study's findings clearly illustrate the substantial benefits of employing artificial neural networks for predicting pavement conditions, as compared to traditional empirical and mechanistic models. Unlike Satybaldina et al. [25], who faced difficulties in accounting for non-linear relationships, our models, by their adaptable structure, have successfully demonstrated the capacity to effectively model intricate dependencies among multiple factors. The predictions' accuracy surpasses the result obtained because of the utilization of more comprehensive and representative data. Integration of models into road infrastructure maintenance optimizes resource allocation for road repair and maintenance. By accurately forecasting pavement deterioration, preventive measures can be taken to avoid excessive degradation and costly reconstruction. This may reduce road infrastructure life cycle costs. This study has limitations. To broaden the models' applicability, future research should include seismic activity and hazardous loads and use more advanced neural network structures.

Pavement condition prediction is difficult, but artificial neural networks excel at it. ANNs can accurately represent complex non-linear relationships between input factors like pavement composition, traffic loads, environmental conditions, and pavement deterioration over time. ANN models consistently predicted well across road sections and data partitions with different construction materials and climatic scenarios [18]. This shows that ANN models generalize well. The models also accurately predicted PCI decay curves, allowing precise long-term deterioration rate estimates. This is crucial for proactive infrastructure maintenance planning. Sensitivity analyses clarified input variable significance, making ANN decision-making transparent and interpretable. Due to their computational efficiency, scalability, and superior performance over statistical methods and other machine learning models, ANNs are a cutting-edge solution for improving pavement management strategies and extending road network lifespans.

The flexible ANN model also introduced a new pavement management method as an intelligent digital replica of road infrastructure. The model analyzed pavement composition, age, traffic patterns, climatic factors, and real-time sensor feeds to create an ultra-high-dimensional road network model [26-28]. Users can test the virtual road surface for accelerated deterioration using hypothetical scenarios to help stakeholders develop optimal maintenance strategies. The ANN can model pavement condition evolution over time, including extreme weather, traffic spikes, and ageing dynamics. This model allows hyper-realistic projections [29-31]. This predictive intelligence was transformed into intuitive 4D visualizations using interactive visual dashboards, allowing stakeholders to assess corrective intervention, material, and life-cycle cost trade-offs [32-34]. The model's self-learning abilities improved as IoT sensor data was seamlessly integrated, creating a closed-loop road management solution that includes planning, execution, and monitoring [35].

This study shows that ANN and ML algorithms can predict road surface deterioration and inform strategic decision-making. The models can accurately predict pavement condition indices and deterioration, allowing for more efficient resource allocation, longer pavement lifespan, and fewer road user disruptions. The study's limitations include using a single dataset from a specific location and not considering other factors that may affect road surface deterioration, such as vehicle speed and drainage conditions.

6. CONCLUSION

The study validates the precision and effectiveness of artificial neural network models in forecasting road surface conditions. These models demonstrated adaptability to various input parameters, ensuring flexibility and versatility. They can assess the rate and likelihood of changes in pavement condition throughout its operational period. The 9-9-1 architecture model achieved peak performance after 22 training cycles, with negligible disparities between the predicted and actual values.

Utilizing these models enables effective allocation of resources for road repair and maintenance through precise prediction of deterioration rates and strategic planning of preventive measures, thereby preventing excessive degradation and costly reconstruction. However, the study is limited by its failure to consider other risk factors, such as seismic activity, and by constrained model structures.

Future research should include additional risk factors, explore more sophisticated neural network structures, integrate with infrastructure asset management systems, and analyze the technical and organizational aspects of large-scale implementation. In conclusion, this neural network-based approach has the potential to monitor various types of infrastructure beyond road networks.

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