An Optimized Machine Learning Model For Pavement Condition Prediction

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Abstract- *Pavement condition prediction is an essential aspect of road maintenance planning, ensuring the safety, efficiency, and durability of transportation infrastructure. Statistical machine learning (ML) techniques have emerged as powerful tools for addressing this challenge, offering data-driven methods to model complex relationships between pavement performance and contributing factors such as traffic loads, weather, and material properties. Traditional prediction models include linear regression, Markov chains, mechanistic-empirical approaches, and time-series models. Although these methods are computationally simple, they often exhibit limited accuracy because pavement deterioration is highly nonlinear and influenced by multiple interdependent factors. Recent developments in artificial intelligence have enabled the use of machine learning models for the purpose. This work presents a PSO- Deep Neural Network hybrid model for predicting pavement conditions. The PSO-Deep Neural Network model is trained with trained using Conjugate Gradient Backpropagation (CGB) with the Fletcher–Reeves restarts offer several important advantages over conventional optimization methods such as standard Gradient Descent, such as immunity to vanishing gradient and local minima stagnation. The model attains an accuracy of 95.2% for pavement condition prediction outperforming existing work in the domain.*

Keywords: Pavement Condition Prediction, Particle Swarm Optimization, Neural Networks, Back Propagation, Conjugate Gradient Back-propagation with Fetcher-Reeves Restarts, Classification Accuracy.

I. INTRODUCTION

Pavement condition prediction is an important aspect of transportation infrastructure management because road networks deteriorate continuously due to traffic loading, environmental effects, and aging. Accurate prediction of pavement deterioration enables transportation agencies to schedule maintenance activities effectively, reduce rehabilitation costs, and improve road safety [1]. Traditional pavement evaluation techniques are often time-consuming and expensive, creating a need for intelligent computational approaches capable of predicting pavement conditions with higher efficiency and accuracy. In recent years, Artificial Intelligence (AI) techniques, particularly Artificial Neural Networks (ANNs), have gained significant attention in pavement engineering applications [2].

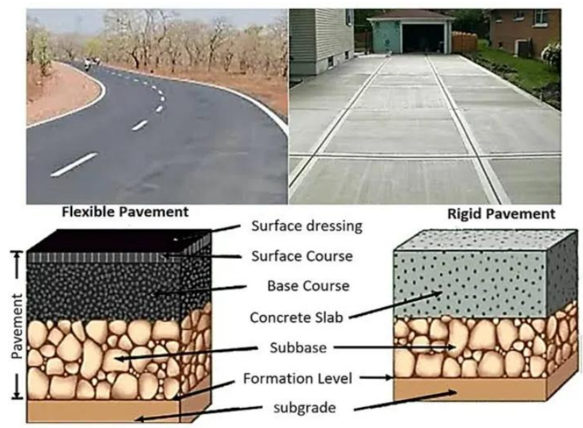

Fig.1 Rigid and Flexible Pavements

Figure 1 depicts rigid versus flexible pavements.Artificial Neural Networks are powerful machine learning models inspired by the functioning of the human brain. ANNs are capable of identifying hidden relationships between input and output variables and can model complex nonlinear systems effectively. In pavement engineering, ANN models are widely used for predicting pavement distress, pavement condition index (PCI), roughness, rutting, and cracking behavior. However, the performance of conventional ANN models largely depends on proper weight initialization and parameter optimization. Improper selection of network parameters can lead to slow convergence, poor prediction accuracy, and local minima problems during training [3].

To overcome these limitations, optimization techniques such as Particle Swarm Optimization (PSO) are integrated with ANN models. PSO is a population-based metaheuristic optimization algorithm inspired by the collective movement behavior of birds and fish schools. The hybrid PSO-ANN model combines the global optimization capability of PSO with the nonlinear learning capability of ANN, resulting in improved pavement condition prediction performance. This hybrid approach enhances the efficiency of

ANN training by optimizing network weights and biases, thereby improving prediction accuracy and convergence speed [4].

The hybrid PSO-ANN model begins with the collection of pavement-related datasets from transportation agencies, pavement surveys, sensor systems, and roadway databases. These datasets generally include parameters such as traffic volume, axle load, pavement age, climatic conditions, pavement thickness, rainfall, temperature, maintenance history, and material properties. Since raw pavement datasets often contain missing values and inconsistencies, preprocessing techniques such as normalization, feature selection, and data cleaning are applied before model training. Proper preprocessing improves the quality of the input data and enhances the learning capability of the ANN model [5].

II. IMBALANCED DATASETS

Pavement condition prediction is a crucial task in infrastructure management, helping agencies allocate maintenance resources effectively and ensure road safety. However, the accuracy of predictive models heavily depends on the quality and distribution of the input data. One major challenge in this domain is the problem of imbalanced datasets, where the number of samples across different pavement condition classes [6]:

1. Good
2. Fair
3. Poor

The samples of survey are generally not uniformly distributed. This imbalance poses significant obstacles to the development of robust and generalizable predictive models[7].

In pavement condition datasets, imbalance typically arises because the majority of roads are often in acceptable or 'Good' condition due to regular maintenance and upgrades, while only a small fraction fall into the 'Poor' category. As a result, data collected from real-world surveys or monitoring systems naturally exhibit class imbalance. Other contributing factors include biased data sampling, insufficient historical records of degraded pavements, and lack of data from remote or less-traveled roads. This skew in class representation leads to an underrepresentation of critical degradation patterns [8].

This imbalance can skew the model's performance, making it less effective at identifying pavement condition. Techniques such as oversampling, undersampling, and synthetic data generation are often employed to address this issue. The Skewness **(Pearson's Moment Coefficient of Skewness)** is defined as [8]:

$$S = \frac{n}{(n-1)(n-2)}\sum_{i=1}^{n}\left(\frac{x_i-\bar{x}}{sd}\right)^3 \quad \textbf{(1)}$$

Here,
n is number of observations.
x_i is each individual data point.
$\bar{x}$ is the mean.
sd denotes standard deviation

One of the most effective techniques is the random oversampling method mathematically described as:

In this case, we need to add copies or synthetic data to minority classes. For minority class C_j , generate new samples until [9]:

$$N'_j = N_{major} = \max(N_i) \quad \textbf{(2)}$$

Thus the new distribution becomes:

$$P' = \left[\frac{N'_1}{N'};\frac{N'_2}{N'},\frac{N'_k}{N'}\right] \approx Uniform \quad \textbf{(3)}$$

The above can be done through cost sensitive learning based on the following formulation:

Assign different misclassification costs to classes to adjust bias.

Let the cost matrix be $C = [c_{ij}]$, then, c_{ij} denotes the cost of predicting class j when the true class is i.

$$c_{ii} = 0; i = j \quad \textbf{(4)}$$

$$c_{ij} = \frac{1}{N_i}; i \neq j \quad \textbf{(5)}$$

In such a case, the loss function becomes [10],

$$L = \sum_{i=1}^{N} C(y_i,\tilde{y}_i) * L(f(x_i)y_i) \quad \textbf{(6)}$$

This penalizes errors more in underrepresented classes, mathematically correcting skewness during model training. It can be implemented through an adaptive approach to update system weights. A swarm intelligence based approach can be effective in this regard.

III. HYBRID PSO-ANN MODEL

The In the ANN component of the hybrid model, the neural network consists of an input layer, one or more hidden layers, and an output layer. The input layer receives pavement-related features, while the hidden layers perform nonlinear transformations and feature extraction. The output layer predicts pavement condition indicators such as PCI or IRI. During training, the ANN attempts to minimize prediction error by adjusting weights and biases. However, traditional back-propagation learning algorithms may suffer from slow convergence and may get trapped in local minima, affecting overall performance [11].

Particle Swarm Optimization improves the ANN training process by searching for optimal weights and biases globally. In PSO, each particle represents a candidate solution corresponding to a set of ANN parameters. The particles move through the search space by updating their positions and velocities according to their individual best solution and the global best solution found by the swarm. Through iterative optimization, PSO identifies optimal network parameters that minimize prediction error. This global optimization capability allows the hybrid PSO-ANN model to avoid local minima and achieve better generalization performance [12]

One of the major advantages of the hybrid PSO-ANN model is its ability to handle highly nonlinear pavement deterioration patterns. Pavement performance is influenced by multiple interacting variables, making conventional statistical models insufficient for accurate prediction. The hybrid PSO-ANN model effectively captures these nonlinear relationships and provides more reliable predictions compared to traditional regression-based techniques. Furthermore, the integration of PSO reduces the dependence on random weight initialization, resulting in improved training stability and consistency [13].

The hybrid PSO-ANN model also offers faster convergence compared to conventional ANN models. Since PSO performs efficient global optimization during the initial training phase, the ANN begins learning from near-optimal parameter values. This reduces the number of training iterations required and improves computational efficiency. Additionally, the model demonstrates better adaptability to different pavement conditions, traffic patterns, and environmental variations, making it suitable for diverse roadway networks and transportation systems.

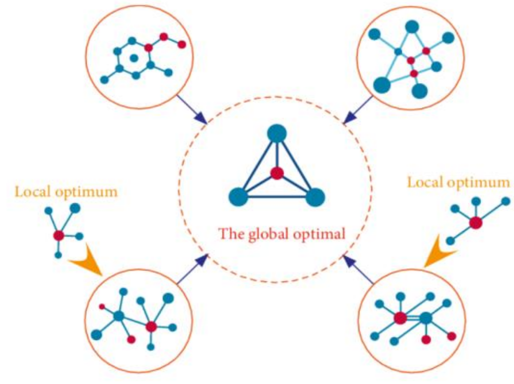

Fig.2 Visualization of Swarm Intelligence

Figure 2 depicts the concept of swarm intelligence.Swarm intelligence, and particularly swarm intelligence exemplifies how nature-inspired algorithms can solve complex optimization problems effectively. By leveraging collective behavior and distributed decision-making, the approach efficient framework adaptable to numerous applications. The PSO algorithm is mathematically governed by [14]:

$$\mathbf{vel_k = w \times vel_{k-1} + L_1\alpha_1[p_i - x_{i(k-1)}] + L_2\alpha_2[p_g - x_{i(k-1)}]} \quad \textbf{(7)}$$

$$x_{i(k)} = x_{i(k-1)} + vel_k \quad \textbf{(8)}$$

Here,

vel is the particle velocity
k is the iteration
L_1andL_2 are learning factor values
$x_i$is the particle position
$\alpha_1$andα_2 are random number values
w represents the weights
$p_i$represents particle's individual best position
$p_g$represents group's best position

IV. METHODOLOGY

The applications of hybrid PSO-ANN pavement prediction models are extensive in modern transportation engineering. These models support intelligent pavement management systems by enabling preventive maintenance planning, budget optimization, and efficient resource allocation. Transportation agencies can use predicted pavement conditions to identify critical road sections requiring immediate rehabilitation and to prioritize maintenance activities accordingly. Moreover, the integration of AI-based pavement prediction systems with smart city infrastructure and

IoT-based monitoring systems can further enhance real-time road condition assessment [15].

Deep Neural Networks Trained with Conjugate Gradient Back-Propagation with Fletcher–Reeves Restarts (CGF) Algorithm:

Deep Neural Networks (DNNs) have emerged as one of the most powerful Artificial Intelligence (AI) techniques for solving complex real-world problems involving classification, prediction, optimization, and pattern recognition. DNNs are capable of learning highly nonlinear relationships from large-scale datasets through multiple hidden processing layers. Due to their superior learning capability, DNNs are widely applied in fields such as transportation engineering, healthcare, image processing, speech recognition, natural language processing, financial forecasting, and intelligent infrastructure systems. However, the effectiveness of a DNN largely depends on the efficiency of its training algorithm [16]..

Training a Deep Neural Network involves adjusting network weights and biases in order to minimize prediction error. Conventional gradient descent and standard back-propagation algorithms are commonly used for training neural networks. Although these methods are simple and easy to implement, they often suffer from several limitations, including slow convergence speed, oscillatory learning behavior, sensitivity to learning rate selection, and the possibility of becoming trapped in local minima. These limitations become more significant when dealing with deep architectures and large datasets. To address these issues, advanced optimization techniques such as Conjugate Gradient Back-propagation with Fletcher–Reeves Restarts (CGF) are employed [17]

This algorithm is based on the concept of feeding back the errors to the neural network i.e. back propagation. The salient feature of the algorithm is its relatively low time complexity and accuracy. The reason for the mentioned phenomena is the fact that the algorithm searches for the direction for the steepest direction right from the first iteration. Mathematically [18],

$$p_0 = -g_0 \qquad \textbf{(9)}$$

Here,
p_0 is the negative of the gradient vector g_0
For the kth iteration [19]:

$$p_k = -g_k + \Theta_k p_{k-1} \qquad \textbf{(10)}$$

It is worth noting that the in addition to the weights, the search vector also keeps updating with the iterations. The term Θ_k is calculated as:

$$\Theta_k = \frac{g_k g_k^T}{g_{k-1} g_{k-1}^T} \qquad \textbf{(11)}$$

The overall training rule for the algorithm can be mathematically expressed as [19]:

$$w_{k+1} = w_k + \beta_k p_k \qquad \textbf{(12)}$$

The Conjugate Gradient Back-propagation algorithm, particularly with Fletcher-Reeves restarts, is a powerful optimization method used in machine learning and neural network training. Combining the efficiency of the conjugate gradient method with restart mechanisms provides numerous advantages over traditional back-propagation and other gradient-based optimization techniques. These advantages contribute to improved convergence rates, computational efficiency, and robustness, making it a preferred choice in many machine learning tasks [20].

The Conjugate Gradient (CG) algorithm is an iterative optimization technique developed to solve large-scale optimization problems efficiently. Unlike standard gradient descent, which always moves in the direction of steepest descent, the conjugate gradient method determines search directions that are conjugate to previous directions. This property allows the optimization process to converge faster and more efficiently. In Deep Neural Networks, the CG algorithm improves training performance by reducing the number of iterations required for minimizing the error function.The Fletcher–Reeves (FR) method is one of the most widely used variants of the conjugate gradient optimization technique. In this approach, the search direction is updated using both the current gradient and the previous search direction. The Fletcher–Reeves coefficient determines the contribution of the previous search direction in the current optimization step.

Despite its advantages, the CGF algorithm also has certain limitations. The algorithm may require high computational memory for large-scale deep learning problems. Performance is sensitive to proper initialization and parameter selection. Additionally, line search procedures used in conjugate gradient optimization may increase computational complexity. Therefore, efficient implementation strategies and proper hyperparameter tuning are necessary for achieving optimal performance.The overall performance metrics are mathematically defined as [21]:

Accuracy: It is mathematically defined as:

$$Ac = \frac{TP+TN}{TP+TN+FP+FN} \qquad (13)$$

Recall: It is mathematically defined as:

$$Recall = \frac{TP}{TP+FN} \qquad (14)$$

Precision: It is mathematically defined as:

$$Precisiosn = \frac{TP}{TP+FP} \qquad (15)$$

F-Measure: It is mathematically defined as:

$$F - Measure = \frac{2.Precision.Recall}{Precision+Recall} \qquad (16)$$

Here.

TP represents true positive
TN represents true negative
FP represents false positive
FN represents false negative

V. RESUTS

The experimental results are obtained on MATLAB. The variables in the study are;

Input Variables (X):

1. Road Type
2. Region
3. Roughness
4. Rubber Modified Asphalt (RMA)
5. Heavy Articulated. Truck Index (HATI)
6. Texture

Output Variable (Y)

1. Condition. (Good, Average, Poor)

The dataset has been collected from: https://discover.data.vic.gov.au/dataset/pavement-condition-data where 6000 samples have been used for testing.

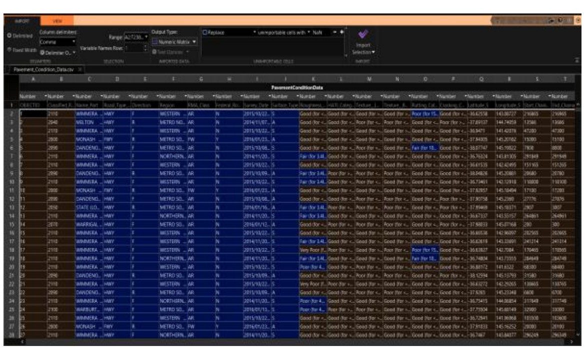

Fig.3 Raw Dataset

Figure 3 depicts the raw dataset.

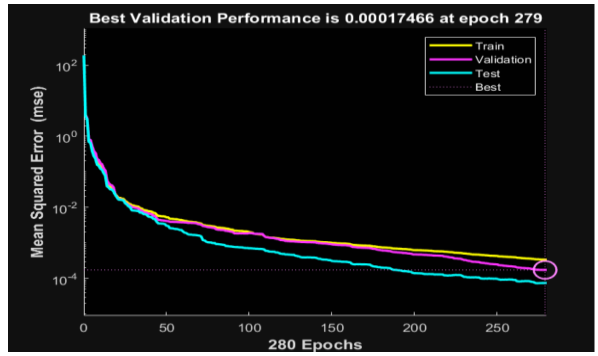

Fig.4 Training Epochs

Figure 4 depicts the MSE variation with epochs.

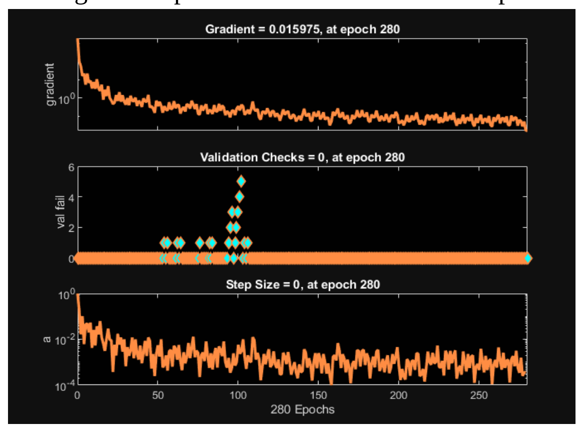

Fig.5 Training Parameters

Figure 5 presents the variation of the training parameters w.r.t. iterations (epochs):

1. Gradient
2. Validation checks to convergence
3. Learning Rate (or step size) of the model

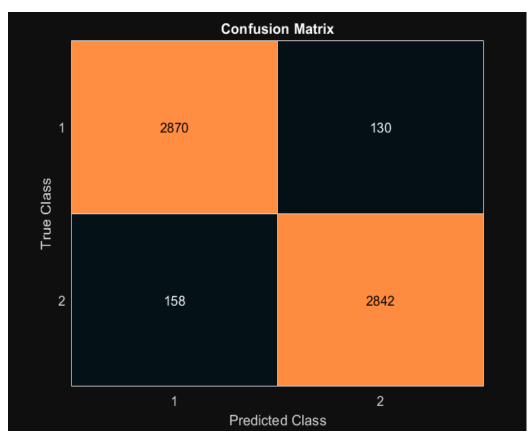

Fig.6 Confusion Matrix

Figure 6 depicts the confusion matrix. The confusion matrix shows the values of True Positive (TP), True Negative

(TN), False Positive (FP) and False Negative (FN). It can be observed that the value of the metrics are:

TP= 2870, TN=2842
FP=158, FN=130

The confusion matrix renders information about the TP, TN, FP and FN rates. The accuracy of classification is computed as:

$$Ac = \frac{TP+TN}{TP+TN+FP+FN} \qquad (17)$$

Substituting values,

$$Ac = \frac{2870 + 2842}{2870 + 2842 + 130 + 158} = 95.2\%$$

Table 1 summarizes the obtained results.

Table 1 Summary of Results

S.No.	Parameter	Value
1	Dataset	https://discover.data.vic.gov.au/dataset/pavement-condition-data
2	No of testing samples	6, 000
3	Model	PSO-DNN
4	Algorithm	Conjugate Gradient Back-propagation with Fetcher-Reeves Restarts
5	Epochs to Convergence	279
6.	Precision	94.78%
7.	Recall	95.67%
8.	F-1 Score	95.32
6	Classification Accuracy (Proposed Work)	95.2% (PSO-CGF Deep Neural Network)
7	Accuracy of Base Paper. Elshaboury et al.	82% (Gradient Boosting using CatBoost)

VI. CONCLUSION

It can be concluded that Pavement condition prediction plays an essential role in intelligent transportation systems and highway infrastructure management. Accurate prediction of pavement deterioration helps transportation agencies schedule maintenance activities efficiently, reduce repair costs, and improve road safety. Traditional statistical methods often fail to capture the nonlinear and complex relationships among pavement influencing factors such as traffic load, environmental conditions, pavement age, moisture, and material properties. Deep Neural Networks trained with the Conjugate Gradient Back-propagation with Fletcher–Reeves Restarts (CGF) algorithm provide an efficient and powerful framework for solving complex optimization and prediction problems. t has been shown that the proposed approach attains an accuracy of 95.2% outperforming existing approaches.

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