Mansoura Engineering Journal

Volume 47 | Issue 3 Article 1

6-14-2022

Modeling of Pavement Maintenance Decisions Using Artificial Intelligence Based on Maintenance Unit.

Hamdy Faheem
Associate Professor of Highway and Traffic Engineering, Dept. of Civil Engineering, Faculty of Engineering, Minia University, hamdyfaheem@mu.edu.eg

Afaf Mahmoud
Professor of Highway and Airport Engineering, Dept. of Civil Engineering, Faculty of Engineering, Minia University,, afaf.abdelhaleem@mu.edu.eg

Mostafa Hashem
Professor of Highway and Airport Engineering, Dept. of Civil Engineering, Faculty of Engineering, Minia University, mostafa.deeb@mu.edu.eg

Mohamed A. Abd El moez
Demonstrator, Dept. of Civil Engineering, Faculty of Engineering, Minia.

Mansoura University
Faculty of Engineering
Mansoura Engineering Journal

Modeling of Pavement Maintenance Decisions Using Artificial Intelligence Based on Maintenance Unit

Hamdy B. Faheem, Afaf A. Mahmoud, Mostafa D. Hashem and Mohamed A. Abd El moez *

KEYWORDS:
Pavement Distress; Pavement Maintenance; Maintenance Decision; Maintenance Unit; Artificial Neural Network.

Abstract— **Recently, all efforts have been directed toward keeping the network functional at a high level by determining the appropriate maintenance or rehabilitation (M & R) treatment. Determining the appropriate M & R strategies for flexible pavements is a complex process and is considered a key component of the Pavement Maintenance Management System (PMMS). Since such a decision system is complex, automated implementation using a pre-trained model via an artificial neural network (ANN) approach is a critical tool for decision-makers. Many studies have been conducted on modeling pavement condition index using ANN to determine the maintenance decision. The Egyptian Code of Practice has recently relied on the maintenance unit (MU) concept for maintenance decision prediction. A few researchers have investigated maintenance decision (MD) predications using the MU modeling by ANN but have not adequately studied Egyptian Code consideration. Therefore, this paper addresses the application of the latest machine learning technique for forecasting the current pavement maintenance decisions based on the MU system according to the Egyptian code considerations to develop a one-step enhanced decision-making tool. A pattern-recognition algorithm (neural network) was applied to 54.3 km of surveyed roads in Minia governorate, Egypt. The results indicated that the ANN model is capable of predicting the MD with a high level of reliability, with a mean square error (MSE) value of 0.02993, 0.03046, and 0.03018, and a percentage error (% E) value of 13.29693, 14.11734, and 13.83215 for the training, validation, and testing datasets, respectively.**

I. INTRODUCTION

A. *Pavement Distress*

TRAFFIC, climate, road geometry and location, soil, and drainage are all significant factors to consider when designing a pavement. Road maintenance is a critical component of the entire road system. Pavement may require maintenance depending on the pavement type [1]. "Surface distress" is a term used to describe defects in the pavement surface. The type, severity, and quantity of surface distress, measured by distress surveys, are required data for evaluating pavement distress. The pavement condition can be calculated based on distress data [2].

Pavement distress is an indication of the pavement surface condition and highway safety, as well as ride comfort. It can also be an indicator of deep-layer distress and failures, as well as performance. A perfect pavement is comfortable for riders and free of cracks of any type. Concurrently, some roads have

Received: (09 February, 2022) - Revised: (05 April, 2022) - Accepted: (07 May, 2022)

Hamdy B. Faheem, Associate Professor of Highway and Traffic Engineering, Dept. of Civil Engineering, Faculty of Engineering, Minia University, (e-mail: hamdyfaheem@mu.edu.eg.)

Afaf A. Mahmoud, Professor of Highway and Airport Engineering, Dept. of Civil Engineering, Faculty of Engineering, Minia University, (e-mail: Afaf.abdelhaleem@mu.edu.eg.)

Mostafa D. Hashem, Professor of Highway and Airport Engineering, Dept. of Civil Engineering, Faculty of Engineering, Minia University, (e-mail: Mostafa.deeb@mu.edu.eg.)

**Corresponding Author, Mohamed A. Abd El moez, Demonstrator, Dept. of Civil Engineering, Faculty of Engineering, Minia. (e-mail: mohamed.elmoez@mu.edu.eg/mohamedelmoez.95@gmail.com).*

various distresses but have not lost structural functionality because they are timely and adequately maintained. This maintenance will keep the pavement performing well, as close to its original performance as possible. Some types of distress have a minor impact on the pavement's condition initially, such as longitudinal and transverse cracking. Based on the methodology used for pavement condition evaluation, distress will be classified into multiple levels. The US Army corps of engineers and the Egyptian code of practice [3] classified pavement conditions into 18 distress, as displayed in Table. I.

TABLE I
DISTRESSES CATEGORIES.

CATEGORY	DISTRESS TYPES	UNITS
Cracks	• Alligator cracks • Block cracks • Slippage cracks	m^2
	• Edge cracks • Longitudinal and transversal cracks	m
Surface distortion	• Corrugations • Depression • Shoving • Rutting • Swelling or Upheaval	m^2
	• Sag and pump • Lane/ shoulder drop off	m
Slippery surface	• Bleeding • Polished aggregates	m^2
Disintegration	• Weathering and raveling • Patching and patch utility cut • Railway crossing	m^2
	• Potholes	number

The visible distress must be treated to keep the road at a high functional level by implementing a pavement management system (PMS).

B. Pavement Maintenance

Pavement maintenance refers to the conservation and protection of road pavement that is as close to its original state as when it was built or as recently upgraded as possible, as well as any additional requirements required to keep up with traffic safely. This includes both periodic maintenance (patching, filling ruts, repairing surface corrugation, refilling cracks, and repairing surface bleeding) and corrective maintenance (reconstruction of asphalt layers, reconstruction up to subgrade, rehabilitation such as overlays)[4].

Pavement distress detection and treatment are critical in the road maintenance process. Researchers are currently developing a fast and effective method for determining the best decisions for detecting and treating pavement distress to increase the road's service life and improve its safety and quality. Then, they make the best decisions to keep the roads in high function during the service life of the road. Furthermore, due to the available budget, operation, and the degree of experience necessary, the authorities concerned have to adopt this concept. As a result, it has become increasingly important to develop a feasible approach for enhancing the quality and durability of pavements [5].

Both functional and structural evaluations are used in determining the current state or performance of the pavement. The structural evaluation of pavement is based on its structural capability or adequacy [6-8]. In contrast, the functional evaluation is based on four characteristics[9]: pavement distress (surface condition), pavement roughness (rideability), pavement deflection (structural failure), and skid resistance (safety). Pavement roughness is an indicator of various imperfections on the road surface that influence the smoothness of the ride. It is evaluated based on a variety of indicators, such as present serviceability rating (PSR), the international roughness index (IRI), and the current serviceability index (PSI). Skid resistance is used to assess the condition of the pavement and is considered an indicator of safety characteristics. Highway agencies continually monitor this aspect to evaluate the pavement's effectiveness in preventing or reducing skid-related accidents.

The structural suitability of the pavement is assessed utilizing two methods: nondestructive and destructive tests. It is evaluated by various indicators, such as the structural condition index (SCI) and rut depth (RD). However, pavement structure evaluation is costly, and hence state agencies rarely use it for pavement condition evaluation. Several indices are used to evaluate the pavement's condition; for example, Pavement Condition Index (PCI). Many countries depend on visual inspection to identify pavement maintenance needs, and they frequently base maintenance decisions on a single index, such as the PCI [10, 11].

Researchers have developed many decision trees to determine maintenance decisions based on PCI; nevertheless, PCI directly indicates overall pavement condition and not for selecting optimal maintenance treatments. Because the determination of the appropriate maintenance and rehabilitation (M & R) treatment for flexible pavements is regarded as a complex process, some transportation agencies rely on "decision trees," which are based on individual distress levels, in order to avoid complex combinations of distress levels (types, quantity, and severity) and maintenance alternatives. When all possible combinations are considered, there are a significant number of options [12].

Figure 1 depicts how it is challenging to decide one treatment option from seven M & R alternatives for a pavement network, which includes 18 distress types with three severity levels. This is with the exception of polished aggregates, which have a single severity level in their impacts (total of 52 severity levels) [12].

Therefore, a research program at Cairo University in Egypt began in 1999 to develop an integrated practical decision to aid highway organizations in detecting existing maintenance requirements. The proposed decision tree bases its treatment decision criteria on the density of required localized repairs (patching, crack sealing, etc.) rather than the level of distress [12]. The results of the developed decision tree are displayed in Figure 2, which was used to determine the maintenance unit (MU) value. Moreover, a combined indicator was able to represent maintenance requirements by establishing a relationship among localized repair states and required M & R alternatives using a particular weighting procedure identical to that used in PCI development [13].

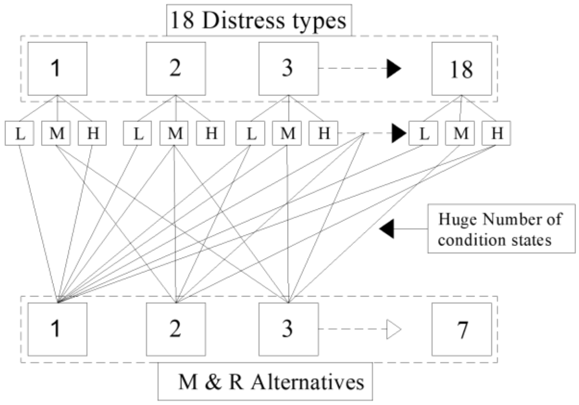

Fig. 1. A Diagram Of The Sequence Of Relationships Between Levels Of Distress And Maintenance Alternatives *[*12*]*.

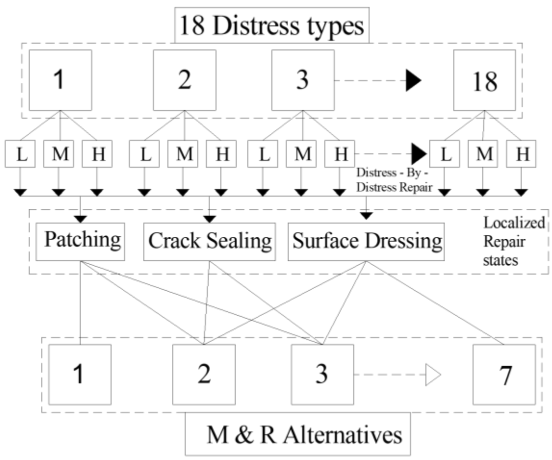

Fig. 2. Schematic Illustration Of Reducing The Number Of Analyses Using Localized Maintenance [*13*].

C. Back-Propagation Artificial Neural Network

An artificial neuron is a mathematically accurate simulation of a human nervous system. A human neuron is the basic functioning unit of the brain. Due to its massively parallel vast network of neurons, the human brain is capable of parallel processing several actions simultaneously. In addition, it comprises thousands and thousands of these neurons linked by a complicated network. Dendrites are the parts of a biological neuron that receive information, whereas a synapse is a point where different dendrites come together. All of the input from the different neurons is effectively summarized in the cell body. The neuron activates, providing a signal down the axon if the total is more significant than a specified target value at a given time. Like a typical neuron, an artificial neuron collects information from other neurons through links [14].

Backpropagation algorithm artificial neural networks (ANN) are robust and adaptable networks trained to transfer data from one dataset to another by providing a sample set of instances. They are among the most commonly implemented networks [*15*]. Figure 3 demonstrates the general structure of the backpropagation neural network, which consists of two exterior layers (input and output) plus one or more hidden layers. Neurons in the input layer receive data into the network. Neurons in the output layer provide the network's result [*16*]. An ANN is a subset of artificial intelligence that may be used to resolve complex, nonlinear engineering issues, including those involving pattern recognition, forecasting, and control [*17*, *18*]. Promising results from using ANN to evaluate current pavement performance have encouraged researchers to use neural networks for prediction problems. These algorithms utilize pavement condition characteristics to forecast the development of particular distress (e.g., cracks, roughness, rutting) or a group of distresses [*19*].

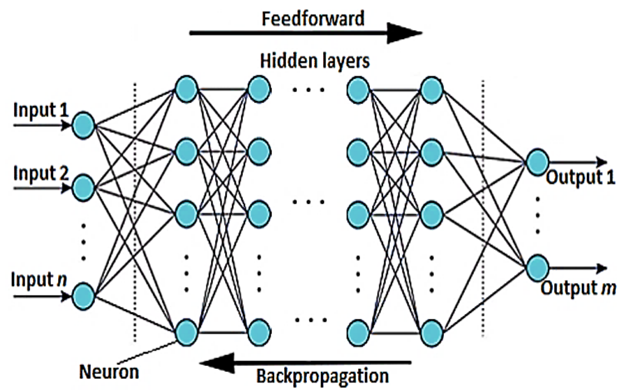

Fig. 3. The Three-Layer Neural Network's Backpropagation Algorithm Principle [16].

D. State of the Art

Artificial intelligence in pavement maintenance management systems (PMMS) can be used to forecast existing and expected pavement conditions and evaluate repair requirements and choose maintenance strategies [20]. This section summarizes research that investigated the use of ANN for different applications in the framework of PMS.

Akyildiz [21], in his thesis, recommended a flow chart for determining the maintenance decisions to improve the road condition from a low surface condition at any value of PCI to a high surface condition depending on the PCI value. Since such a decision system is complex, its automated implementation using a pre-trained model is fundamental to assisting decision-makers as information technology and artificial intelligence advance. Limitless possibilities for its application in pavement engineering are emerging [19]. Accordingly, Thube [22] suggested four integrated ANN models forecast the advancement of a wide range of pavement distresses (cracking, raveling, rut depth, and roughness) on low-volume highways. He concluded a significant relationship between observed and ANN-predicted distresses, which revealed that the proposed ANN models might be used to predict the investigated distresses.

On the contrary, Mosa [14] suggested a neural network-based system for evaluating pavement distress and enhancing solutions for maintenance methods and material suggestions. The proposed model provided an acceptable result based on the technical, economic, and environmental factors. Furthermore, three distinguishable ANN models created by Yang et al. [23] were used to forecast three significant indicators used by the Florida Department of Transportation for pavement assessment: crack rating, ride rating, and rut rating. The findings of the three models may be used to forecast PCI. Moreover, Lin et al. [24]

used a distress rating to produce a backpropagation ANN to predict the International Roughness Index (IRI). The study revealed a strong relationship between IRI and distress attributes, which indicates that IRI may properly reflect pavement distress conditions.

Moreover, Gebely [25] developed two ANN maintenance decision models. He revelated that ANN is suitable for forecasting current and future flexible pavement maintenance decisions. Based on the findings of the prior studies, it can be concluded that ANN may analyze and appropriately model complicated, nonlinear pavement engineering issues [19]. In addition, MU can determine M & R activities based on a combination of distress levels and maintenance alternatives.

II. GENERAL AIM OF THE STUDY

According to the literature review, many studies on PCI modeling by ANN have been conducted to determine the maintenance decision. The Egyptian Code of Practice for Urban and Rural Roads recently based maintenance decisions on the MU concept. Because a few researchers have studied the MU modeling by ANN, this study's general aim was to develop a high-accuracy model of ANN that may be used for automatic implementation of MU according to the Egyptian code consideration (ECP-2020). This paper investigates the application of the latest machine learning technique—artificial neural networks—for forecasting the current pavement maintenance decisions based on the MU system to develop a one-step enhanced decision-making tool. A pattern-recognition algorithm neural network will be created using 54.3 km of investigated roads in Minia government, Egypt.

III. STUDY AREA

Data was collected from roads located in Minia government, Egypt. It is located roughly 245 km south of the city of Cairo. The selected roads belong to two institutions. The first is the General Authority for Roads and Bridges and Land Transport (GARBLT) Ministry of Transport, which divides the Egyptian main road network into 14 districts. District 7 is responsible for all main roads in Minia and Asyut governorates. The second institution is the Roads Directorate, Minia Governorate, which divides the road network in Minia into paved roads with a total length of 2470.945 km and unpaved roads with a total length of 163.65 km. Five roads have been selected for this study, with a total length of 54.3 km (Figure 4).

According to the Egyptian Meteorological Authority's considerations, the research area is classified as dry [26]. This classification results from eleven years (2010 to 2020) of data collected by the Egyptian Meteorological Authority, used to determine the weather conditions if it is dry or wet weather in the city of Minia, which will give an indicator for pavement distress caused. The highest relative humidity is 54.1% in January, while the lowest relative humidity is reached in May at 26.8%. The highest air temperature varies from 23.2 to 41°C in January and July, respectively, while the lowest air temperature ranges from 5.5 to 21.1 °C in January and September, respectively

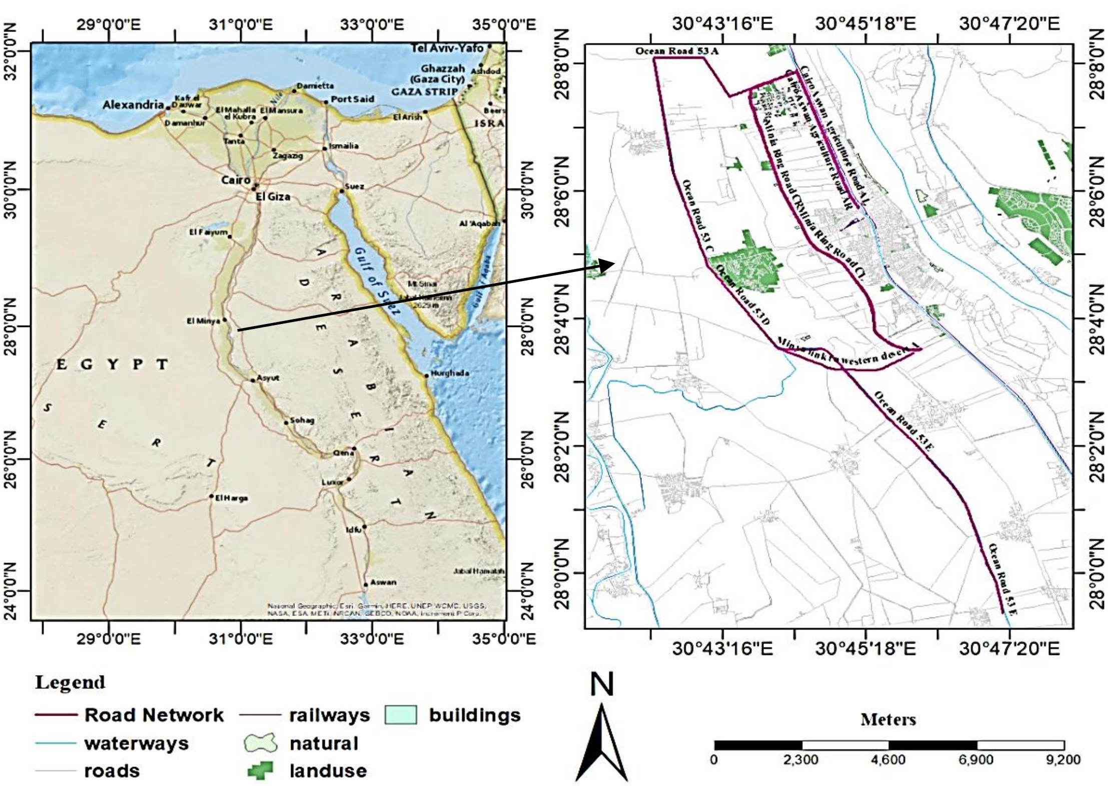

Fig. 4. Data Collection Location.

IV. RESEARCH METHODOLOGY

The severity and density of the existing pavement distress in the inspected roads, caused by various reasons such as meteorological factors, loads, or both, are used to estimate the type of maintenance required for the existing pavement deterioration. As previously stated, there is 18 pavement distress (Table I). Each distress has three severity levels based on its impact on the structure, road performance, and riding quality, except for polished aggregate. Moreover, it has a single severity level based on its impact on pavement condition: low (L), medium (M), and high (H). The Egyptian code of practice provided a comprehensive and completed distress identification for data collection and analysis [3]. In general, the railway crossing, out of the 18 different types of distress, the railway crossing, and swelling distress does not exist in the studied area in Minia governorate.

The following sections illustrate the Egyptian code of practice procedure [3] used in calculating the MU:

The ratio of observed distress quantity divided by the section area is known as distress density. It is measured in percentages. Even though they all relate to the same distress type, each level of distress severity is generally considered independently from the others when determining the distress density. Figure 5 demonstrates the MU scheme for significant roadways. This graphic can compute the overall MU value for a particular segment depending on the density of localized maintenance alternatives. According to the correction part of the MU system, the density of surface dressing is the total densities of slurry seal, sand seal, and Multiple Surface Treatments (MST). Table II shows the recommended maintenance decision based on the total MU value.

The initial stage for achieving the study's objectives is to collect essential variables such as distress type and severity level, segment width, etc. Consequently, five separate roads were selected and surveyed in each direction. For model training, roads were divided into various directional segments of 25 m in length. The widths of those parts were measured, as well as the type, severity, and location of each distress level for each segment were recorded. For further analysis, all data extracted were entered into a database framework. In total, 2172 segments were separately investigated. In the second stage, all the collected data were utilized to calculate the existing maintenance unit (MU) for every segment and determine the existing maintenance decisions (MD). The recommended maintenance decision is depicted in Table. II shows the recommended maintenance decision based on the total MU value [3]. After calculating the MD for each segment, additional statistical studies were conducted to obtain the input and output matrices.

The third stage in this study was to develop an ANN model that can be employed to forecast existing MD based on previously provided inputs. Several ANN models will be investigated to find an approach design that is generic and efficient enough to forecast MD based on pavement section characteristics. Figure 6 demonstrates the proposed framework of the study

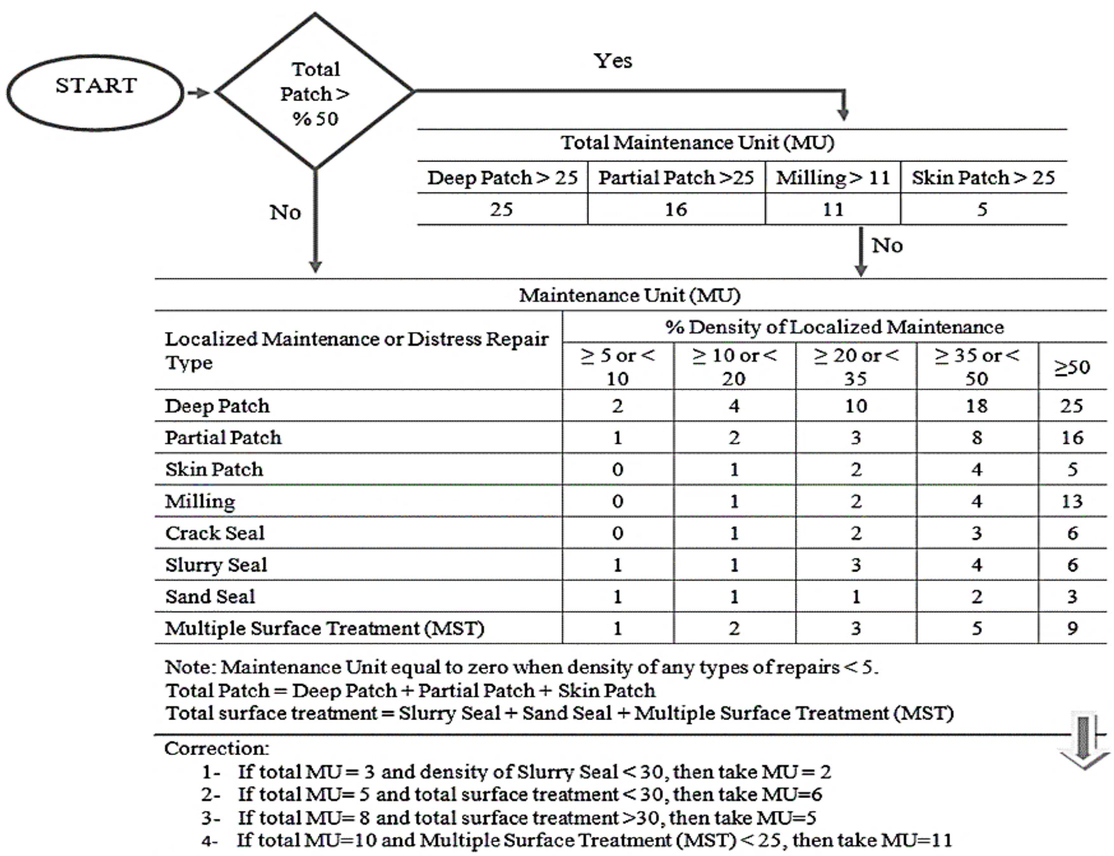

Fig. 5. Maintenance Unit Value For Major Highways [3].

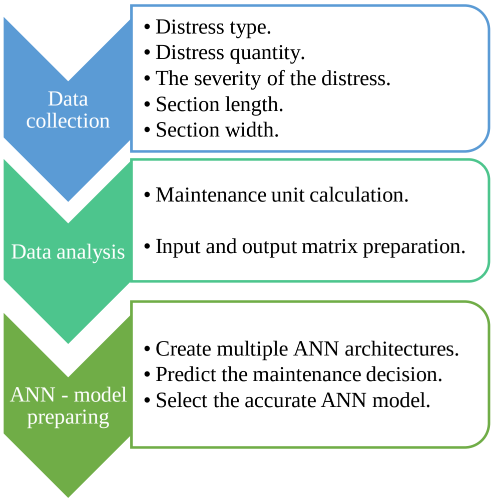

Fig. 6. Proposed Research Methodology Steps.

A. *Data Collection and Processing*

Data were collected from five different roads in the Minia government, Egypt. Each road was divided into various segments, each approximately 25 meters in length, and the divided roads, each direction, were divided up separately. All of these segments were visually inspected and evaluated. The width and length of these roads vary; hence, these segments' details are summarized in Table III.

A total of 54,300 m (2172 segments of 25 m each) were inspected, covering an area of roughly 445,775 m2. The locations of the surveyed segments are illustrated as mentioned earlier on a map of the Minia government in Figure 4. For each of the 2172 segments studied, the segment width and distress area per type and severity were recorded. The "Rail-Road Crossing & Slippage Cracks and Swelling Upheaval" distress does not exist in the studied area in the Minia government, out of the 18 different types of distress mentioned earlier in Table I. Each distress is classified according to the Egyptian code of practice procedure.

Figure 7 depicts the existing distress quantity for every distress type (not categorized into levels). According to the figure, weathering, and raveling, longitudinal and transverse cracks, polished aggregate, alligator cracking, edge cracking, lane and shoulder drop, and block cracking accounted for 91.6 percent of the total detected distress. Weathering and raveling distress were discovered to be the most frequent occurrences (16.57%). On the contrary, raveling distress is determined to be the smallest of the top 7 frequent distresses, with a rate of 9.5 percent. It is worth noting that the appearance of other categories of distress is less frequent than the occurrence of the top seven distresses. Rutting, for example, was ranked eighth but accounted for only 2.28 percent of the total. Figures 8-10 shows the descending order for distress quantities versus the severity level for the top seven frequently occurring distresses.

TABLE II
MAINTENANCE DECISIONS BASED ON MU [3].

RECOMMENDED MAINTENANCE DECISION (M & R ACTION)	MAINTENANCE UNIT (MU)
Reconstruction up to subgrade	MU > 20
Reconstruction of asphalt layers	15 < MU ≤ 20
Milling and Overlay	10 < MU ≤ 15
Multiple surface treatment or Thin overlay without milling	8 < MU ≤ 10
Slurry seal	3 < MU ≤ 8
Sand seal	2 < MU ≤ 3
Surface preparation only (distress-by-distress)	MU ≤ 2

TABLE III
CHARACTERISTICS OF THE STUDY AREA'S ROAD NETWORK.

ROAD CODE	ROAD NAME	SECTION NAME(A)	CONSTRUCTION DATE	LENGTH (M)	WIDTH (M)	TOTAL SEGMENTS
1	*Minia Ring Road*	A1	2010	1100	7	44
				1100	7	44
		B1		1050	7	42
				1050	8	42
		C1		8050	8	322
				7950	8	318
2	*El Mohit road 53*	A2	2018	1100	8.5	44
		B2	2014	750	6	30
		C2		5450	7	218
		D2		2400	7	96
		E2		500	7	20
		F2		10000	7	400
3	*Minia - Western desert highway*	A3	2018	3400	13	136
4	*Cairo - Aswan agriculture highway*	A4	1996	4250	10.5	170
				4250	10	170
5	*El gomhorya road*	A5	2018	600	6.5	24
		B5		1300	7	52

Section Name(a): Each road in the study area is divided into sections according to the road geometry and construction date identified by letters and road codes.

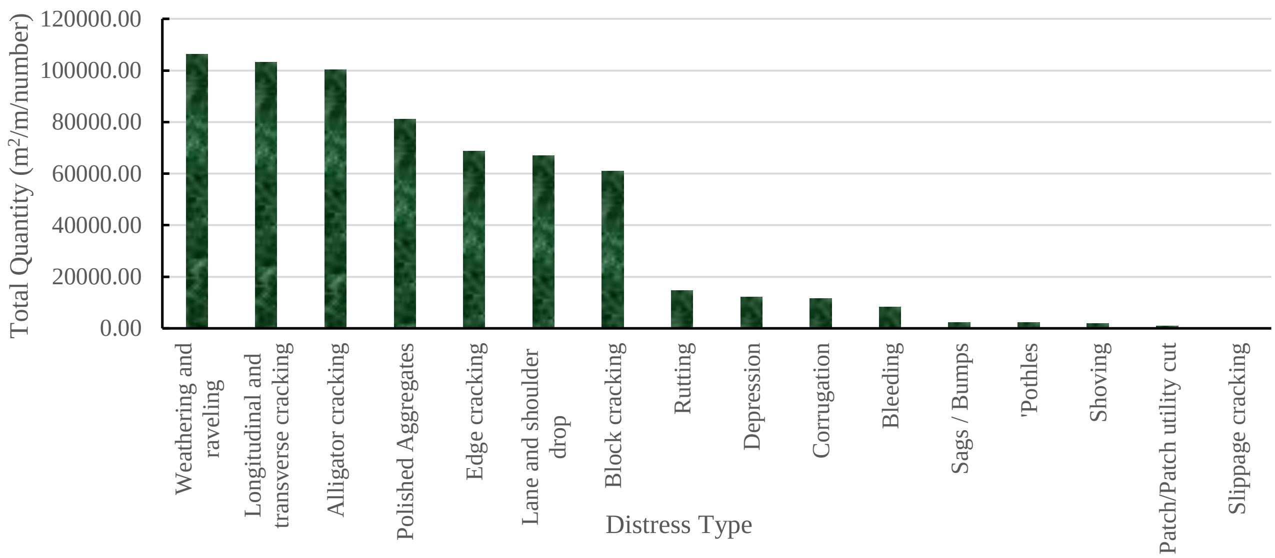

Fig. 7. The Total Distressed Quantity Per Distress Type.

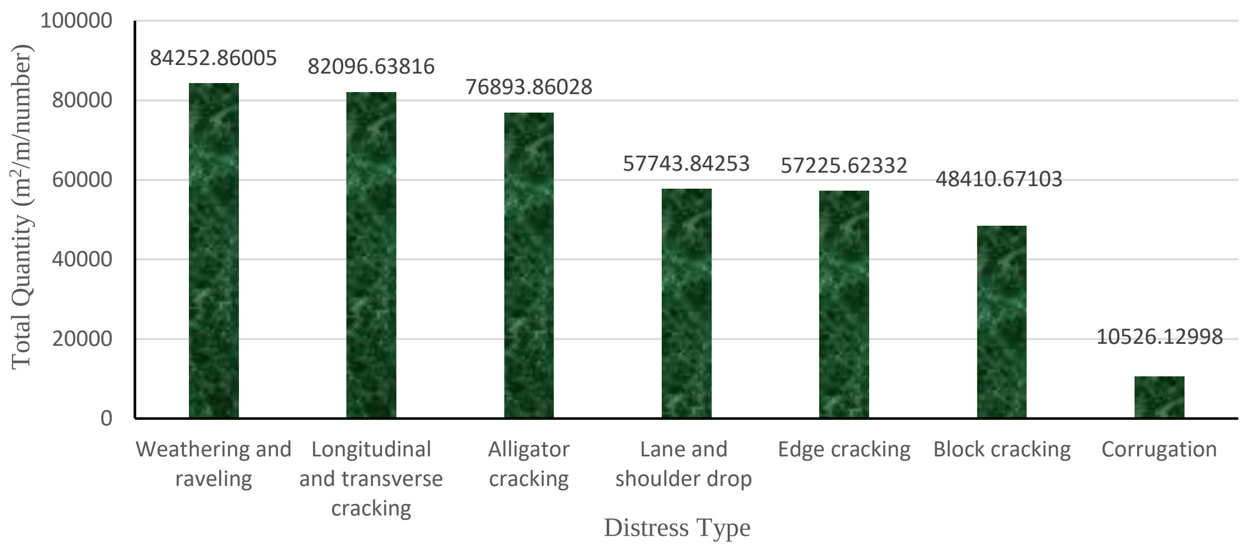

Fig. 8. Low Severity Level Distribution of The Top Seven Distresses.

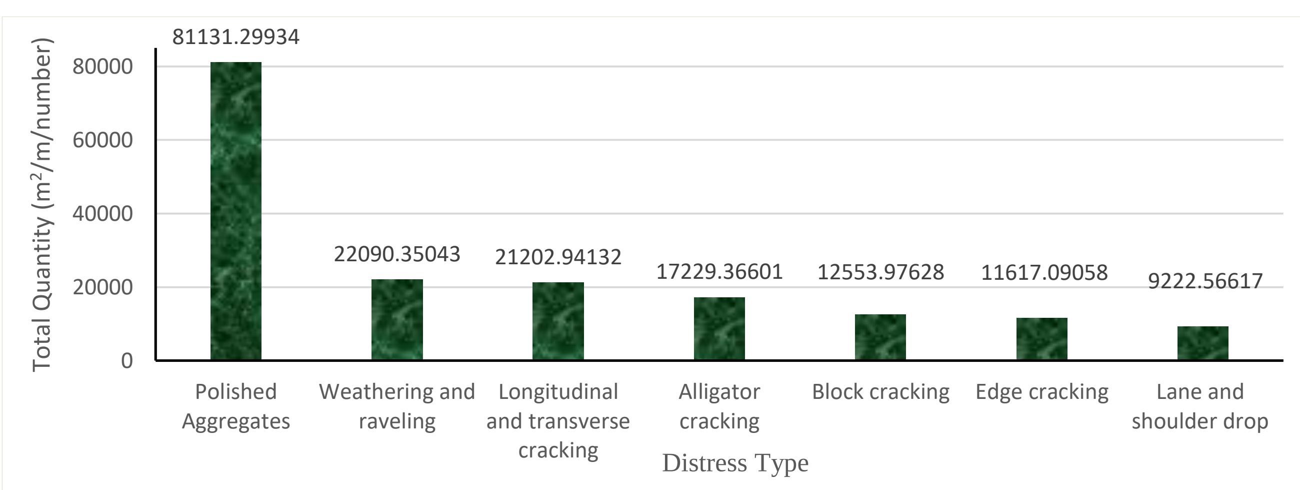

Fig. 9. Medium Severity Level Distribution of The Top Seven Distresses.

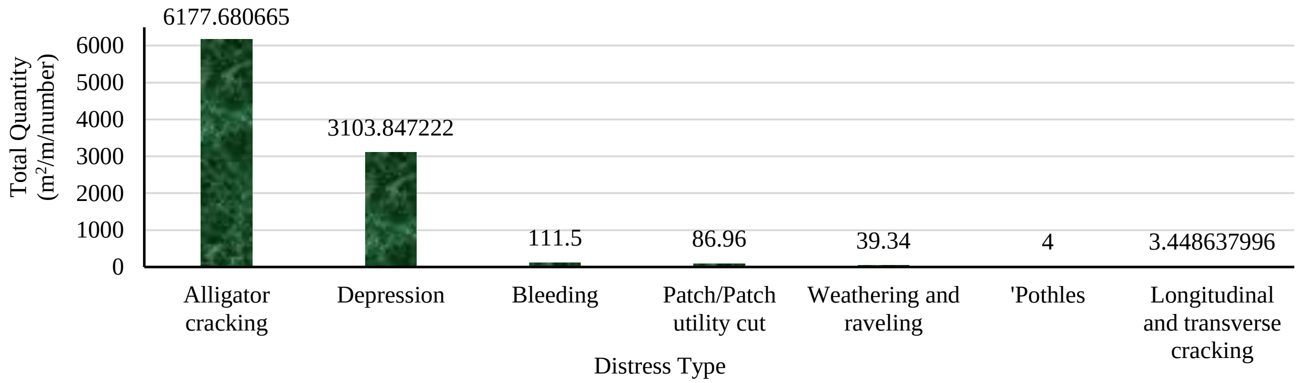

Fig. 10. High Severity Level Distribution of The Highest 7 Distresses.

The distribution of sections based on their MU value is demonstrated in Figure 11, which shows that 45.4% of the surveyed sections with an MU value ranging from 0 to 8, "Low-level treatment." In contrast, 54.6% of sections with an MU value ranging from 8.1 to 20 or more "High-level treatment." Figure 12 demonstrates the distribution of sections along with their MD. The figure shows that the reconstruction of asphalt layers, milling and overlay, slurry seal, and distress-by-distress are responsible for 82% of the overall obtained maintenance decision. Slurry seals were obtained at the highest occurrence of 26.9%, and milling and overlay were the second-highest occurrence of 21.8%, while 0.1% of the investigated segments were decided as sand seal decisions.

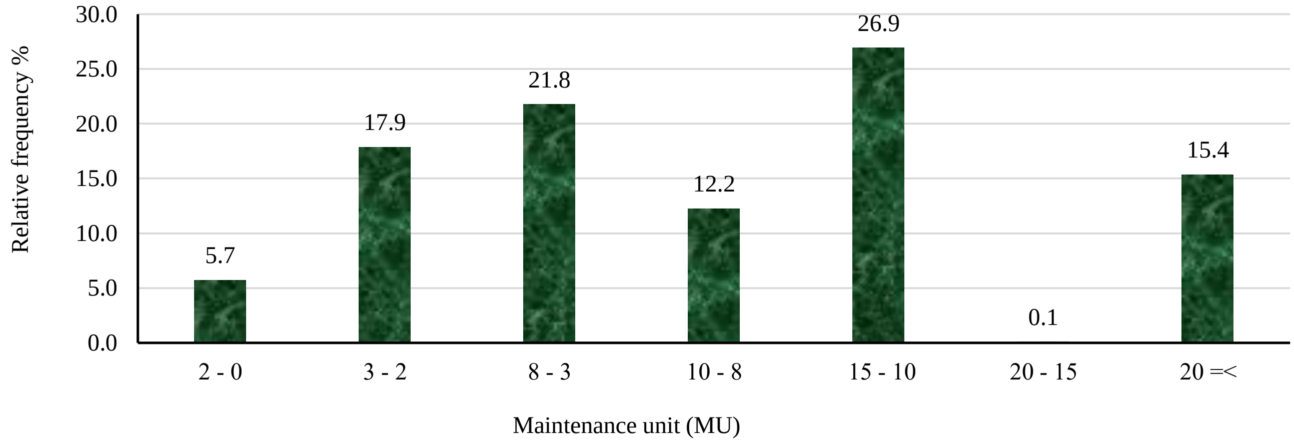

Fig. 11. Relative Frequency of MU Distribution.

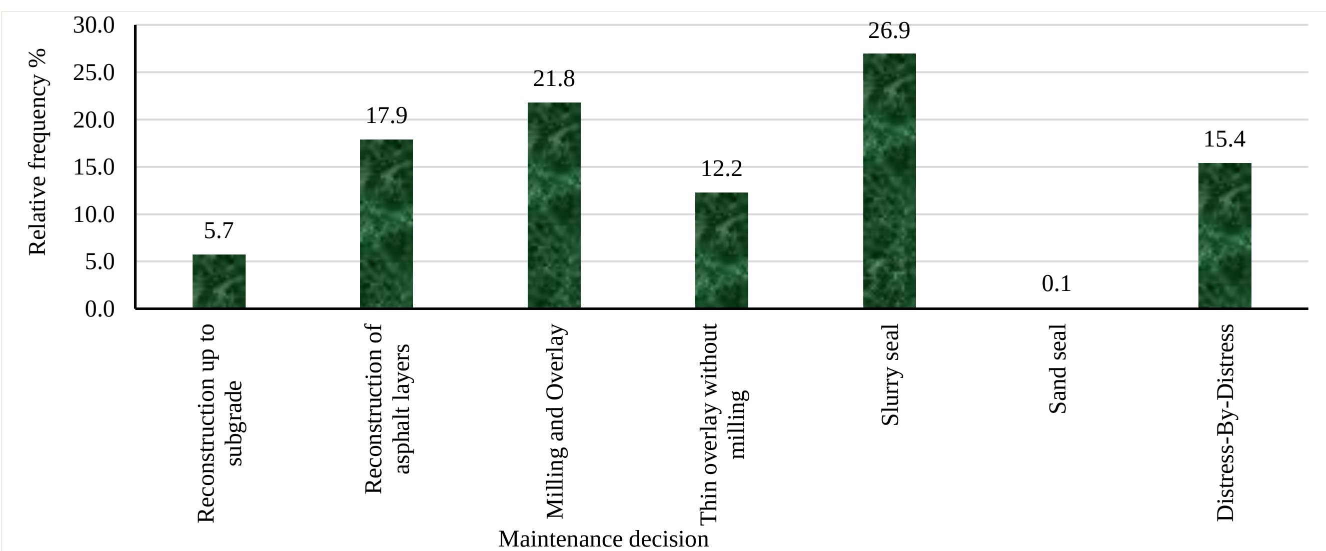

Fig. 12. Relative Frequency of MD Distribution.

B. ANN Modeling

A feedforward backpropagation neural network model consists of three main layers [27-30], major external layers (input and output), and one or more hidden layers. The first layer is known as the input layer, and it consists of a vector representing all the input variables, which includes 2172 samples of 52 components (distress) in this model. Before being fed into the input layer, the inputs are usually prepared in a matrix form. The "hidden layer" is the second layer, and its neurons receive and transmit the transformed signals from the input layer to the output layer. Furthermore, the output layer collects all of the hidden layer's converted signals and integrates them into the output vector. At each iteration or epoch, the weights of the network of each neuron are adjusted based on a variety of criteria, including the training algorithm and learning algorithm, which aims to minimize the set of parameters to their lowest possible size.

As previously stated, the total number of segments in the created framework was 2172. A random selection of data constructed the following three datasets:

Training data: This data is employed to train the machine learning algorithm [31]; scientists feed data into the algorithm, which correlates to the desired outcomes. The model analyses the data regularly to learn more about its function and then adapts itself to achieve its intended function. This group accounts for 60% of the total data collected, corresponding to 1303 samples.

Validation data: During training, validation data is beamformed into the model that it has not previously analyzed [31]. Validation data is used as the first test against previously unknown data, allowing data scientists to assess how well the model predicts based on the new data. Although not all data scientists use are validation data, it may provide essential indicators for optimizing model parameters, influencing how it assesses data. This group accounts for 25% of the total data collected, corresponding to 543 samples.

Tests data: After the model has been constructed, testing data confirms that it can generate correct predictions [31]. The testing data should remain unlabeled if the training and validation data contain labels to monitor the model's performance metrics. Test data is a final, genuine evaluation of an uncertain dataset to verify that the machine learning algorithm has been successfully trained. This group accounts for 15% of the total data collected, corresponding to 326 samples.

The ANN architecture's structure and related algorithms characterize it in general. There are three layers in the recommended ANN architecture in the current study: one input layer, one hidden layer, and one output layer. Each input and output layer's number of neurons is dependent on the number of input parameters and target variables. This study focused on a variety of ANN structures and learning algorithms. Figure 13 shows a schematic of the recommended ANN model, which consists of 52 neurons (representing 52 severity levels for pavement distress) in the input layer, 23 neurons in the hidden layer, and seven neurons (each of the maintenance decisions has a value of either 0 or 1) in the output layer.

Following training the network, the system's weights are varied to decrease the variance between the system's output and the corresponding output. This difference is known as the error, and it may be assessed in a variety of ways. The most widely used measurements to determine the model accuracy are Mean Squared Error (MSE) and Percent Error (percent E). The MSE stands for the mean squared variation across outputs and targets. Lower values are preferable, whereas zero signifies that there is no miscalculation. Percent Error denotes the percentage of samples that are incorrectly classified. A value of "0" indicates no prediction error, whereas a value of "100" represents the most significant number of errors. Equations 1 and 2 [31] provide the mathematical formulas for MSE and percent E based on observed values or target vector (t) and forecast values vector (y) at the total number of samples (N).

$$\text{MSE}=\frac{\sum(y-t)^2}{N} \quad \text{Eq. 1}$$

$$\text{E\%}=\left(\sum\frac{y-t}{t}\times 100\right)/N \quad \text{Eq. 2}$$

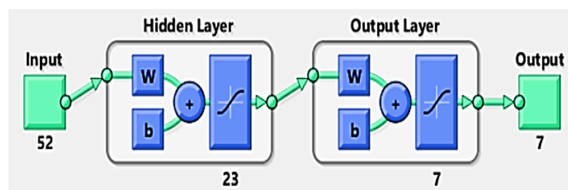

Fig. 13. The Developed ANN Model's Architecture.

V. RESULTS AND DISCUSSION

The training process was terminated after reaching 1000 epochs. The results of the selected performance measures are listed in Table IV.

TABLE IV
A SUMMARY OF THE MSE AND PERCENT E FOR THE DIFFERENT GROUPS IN THE ANN MODEL.

DATA SOURCE	SAMPLES	MSE × 10^{-2}	% E
Training Dataset	1303	2.993	13.29
Validation Dataset	543	3.046	14.11
Testing Dataset	326	3.018	13.83

As demonstrated in Figure 14, the plot roc illustrates that the curve hugs the plot's left and top edges closer, indicating better categorization. Figure 15 shows the plot performance (TR) that indicates the training, validation, and test performances given the training record TR returned by the function train. In general, the error decreases as the number of training epochs increases. Nevertheless, it may gradually climb on the validation data set as the network begins to overfit the training data. In the default setting, the training is ended after six consecutive increases in a validation error, and the best performance is achieved from the epoch with the lowest validation error.

The fluctuation in gradient coefficient with regard to the number of epochs is depicted in Figure 16. At epoch 1000, the ultimate value of the gradient coefficient is 0.0021131, which is very close to zero. The lower the gradient coefficient, the better the training and testing of networks will be. As can be seen in the graph, the gradient value decreases as the number of epochs increases. Figure 17 depicts a histogram created in the MATLAB workspace. At 20 bins, the horizontal axis shows the range of errors, while the vertical axis represents the variation between instances. The mean square error (MSE) for all groups of training, validation, and testing samples is 3.019×10^{-2}. Additionally, the percentage error (% E) is 13.748.

Gebely [25] developed two ANN-based maintenance decision models in his master's thesis. Four different roads were selected and inspected in each direction. Roads were divided into multiple directional sections with a 100 m section length for model training. The current ANN-based maintenance decision model trained on the database was created by visually collecting and recording distress characteristics of 51.3 km of road segments located in Fayoum governorate, Egypt. In total, 2,036 sections were individually inspected, and their data was gathered. The research concluded that the mean square error (MSE) for all groups of training, validation, and testing samples was 4.756×10^{-2}, and the percentage error (%E) was 31.4825.

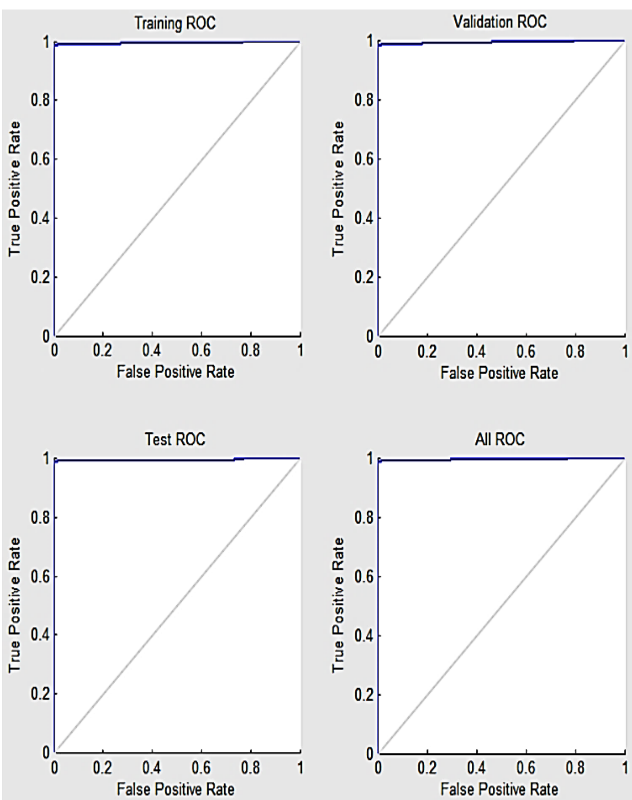

Fig. 14. Model ROC Curve.

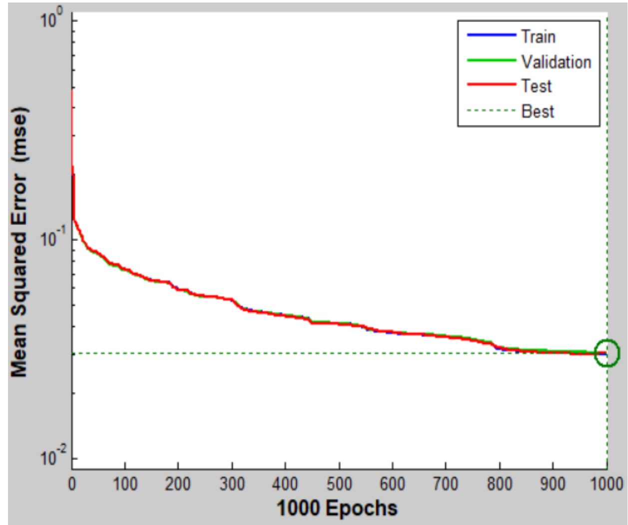

Fig. 15. Model Training Performance.

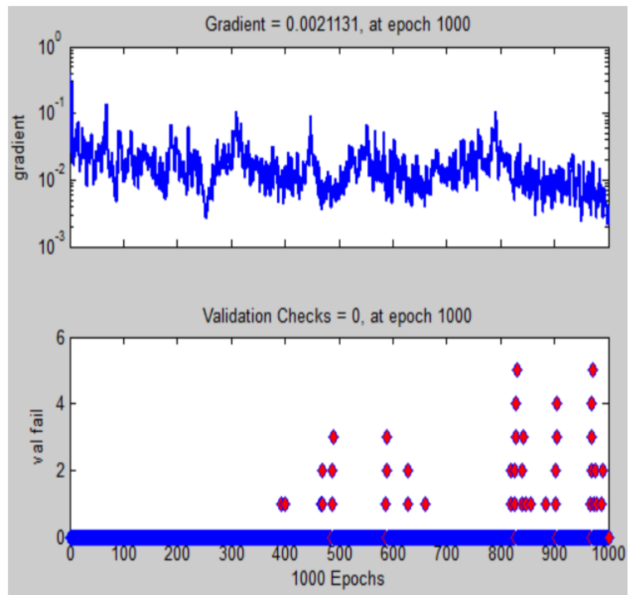

Fig. 16. Model Training State.

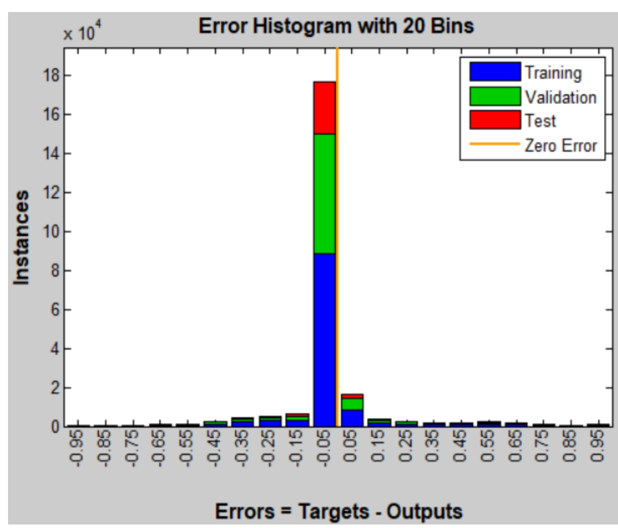

Fig. 17. Model Training Error Histogram.

Finally, the results indicate that the trained network made a maintenance decision close to the actual decision identified using the MU system with an MSE and a %E less than previous studies. Also, this ANN model is the first model that may be used for predicting maintenance decisions according to the Egyptian Code of Practice for Urban and Rural Roads considerations (ECP – 2020).

VI. CONCLUSIONS AND RECOMMENDATION

Based on distress surveying, the maintenance unit (MU) evaluates maintenance decisions (MD) for the existing pavement. The traditional approach to pavement evaluation focuses mainly on visual inspection, which identifies existing pavement distress and quantifies the type, severity, and segment geometry. In addition, it determines MU and MD from a recommended schematic and tables by the Egyptian code of practice. Furthermore, due to the complicated interaction between existing distress levels as input variable and the output MD, the unavailability of a simplified approach to estimate MD is always a concern.

The present paper illustrates the availability of using the artificial intelligence approach to forecast the MD. An ANN approach is presented instead of the traditional method to model the complex relationship between the MD and all current distress densities. To create a road database, 54.3 km of road segments located in Minia, Egypt, were surveyed to collect the distress data. The data in this database is then used to create an ANN model that can forecast MD based on a set of inputs that describe the section geometry and distress data.

The mean square error (MSE) for all groups of training, validation, and testing samples is 3.019×10^{-2}. In addition, the percentage error (% E) is 13.748. Even though the findings demonstrate that the recommended ANN model can accurately forecast MD, the authors recommend that a new model be developed based on the existing model that will forecast MD in the future to keep the road along the design period.

AUTHOR CONTRIBUTION STATEMENT

1. Conception or design of the work ***(****Dr. Hamdy Badee Faheem 40% - Eng. Mohamed Ahmed Abd El moez 40% - Dr. Afaf Abd El Haleem Mahmoud 10 % - Dr. Mostafa Deep Hashem 10 %)*
2. Data collection and tools (*Eng. Mohamed Ahmed Abd El moez* 100%)
3. Data analysis and interpretation *(Dr. Hamdy Badee Faheem 50% - Eng. Mohamed Ahmed Abd El moez 50 %)*
4. Investigation *(Dr. Hamdy Badee Faheem 60% - Dr. Afaf Abd El Haleem Mahmoud 25 % - Dr. Mostafa Deep Hashem* 15 %*)*
5. Methodology *(Dr. Hamdy Badee Faheem 35% - Eng. Mohamed Ahmed Abd El moez* 35% - *Dr. Afaf Abd El Haleem Mahmoud* 20 % - *Dr. Mostafa Deep Hashem* 10 %)
6. Project administration *(Dr. Hamdy Badee Faheem 30% - Eng. Mohamed Ahmed Abd El moez 30% - Dr. Afaf Abd El Haleem Mahmoud 20 % - Dr. Mostafa Deep Hashem 20 %)*
7. Resources *(Dr. Hamdy Badee Faheem 50% - Eng. Mohamed Ahmed Abd El moez 50 %)*
8. Software *(Dr. Hamdy Badee Faheem 50% - Eng. Mohamed Ahmed Abd El moez 50 %)*
9. Supervision *(Dr. Afaf Abd El Haleem Mahmoud 35 % - Dr. Mostafa Deep Hashem 35 % - Dr. Hamdy Badee Faheem 30 %)*
10. Drafting the article (*Dr. Hamdy Badee Faheem* 40% - *Eng. Mohamed Ahmed Abd El moez* 40 % - *Dr. Afaf Abd El Haleem Mahmoud* 10 % - *Dr. Mostafa Deep Hashem* 10 %)
11. Critical revision of the article (*Dr. Hamdy Badee Faheem* 50% - *Eng. Mohamed Ahmed Abd El moez* 30 % - *Dr. Afaf Abd El Haleem Mahmoud* 10 % - *Dr. Mostafa Deep Hashem* 10 %)

FUNDING STATEMENT:

No funds, grants, or other support was received.

DECLARATION OF CONFLICTING INTERESTS STATEMENT:

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCESS

[1] N. G. Sorum, T. Guite, and N. Martina, "Pavement distress: a case study," presented at the National Conference on Recent Advances in Civil Engineering (NCRACE-2013), Nirjuli, Itanagar, Arunachal Pradesh, India, 2014.

[2] FHWA, *An Advanced Pavement Course in Pavement Management Systems*. Federal Highway Administration, December 1989.

[3] E. 2020, *Egyptian Code of Practice for Design and Construction of Urban and Rural Roads, Road Maintenance*. Ministry of Housing, Utilities and Urban Communities, Housing and Building National Research Center, Cairo, Egypt., 2020.

[4] AASHTO. 1990, *AASHTO guidelines for pavement management systems*. Washington DC, 1990.

[5] A. Habib and M. M. Kunt, "A framework for pavement crack detection and classification," in *IOP Conference Series: Materials Science and Engineering*, 2020, vol. 800, no. 1, p. 012020: IOP Publishing.

[6] M. Y. Shahin, "Airfield pavement distress measurement and use in pavement management," presented at the 61st Annual Meeting of the Transportation Research Board, Washington District of Columbia, United States, 1982.

[7] R. C. G. Haas, *Pavement design and management guide*. English and held by 39 libraries worldwide: Transportation Association of Canada Waterloo , Canada, 1997.

[8] S. Richie, C. Yeh, J. P. Mahoney, and N. C. Jackson, "Development of an expert system for pavement rehabilitation decision-making," *Transportation Research Board*, no. UCI-ITS-WP-86-2, 1986.

[9] N. J. Garber and L. A. Hoel, *Traffic and highway engineering*. Nelson Education Ltd, Canada: Cengage Learning, 2014.

[10] M. Y. Shahin and S. D. Kohn, "Pavement maintenance management for roads and parking lots," us army construction engineering research laboratory champaign il, Defense Technical Information Center1981.

[11] E. Ibrahim, S. El-Badawy, M. Ibrahim, and E. Elbeltagi, "A modified pavement condition rating index for flexible pavement evaluation in Egypt," *Innovative Infrastructure Solutions*, vol. 5, pp. 1-17, 2020.

[12] E. SHARAF, "A simplified maintenance decision system for flexible pavements in developing countries," in *6th International Conference on Managing Pavements*, Queensland, Australian, 2004.

[13] M. A. Abo-Hashema and E. A. Sharaf, "Development of maintenance decision model for flexible pavements," *International Journal of Pavement Engineering,* vol. 10, no. 3, pp. 173-187, 2009/06/01 2009.

[14] A. M. Mosa, "Neural network for flexible pavement maintenance and rehabilitation," *Applied Research Journal,* vol. 3, no. 4, pp. 114-129, 2017.

[15] H. Ceylan, M. B. Bayrak, and K. Gopalakrishnan, "Neural Networks Applications in Pavement Engineering: A Recent Survey," *International Journal of Pavement Research Technology,* vol. 7, no. 6, 2014.

[16] R. Apanavičienė and A. Juodis, "Construction Projects Management Effectiveness Modelling With Neural Networks," *Journal of Civil Engineering and Management,* vol. 9, no. 1, pp. 59-67, 2003/01/01 2003.

[17] H. Adeli, "Neural networks in civil engineering: 1989–2000," *Computer-Aided Civil Infrastructure Engineering,* vol. 16, no. 2, pp. 126-142, 2001.

[18] G. Bosurgi and F. Trifirò, "A model based on artificial neural networks and genetic algorithms for pavement maintenance management," *International Journal of Pavement Engineering,* vol. 6, no. 3, pp. 201-209, 2005/09/01 2005.

[19] J. Domitrović, H. Dragovan, T. Rukavina, and S. Dimter, "Application of an artificial neural network in pavement management system," *Tehnički vjesnik*, vol. 25, no. Supplement 2, pp. 466-473, 2018.

[20] S. Sundin and C. Braban-Ledoux, "Artificial intelligence–based decision support technologies in pavement management," *Computer-Aided Civil Infrastructure Engineering* vol. 16, no. 2, pp. 143-157, 2001.

[21] S. Akyildiz, "Development of new network-level optimization model for Salem district pavement maintenance programming," Master of Science, Civil Engineering, Virginia Polytechnic Institute and State University, Virginia Tech, 2008.

[22] D. T. Thube, "Artificial neural network (ANN) based pavement deterioration models for low volume roads in India," *International Journal of Pavement ResearchTechnology* vol. 5, no. 2, p. 115, 2012.

[23] J. Yang, J. J. Lu, and M. Gunaratne, "Application of neural network models for forecasting of pavement crack index and pavement condition rating," transportation research board2003.

[24] J. Lin, J. Yau, and L. Hsiao, "Correlation analysis between international roughness index (IRI) and pavement distress by neural network," in *82nd Annual Meeting of the Transportation Research Board*, 2003, pp. 12-16.

[25] H. R. Gabely, "Pavement maintenance decision model using artificial neural networks," Master of Science, Faculty of Engineering, Civil Engineering Department, Fayoum University,http://www.fayoum.edu.eg/thesesdatabase/abstracts/. 2015.

[26] Meteorological. (2010 - 2020). *Global Historical Weather and Climate Data, Monthly meteorological reports, Minya, Egypt.*

[27] M. S. Ghanim and G. Abu-Lebdeh, "Real-Time Dynamic Transit Signal Priority Optimization for Coordinated Traffic Networks Using Genetic Algorithms and Artificial Neural Networks," *Journal of Intelligent Transportation Systems,* vol. 19, no. 4, pp. 327-338, 2015/10/02 2015.

[28] M. S. Ghanim and K. Shaaban, "Estimating turning movements at signalized intersections using artificial neural networks," *IEEE Transactions on Intelligent Transportation Systems,* vol. 20, no. 5, pp. 1828-1836, 2018.

[29] M. S. Ghanim and G. Abu-Lebdeh, "Projected state-wide traffic forecast parameters using artificial neural networks," *IET Intelligent Transport Systems,* vol. 13, no. 4, pp. 661-669, 2019.

[30] M. S. Ghanim, "Florida statewide design-hour volume prediction model," presented at the Transportation Research Board 90th Annual Meeting Washington DC, United States, 2011.

[31] A. Issa, H. Samaneh, and M. Ghanim, "Predicting pavement condition index using artificial neural networks approach," *Ain Shams Engineering Journal,* vol. 13, no. 1, p. 101490, 2022/01/01/ 2022.

TITLE ARABIC:

نمنجة قرارات صيانة الرصف بإستخدام الذكاء الاصطناعي بناءً على وحدة الصيانة

ARABIC ABSTRACT:

تعتبر شبكات الطرق من أهم مكونات نظام النقل. وبالتالي ، يتم توجيه جميع الجهود نحو الحفاظ على عمل الشبكة على مستوى عالٍ من خلال تطبيق نظام إدارة صيانة الرصف (PMMS). يعد تحديد العلاج المناسب للصيانة أو إعادة التأهيل (M & R) للأرصفة المرنة مكونًا رئيسيًا لنظام إدارة الرصف ، وهي عملية معقدة. نظرًا لأن نظام القرار هذا معقد ، فإن التنفيذ الآلي باستخدام نموذج مدرب مسبقًا عبر نهج الخلايا العصبية الاصطناعية (ANN) يعد أداة مهمة لصانعي القرار.

تم إجراء العديد من الدراسات حول نمنجة مؤشر حالة الرصف باستخدام ANN لتحديد قرار الصيانة. إعتمد الكود المصري مؤخرًا على مفهوم وحدة الصيانة (MU) للتنبؤ بقرار الصيانة. قام عدد قليل من الباحثين بدراسة التنبؤات بقرار الصيانة (MD) بنمنجة وحدة الصيانة (MU) بواسطة الخلايا العصبية الاصطناعية (ANN) لكنهم لم يدرسوا اعتبارات الكود المصري بشكل كافٍ.

لذلك ، يتناول هذا تطبيق أحدث تقنيات التعلم الآلي للتنبؤ بقرارات صيانة الرصف الحالية بناءً على نظام وحدة الصيانة (MU) وفقًا لاعتبارات الكود المصري، لتطوير أداة اتخاذ قرار من خطوة واحدة. تم تطبيق خوارزمية التعرف على الأنماط (الشبكة العصبية) على 54.3 كم من الطرق التي تم مسحها في محافظة المنيا ، مصر.

تم سرد النتائج التي تم الحصول عليها، حيث بلغ متوسط الأخطاء التربيعية (MSE) لجميع مجموعات عينات التدريب والتحقق والاختبار 0.03019 ، وكانت النسبة المئوية للخطأ (E)٪ 13.748. تشير هذه النتائج إلى أن النموذج المطور أكثر دقة من النماذج التي تمت مراجعتها ، ويمكن استخدامه لتقييم استراتيجيات الصيانة وإعادة التأهيل.