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Classification Based on Artificial Neural Network for Regency Road Maintenance Priority

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ABSTRACT

The priority classification of road maintenance is an important issue in regional infrastructure management. This study developed a classification model based on Artificial Neural Network (ANN) to determine the priority of district road maintenance automatically based on actual condition data. The data covered 141 road sections, reduced from 15 to 9 main variables using Principal Component Analysis (PCA), and normalized with the Min-Max Scaler. The ANN model consists of 10 input neurons, 30 hidden neurons, and 5 priority class outputs. The data is divided in a 55-15-35 ratio for training, validation, and testing. The model produces 92% accuracy, 91.7% accuracy, 90.4% recall, and 90.9% F1-score. These findings demonstrate the reliability of ANN in multi-class classifications to support more efficient road maintenance decision-making. The novelty lies in the integration of actual field data, multi-criteria classification, and the application of ANN in the context of complex and underexplored district roads in the literature.

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1. INTRODUCTION

The construction and maintenance of road infrastructure is a fundamental element in supporting regional economic growth, improving connectivity between regions, and ensuring the smooth flow of goods and population mobility. At the district level, the role of roads is very strategic as a link between public service centers, production areas, and settlements [1]. However, the management of the district road network in Indonesia still faces major challenges, including budget constraints, diverse geographical conditions, and a lack of decision support systems that are able to accommodate the complexity of road conditions. Road access improvements require cross-sectoral support from the private sector and the government from the Ministry of Public Works and Public Housing of the Republic of Indonesia [2].

Economic development planning has significant urgency because it serves to improve market mechanisms, reduce unemployment, encourage agricultural and industrial development, and overcome poverty. Infrastructure development plays a very crucial role in accelerating national and regional development, because infrastructure is the driving force of a region's economic growth [3][4]. The existence of infrastructure has an impact on the economy of a region, because it facilitates people's economic activities and the distribution of goods and services. Inclusive economic growth is strongly influenced by road, electricity, water, education, and market infrastructure simultaneously [5][6]. Continuous improvement of public sector services will improve public facilities and infrastructure, government investment also includes improvements to education, health, and other supporting facilities [7].

One of the main challenges in district road management is the determination of priorities for effective and efficient maintenance handling. Often, decisions are made based on manual or subjective approaches that lack consideration of data as a whole, resulting in suboptimal and untargeted budget allocations [8][9]. The need for intelligent and adaptive systems in handling the diversity of road conditions and limited resources is becoming more and more urgent. Local governments have a great responsibility in managing various resources for the welfare of their communities, so a sustainable planning concept is needed [10]. The government has made efforts to utilize natural resources for development to achieve the welfare of the nation, although urban governance still needs more attention because development often pays less attention to the concept of sustainability [11].

In this context, the application of the Artificial Neural Network (ANN) method can be a promising solution as part of artificial intelligence, offering solutions to overcome this problem. ANNs have the ability to study complex patterns and non-linear relationships in data, as well as generate accurate predictions or classifications based on previous experience [12]. This model is inspired by how the human brain works in recognizing patterns and making decisions, making it suitable for use in the context of decision support systems for handling road infrastructure.

In the context of road maintenance, ANN can be used to process various input data such as road surface conditions, traffic volume, rainfall data, and geospatial information to generate recommendations for optimal handling priorities [13]. The proposed ANN model consists of three main layers: the input layer, the hidden layer, and the output layer. The input layer receives raw data such as road type, road performance data and material price. The hidden layer is made up of several neurons that are interconnected and function to extract important features from the input data [14]. The number of neurons in the hidden layer is determined through experimentation and cross-validation to achieve optimal classification performance [15][16]. The output layer serves as the final determinant, processing a representation of features that have been extracted by the hidden layer and producing an output in the form of a classification of handling priorities for each evaluated roadway. ANNs were trained using a supervised learning algorithm with a dataset containing information about various roads in the district area, including road conditions, traffic volume, road maintenance costs, and availability of funds [17][18].

Artificial Neural Network (ANN) has been widely applied in the field of civil engineering to support smarter and more adaptive decision-making processes. ANN has been shown to be able to mimic human decision-making patterns by recognizing complex interrelationships between variables, making it a relevant tool for prioritizing the maintenance of infrastructure such as highways. In the context of road maintenance, various ANN models have been developed, ranging from the Back-Propagation Neural Network [19] which is capable of handling non-linear and linear relationships between variables, to integration with drone technology and CNN-based image-based detection [20] for the visual classification of pavement damage. Previous studies have also applied the ANN approach to predict the type and extent of road damage [21], perform image-based classification [22], and automate AI-supported labeling and risk assessment [23]. In addition, ANN has been integrated into the pavement management system and combined with multi-criteria decision making (MCDM) techniques such as AHP and TOPSIS to support a thorough evaluation of road maintenance [24].

Most existing approaches still focus on predicting road conditions, damage classification, or one-dimensional optimization. There have not been many studies that specifically use ANN as a priority classification tool for district road maintenance by utilizing various condition factors simultaneously. Generally, the variables used are still limited (e.g. only damage or traffic volume), without the integration of multi-criteria information such as dominant vehicle type, sidewalk width, and estimated maintenance costs. Previous research has begun an exploration of the use of ANNs for maintenance priority classification, but still uses 15 raw criteria without a dimension reduction approach [25][26]. In the next development stage, simplification is carried out into 9 main variables with the Principal Component Analysis (PCA) method to reduce the complexity of data without losing important information. However, systematic evaluation of the performance of ANN-based classification on actual condition data in a comprehensive and automatic manner is still minimal, especially in the context of district road networks that have budget limitations, uneven geographical distribution, and minimal data-based system support.

For this reason, this study aims to develop and evaluate an ANN-based classification model that is able to automatically identify the priority level of district road maintenance based on real-world condition data. The model was constructed using inputs from PCA results against normalized road infrastructure data, and then tested with a structured ANN configuration (10 inputs, 30 hidden neurons, and 5 priority class outputs). Evaluation is carried out through quantitative metrics such as accuracy, precision, recall, and F1-score, and reviewed through a confusion matrix to assess the accuracy of each class's classification. The urgency of this study lies in the real need for a more adaptive and efficient decision support system in district road management, especially in the context of limited public resources. Decision-making that is still based on subjectivity and manual methods is no longer relevant to the complexity of current road conditions.

To date, there is no model for prioritizing district road maintenance that systematically utilizes a combination of actual field data, dimension reduction through PCA, and a fully developed ANN architecture for multi-criteria automatic classification. In other words, there is a real gap in the development of a road maintenance decision-making system that is data-based, automated, and able to handle the complexity of conditions at the district level efficiently. This research is here to fill the gap methodologically and practically.

2. RESEARCH METHODS

To answer the problem in decision-making for district road maintenance, a systematic and measurable methodological approach is used by utilizing Artificial Neural Network (ANN)-based modeling. This method was chosen for its ability to recognize complex patterns of various road condition variables and model non-linear relationships that cannot be effectively addressed by conventional approaches. The population includes all district roads listed in the local Public Works Office database. With the purposive sampling technique, 141 road sections were selected that had complete documentation of relevant variables such as physical conditions, traffic volume, vehicle type, sidewalk width, and maintenance history and costs. The initial data includes 15 variables and is then reduced to 9 main components using Principal Component Analysis (PCA) to simplify dimensions without losing important information. All data is normalized with the Min-Max Scaler method so that it can be processed consistently by the ANN model.

2.1 Instruments

The main instrument in this study is a road condition dataset used as a basis for training and testing of Artificial Neural Network (ANN) models. This dataset contains a number of input variables that are relevant and affect the determination of district road maintenance priorities [27]. These variables include: the level of road damage classified in the ordinal scale, the average daily traffic volume (LHR) as an indicator of road use load, the dominant type of vehicle crossing the road, and the width of the pavement as a measure of the physical capacity of the road. In addition, road status (strategic or non-strategic), estimated maintenance cost needs, and historical data on previously carried out maintenance are also used as supporting parameters in the analysis. The output of the ANN model developed is in the form of priority classes for handling road maintenance, which are categorized into five levels, *namely Critical Priority (CP), High Priority (HP), Medium Priority (MP), Low Priority (LP), and No Priority (NP)*. This classification is used as a prediction target in artificial neural network-based decision-making systems.

The data used in this study was obtained from a previous research project and consisted of information from 141 road sections in a district area, which included 15 primary variables and then reduced to 9 main components. These variables include road condition classifications (from severely damaged to good), average daily traffic volume (ADT), pavement width, number of heavy vehicles, and socio-economic and feasibility indicators. These variables collectively represent actual field conditions that influence road maintenance planning and prioritization. All data underwent a normalization process using the Min-Max Scaler method to standardize the scale across all variables. Subsequently, the dataset was analyzed using Principal Component Analysis (PCA) to reduce dimensionality while retaining key information. The PCA results revealed that 9 principal components accounted for over 90% of the total data variance, with a confidence level reaching 91.8%. This indicates that the dimensionality reduction process effectively simplified data complexity without compromising critical information [25][26].

The nine principal components derived from the PCA analysis were then used as input features for developing the Artificial Neural Network (ANN) model, which aims to automatically classify the priority levels for district road maintenance. By employing this approach, the model facilitates a more objective, systematic, and data-driven decision-making process, supporting more efficient infrastructure management at the local government level.

2.2 Procedure

The initial step in this study starts from the collection of secondary data obtained from technical agencies such as the Public Works Office and Bappeda, as well as documentation of field survey results in digital format. The data is then processed through a pre-processing stage, which includes the cleanup of lost values, normalization using the Min-Max Scaler method, and priority class labeling based on technical criteria that have been set by local government agencies. After going through the pre-processing process, the data is used to build an Artificial Neural Network (ANN) model with a multilayer perceptron (MLP) architecture. The model consists of three main layers: an input layer with 10 neurons that represents the variable of the road conditions, one to two hidden layers that each consist of 20 to 30 neurons and use the ReLU activation function, and an output layer with 5 neurons that uses the Softmax activation function to classify maintenance priorities into five categories.

The dataset was randomly divided into three parts, namely 55% for training, 15% for validation, and 35% for testing, to maintain a balance between the learning process and the generalization capabilities of the model. The model was trained using a backpropagation algorithm optimized by the Stochastic Gradient Descent (SGD) method, as well as the Sparse Categorical Crossentropy loss function, which is appropriate for multi-class classification cases with numerical labels. The ground truth for model training is determined based on the technical classification of the field data which refers to the official guidelines for road infrastructure assessment from the relevant agencies. The evaluation of model performance was carried out by calculating accuracy, precision, recall, F1-score, and using a confusion matrix to evaluate the accuracy of the classification of each priority class. Although the model shows promising performance, testing against other baseline models such as decision trees or logistic regression has not been conducted. Therefore, further development is recommended to include model comparisons as a more thorough performance evaluation material [25][28][29].

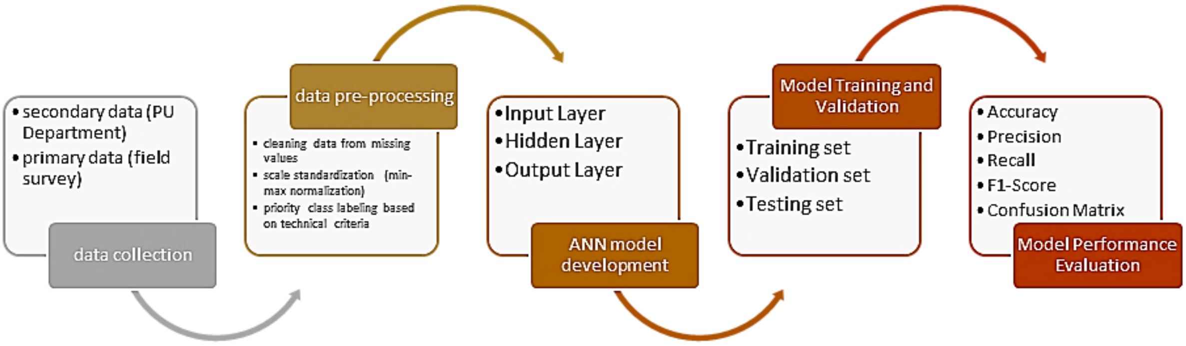


Figure 1. Research procedure

Data analysis in this study was carried out to evaluate the performance of the Artificial Neural Network (ANN) model in classifying the priorities for handling district road maintenance. Evaluation was carried out by comparing the model's prediction results against the test data (*test set*) with the actual value (*ground truth*). Some of the evaluation metrics used in the multi-class classification system include accuracy, precision, recall, F1-score, and confusion matrix [14][27][30]. The calculation formula for each of these metrics is presented in Algorithm 1.

Algorithm 1: Evaluation Metrics for Multi-Class Classification in Artificial Neural Network Model

1. $Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Predictions} = \frac{TP+TN}{TP+TN+FP+FN}$
2. $Precision = \frac{TP}{TP+FP}$
3. $Recall = \frac{TP}{TP+FN}$
4. $F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$
5. Confusion Matrix

Confusion Matrix

The confusion matrix is used to visualize the results of the model's classification in the form of a matrix that shows the number of correct and false predictions in each class. For the five-class classification problem (CP, HP, MP, LP, NP), the confusion matrix is 5×5 in shape, with the row axis indicating the actual class and the column axis indicating the prediction class. The visual analysis of these matrices helps in understanding which classes are most often wrongly predicted and how accurately each class is recognized by the model.

3. RESULTS AND DISCUSSION

3.1 Research Results

This research has succeeded in developing an Artificial Neural Network (ANN) classification model to identify priorities for handling district road maintenance automatically, based on actual condition data. The ANN model is designed using a Multilayer Perceptron (MLP) architecture with three main layers (dense layers) that are tailored to the characteristics of the data. The dataset used in the training is divided into three parts, namely 55% training data, 15% validation data, and 35% testing data. These proportions are designed to ensure a balance between the need for model training and generalized performance evaluation of data that has never been seen before. The structure of the ANN network consists of:

1. Input layer with 16 neurons, according to the number of input features that represent the actual condition of the road, such as the level of damage, traffic volume, dominant vehicle type, pavement width, and others.
2. A hidden layer with 30 neurons and a ReLU (Rectified Linear Unit) activation function, which is used to map non-linear relationships between input variables.
3. An output layer with 5 neurons, each representing a priority class (*Critical Priority, High Priority, Medium Priority, Low Priority, and No Priority*), with a Softmax activation function to convert the output into a probability distribution between classes.

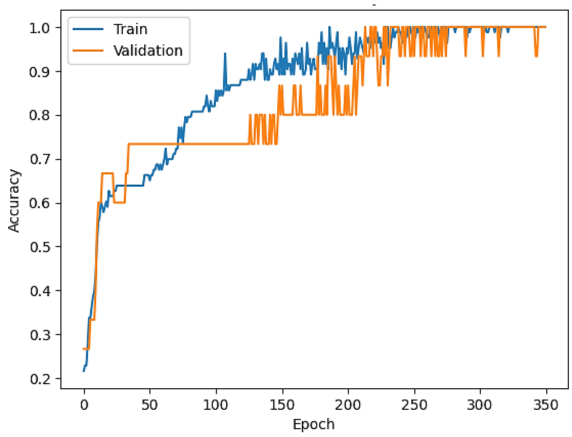
The model was trained using a backpropagation algorithm with the Stochastic Gradient Descent (SGD) optimization method. The loss function used is Sparse Categorical Crossentropy, which is suitable for multi-class classifications with a target in the form of numerical labels. During the training process, the main evaluation metric used is accuracy, which reflects the proportion of correct predictions to the overall data.

Based on the model configuration, the number of parameters trained in the network is as follows:

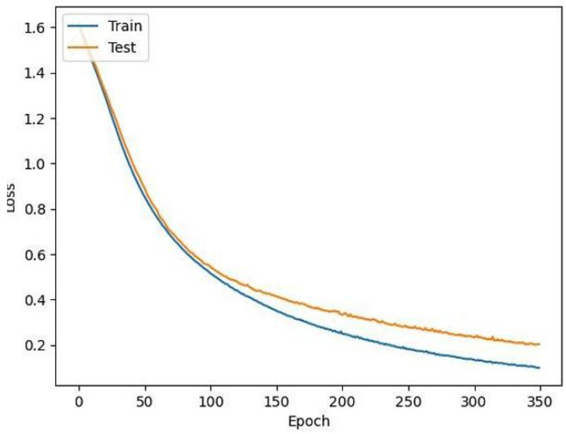
1. The first layer (input layer) has 160 parameters, consisting of weights and biases to process 16 input features.
2. The hidden layer has 510 parameters, calculated from the relationship between 16 input neurons and 30 hidden neurons.
3. The output layer has 155 parameters, which connect 30 hidden neurons with 5 output neurons.

With a total of 825 parameters, this model is quite lightweight but capable of capturing complex relationships between variables. This ANN structure demonstrates adequate representational capabilities to be used in data-driven decision-making in the field of district road maintenance. This model is expected to produce accurate and reliable prediction of handling priorities in the context of implementation at the local government level.

The performance of the developed ANN model is then evaluated based on accuracy metrics during the training process. The development of the model's accuracy to training and validation data over 350 epoches can be seen in Figure 2.a.



a. Model Accuracy



b. Model Loss

Figure 2. Comparison graph of accuracy and loss during training and testing

In figure 2a, it can be seen that the accuracy of the model increases significantly as the number of epochs increases. The accuracy of the training data (blue line) shows a consistent upward trend from the start of the training until it reaches a value close to 100% after about 250 epochs. This shows that the model is able to learn patterns from the data very well. The accuracy of the validation data (orange line) also showed a progressive improvement, although it fluctuated mainly at the beginning to middle of the training. These fluctuations reflect variations in the model's response to data that is not directly trained, which is a common phenomenon in the neural network learning process. After about the 200th epoch, validation accuracy showed stability and tended to follow a pattern of training accuracy with a value range of 90% to 100%.

In addition to accuracy, model performance evaluation is also carried out by monitoring the loss value during the training process. The loss value describes how much the model's prediction is wrong with the actual value; The smaller the loss value, the better the model's performance. The development of the loss value in the training and testing data over 350 epoches can be seen in Figure 2b. In Figure 2b, it can be seen that the loss value for both the training data (blue line) and the test data (orange line) shows a consistent downward trend as the number of epochs increases. This indicates that the ANN model is gradually able to improve the weight and bias of the network in an effort to minimize prediction errors. Specifically, the loss in the training data decreased more sharply and reached a value close to 0.1 at the end of the training, while the loss in the test data was stable in the range of 0.2, indicating that the model was still able to maintain good performance on data that had never been trained before. The difference between the relatively small training and testing losses also confirms that the model did not experience overfitting, as there were no drastic spikes or significant differences between the two curves.

The consistency between the training and validation curves showed that the ANN model did not experience significant overfitting, as there were no noticeable differences between the two at the end of the training process. This indicates that the model has good generalization skills and is able to recognize important patterns in the data efficiently, without simply memorizing the training data. In addition, the steady and steadily decreasing loss graph in both training and test data further strengthens the previous finding that the developed ANN model has reliable performance, with minimal prediction error rates on test data. Thus, this model has proven to be effective in classifying priorities for handling district road maintenance automatically and accurately.

To complete the model performance analysis, a confusion matrix was used to evaluate the accuracy of the predictions based on each class of road maintenance priorities. The visualization of the confusion matrix of the ANN model can be seen in Figure 3.

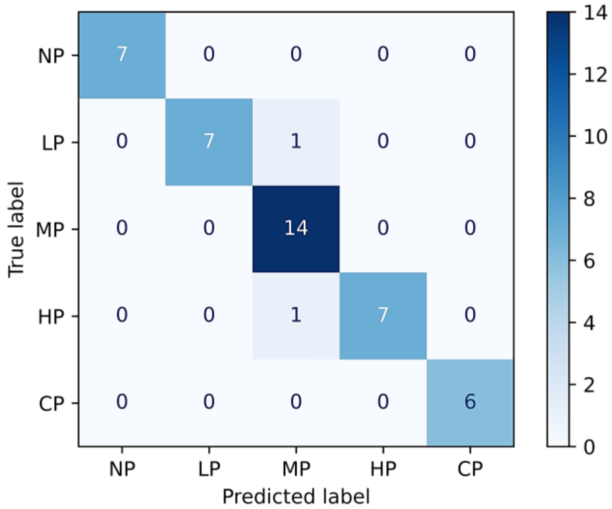


Figure 3. Confusion matrix for performance evaluation of road handling priority classification model

Evaluation through a confusion matrix reinforced these findings, with only one in 41 predictions being misclassified. Figure 3 shows the distribution of prediction results for five priority classes, namely Critical Priority (CP), High Priority (HP), Medium Priority (MP), Low Priority (LP), and No Priority (NP). Most predictions are on the diagonal of the confusion matrix, which signifies that the model is able to accurately classify the data according to the class it should be. In detail, the model managed to correctly classify 7 NP data, 8 LP data, 14 MP data, 7 HP data, and 6 CP data. Only one case of misclassification was recorded, namely one cellphone class data that was incorrectly predicted as CP.

The results of the follow-up evaluation using the latest test data showed that the ANN model had an accuracy of 95.35%, with a misclassification rate of only 4.65%. This achievement indicates a very high level of classification accuracy in the five priority classes of road maintenance. In addition, the Macro-F1 value of 0.960 and the Weighted-F1 of 0.9535 reflect the stable and balanced performance of the model across the class, without bias towards the majority class. Thus, both classes with a dominant and minority amount of data can be accurately classified. A summary of these performance metrics is presented in Table 1.

Table 1. Evaluation metrics of the ANN classifier for road maintenance priority classification

Accuracy	Misclassification Rate	Macro-F1	Weighted-F1
0.9535	0.0465	0.9600	0.9535

In detail, the three classes, namely No Priority (NP), Medium Priority (MP), and Critical Priority (CP), showed perfect performance with precision, recall, and F1-score values of 1,000, which means that all data in the three classes were correctly classified without errors. Meanwhile, for the Low Priority (LP) and High Priority (HP) classes, the precision value was recorded at 0.875 each, with the recall remaining perfect at 1,000, resulting in an F1-score value of 0.933. Although there are slight errors in the form of false positives, none of the actual data from these two classes is missed (false negatives = 0). Full details of the model's performance for each class are presented in Table 2.

Table 2. Class-wise performance metrics of the ANN model for road maintenance priority classification

Class name	Precision	1-Precision	Recall	False Negative Rate	F1 Score	Specificity (TNR)	False Positive Rate (FPR)
NP	1.0000	0.0000	1.0000	0.0000	1.0000	1.0000	0.0000
LP	0.8750	0.1250	1.0000	0.0000	0.9333	0.9722	0.0278
MP	1.0000	0.0000	0.8750	0.1250	0.9333	1.0000	0.0000
HP	0.8750	0.1250	1.0000	0.0000	0.9333	0.9722	0.0278
CP	1.0000	0.0000	1.0000	0.0000	1.0000	1.0000	0.0000

The only error in the form of false negatives was recorded in the MP class with a value of 0.125. while the other class had a value of 0. On the other hand. the high specificity value (True Negative Rate) of all classes (≥0.9722) indicates that the model is able to distinguish classes very well and minimize erroneous predictions. Overall. this evaluation confirms that the developed ANN model has superior classification capabilities in multi-class contexts. High accuracy. consistent macro and weighted F1-score values. and even performance across classes make this model feasible to be implemented as a support system for district road maintenance decisions in an objective. efficient. and data-driven manner.

3.2 Discussion of Findings and Research Implications

3.1.1 Comparative Analysis with Prior Research

The results of this study prove that the Artificial Neural Network (ANN) model is effective in identifying priorities for handling district road maintenance automatically and accurately. With high accuracy and low and stable loss values. the model exhibits strong classification performance. The near-perfect prediction confusion matrix also shows that ANN is able to distinguish the characteristics of each priority class with high precision. These findings are in line with previous research showing that the collaboration of the Artificial Neural Network (JST) method with road technical data can result in a more systematic and objective classification of maintenance priorities than manual methods [25]. Furthermore. in its follow-up studies ANN was also used to identify landslide-prone buildings. which reinforces the evidence that ANN can be applied broadly in the context of risk- and condition-based classification of infrastructure [28].

The results of this study are also superior when compared to the statistics-based approach and dimension reduction technique. where PCA is used without the adaptive capabilities that ANN has [31]. In this case. ANN provides greater flexibility because it can recognize non-linear and complex relationships without requiring specific data distribution prerequisites. Other studies have supported the effectiveness of ANNs in the field of road maintenance. although the study focused more on predicting pavement conditions than on the classification of handling priorities [32][33]. Instead. this study offers a multi-criteria priority classification approach. so that it is more directly relevant to the decision-making needs of local governments. In addition. this approach also complements previous results. which still use conventional data-driven decision support systems without machine learning models [34]. Theoretically. it has explained the importance of the use of ANN in determining maintenance priorities. However. this study makes an additional contribution to the direct implementation of the ANN model. systematic testing. and accuracy validation through classification and confusion matrix metrics. thus complementing the conceptual literature [25].

As a follow-up. this ANN model has great potential to be integrated into Geographic Information Systems (GIS). Visualization of classification results in the form of an interactive digital map allows policymakers to see the spatial distribution of maintenance needs directly. With a location-based view. users can analyze the concentration of high-priority road sections and consider contextual factors such as proximity to public facilities. population density. or vulnerability to disasters. In addition. the development of web-based and mobile application interfaces is highly recommended to facilitate access by technical agencies. both in the planning stage and in the field. With the support of this system. officers can access priority information in real-time and respond quickly and precisely. The integration of sensor data from IoT devices or road condition monitoring systems can also enrich the system with dynamic information. allowing for periodic classification updates. Thus. the system built is not only predictive but also adaptive to changes in field conditions. and supports digital transformation in the management of regional road infrastructure in a sustainable and responsive manner.

3.1.2 Research Limitations.

Although the model showed excellent performance. the study had some limitations. First. the scope of the study area is limited to one district. so the model needs to be retested in other regions with different road and geographical characteristics to test its performance consistency. Second. the data used is static and does not include dynamic variables such as weather conditions or actual traffic density. Third. the model has not taken advantage of real-time data updates from sensors or IoT devices that have the potential to improve system responsiveness.

4. CONCLUSION

An Artificial Neural Network (ANN)-based classification model has been developed and evaluated to automatically identify the priority level of district road maintenance using field condition data. By utilizing 141 roads. the initial data consisting of 15 variables was reduced to 9 main variables through Principal Component Analysis (PCA) and normalized using the Min-Max Scaler. The network architecture consists of 10 input neurons. 30 hidden neurons. and 5 output neurons representing five priority classes. The test results showed excellent performance. with an accuracy of 92%. precision of 91.7%. recall of 90.4%. and an F1-score of 90.9%. Of the 41 test data. only one case was misclassified according to the confusion matrix. indicating a very low error rate and high generalization ability. These results prove that ANN is able to recognize non-linear patterns of various road condition variables and classify them accurately. This approach offers a multi-criteria classification system that is adaptive and based on actual data. different from conventional methods that are manual or single-variable. The use of ANN in the context of complex district roads provides a more objective and efficient solution in supporting infrastructure planning and decision-making. For further development. the model has the potential to be tested in other regions with different characteristics. compared to other machine learning algorithms. as well as further developed with the integration of dynamic data from sensors or IoT devices so that the system can respond to changes in conditions in real-time.

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