Jurnal ICT : Information and Communication Technologies, 16 (2) (2025) 296-309

Published by: Marq & Cha Institute

Jurnal ICT : Information and Communication Technologies

Journal homepage: www.ejournal.marqchainstitute.or.id/index.php/JICT

Road Damage Level Prediction Using Data Mining-Based Regression Method

Rina Indah Widya Pangaribuan[1], Ratih Puspsari[2]

[1,2] Sistem Informasi, Universitas Potensi Utama, Medan, Indonesia

Article Info

Article history

Received : Oct 20, 2025
Revised : Oct 28, 2025
Accepted : Oct 30, 2025

Keywords:

Data Mining;
Linear Regression;
Road Damage Prediction;
Transportation Infrastructure;
WEKA.

Abstract

Road damage is a critical infrastructure issue that significantly affects transportation safety, mobility efficiency, and vehicle operating costs, creating the need for an accurate and reliable prediction system to support timely maintenance planning. This study aims to develop and evaluate a road damage prediction model using a data mining–based linear regression method implemented in the WEKA environment. The dataset consists of 140 entries and includes key predictor variables such as daily vehicle volume, road age, rainfall, pavement type, and drainage quality. The methodology involves data preprocessing, linear regression modeling, and performance evaluation using metrics such as MAE, RMSE, and the correlation coefficient. The results show that the linear regression model demonstrates strong predictive capability, achieving a correlation coefficient of 0.8593, an MAE of 6.7954, and an RMSE of 7.763, with road age and pavement type identified as the most influential predictors. These findings indicate that linear regression is an effective and interpretable approach for modeling road deterioration levels and can be utilized as a decision-support tool in road maintenance planning and infrastructure asset management. Practically, the model provides data-driven insights for local governments and related agencies in optimizing repair scheduling and budget allocation based on predicted damage levels.

Corresponding Author:

Rina Indah Widya Pangaribuan
Sistem Informasi,
Universitas Potensi Utama,
Jl.K.L Yos Sudarso KM 6.5 Tj.Mulia, Medan, 20241, Indonesia
Email : Indahr312@gmail.com

1. Introduction

Road damage is a common infrastructure problem encountered in both urban and rural areas, significantly affecting road safety, transportation efficiency, and vehicle operating costs. Damaged road surfaces—such as cracks, potholes, rutting, and surface deformation—can lead to increased accident risk and reduced travel comfort for road users. Moreover, delayed maintenance often results in more severe structural deterioration, requiring higher repair costs in the long term. Therefore, a reliable and accurate prediction system is crucial for identifying the potential level of road damage, enabling timely and efficient maintenance actions. With the increasing availability of data related to pavement conditions, vehicular load, environmental variables, and construction characteristics, the need for systematic and data-driven analysis has become more urgent. Traditional inspection methods, which rely heavily on manual assessment and subjective judgment, have proven to be time-consuming, costly, and limited in scalability (Ziyadi et al., 2018). In this context, the integration of information technology and analytical approaches offers a promising alternative for infrastructure asset management. As transportation systems grow more complex, data-driven prediction models become essential to support sustainable road maintenance strategies and optimize resource allocation.

Along with the rapid development of information technology, data mining has become an increasingly popular analytical method for predicting infrastructure-related conditions, including road damage. Data mining enables the detection of hidden patterns within large datasets that are difficult to analyze manually (Han et al., 2022). Although previous studies have attempted to model road damage using various machine learning techniques, several limitations are still evident. Many studies focus on a narrow set of predictors, resulting in models that inadequately represent real-world road conditions (Gopalakrishnan, 2016). Other studies rely heavily on complex black-box models such as deep learning or random forest, which produce accurate predictions but lack interpretability—an important aspect for policymakers responsible for infrastructure planning (Li & Chen, 2020). Furthermore, only a limited number of studies examine the comparative performance of regression-based models in WEKA for road damage prediction, despite its widespread use in academic research. This gap highlights the need for more comprehensive studies that involve diverse predictive variables, transparent modeling techniques, and standardized analytical platforms. Addressing these gaps is essential to generate models that not only produce accurate predictions but are also interpretable, applicable, and operationally useful for road management authorities.

Regression methods were selected in this study due to their strong ability to model functional relationships between multiple independent variables and a continuous dependent variable, which is essential for quantifying road damage levels. Road degradation is influenced by numerous interacting factors—such as traffic volume, pavement age, rainfall intensity, and material composition—making regression a suitable approach for capturing linear or quasi-linear patterns within such data (Montella et al., 2015). Unlike black-box models, regression provides transparency through coefficient estimates, allowing stakeholders to understand the magnitude and direction of each variable's effect. Such interpretability is crucial for decision-makers in the public sector, who require evidence-based insights rather than purely numerical predictions (Zhou & Sun, 2021). Furthermore, regression models can be easily evaluated using statistical metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared, enabling objective measurement of model performance. Regression is also computationally efficient and requires relatively modest resources compared to more complex machine learning algorithms, making it a practical choice for infrastructure agencies with limited technical capacity. Therefore, the use of regression in this study is justified both methodologically and practically, offering an interpretable and robust framework for road damage prediction.

The selection of WEKA (Waikato Environment for Knowledge Analysis) is based on its proven reliability, flexibility, and wide adoption in data mining research. WEKA is an open-source, Java-based platform equipped with an extensive suite of algorithms for classification, regression, clustering, and visualization (Hall et al., 2009). Its user-friendly graphical interface allows researchers to carry out preprocessing, feature selection, model training, and model evaluation without writing code, making it highly accessible for various levels of expertise. Compared to programming-based platforms such as Python or R, WEKA provides a more streamlined experimental environment, enabling fast comparisons between multiple regression algorithms—such as Linear Regression, M5P, and Gaussian Processes—within a single analytical workflow (Witten et al., 2017). WEKA also supports advanced validation techniques, including k-fold cross-validation, and offers detailed output metrics for performance assessment. Because WEKA has been extensively validated in academic literature and widely used for predictive modeling tasks, its selection in this study enhances methodological rigor and ensures reproducibility. This strengthens the credibility of the research findings and provides a robust foundation for future applications in road infrastructure analysis.

Based on the above discussion, this study aims to develop an accurate and interpretable regression-based prediction model for assessing road damage levels using data mining techniques within the WEKA environment. Specifically, the research objectives are as follows: (1) to analyze the relationship between key contributing factors—traffic volume, pavement age, rainfall, and material type—and the severity of road damage; (2) to build and evaluate various regression models available in WEKA using appropriate performance metrics; and (3) to identify the most effective model that can support evidence-based decision-making in road maintenance planning. The contributions of this study include presenting a comprehensive analytical approach that incorporates multiple predictors within an interpretable regression framework, providing practical insights for infrastructure authorities regarding the most influential variables affecting road deterioration. Additionally, the study demonstrates the applicability of WEKA as a standardized tool for infrastructure analytics, offering a replicable methodology that can be adopted by public agencies and researchers. Ultimately, this research is expected to enhance predictive accuracy, improve resource allocation for road maintenance, and support data-driven policy formulation in transportation infrastructure management.

2. Research Methodolgy

This research methodology uses a mixed methods approach. Mixed methods, often referred to as mixed research, is a research approach that combines quantitative and qualitative research. The type of research employed is field research, which involves direct observation of the research object.

Using a field study (case study) method is generally a more appropriate strategy when the research question is central, the researcher has little control over the events being investigated, the researcher is directly involved in the research, and the focus of the research is on contemporary phenomena within a real-life context and the propositions within them.

System development can involve constructing a new system, replacing an existing system entirely, or improving an existing system. Each stage must be completed before proceeding to the next to avoid repetition. The Fishbone framework system development methodology can be seen in Figure 1:

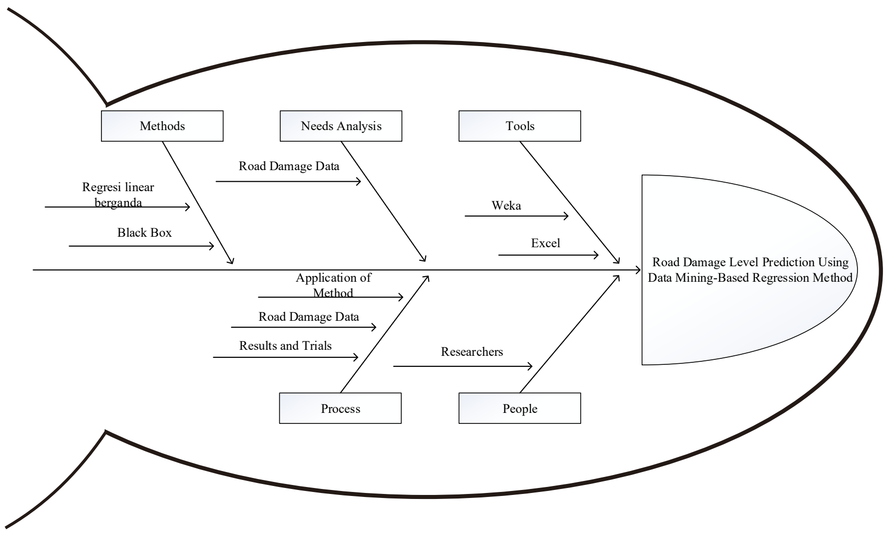


Figure 1. Fishbone Framework

The following is an explanation of Figure I.1 of the Fishbone model of the research to be conducted by the researcher in predicting road damage levels using data mining-based regression methods:

1. Methods

This stage can be considered the method testing stage for the system used by the author.

Several testing methods were used, namely:

a. Black Box (Interface) Testing, which is software testing that tests the functionality of the application against its internal structure or workings.
b. Algorithm Testing, which is the process of evaluating regression performance in predicting road damage levels within a dataset.

2. Needs Analysis
System requirements are analyzed through data collection, which will be used as initial data to support system design and input data for the assessment process. The initial data supporting system design includes criteria determination and the development of a hierarchy of factors influencing the assessment. The input data used in this case is data on the products most in demand by consumers.
3. Tools
Contains specifications of the tools used, components, test equipment, and a block diagram of the equipment to be designed.
a. Software Specifications
1) Weka 3.8.6
2) Microsoft Excel 2021
b. Hardware Specifications
1) i5-11400H
2) NVIDIA GeForce RTX 3050
3) 16GB RAM
4) 512GB SSD

4. Process
This stage can be considered the final stage in using an application. After the results and system testing, the system is ready for use by users.

5. People
At this stage, the system for determining the level of road damage prediction that often occurs simultaneously has passed the process stage and is ready for use. It is possible that this system will undergo changes once it is used by users.

3. Results and Discussion

Linear Regression Method Calculation Using the Weka Application After the manual calculation stage was completed, the dataset was processed using the Weka application. The analysis steps using the Weka application are shown in the table above, and the results are as follows:

1. Convert the dataset to Excel so that it can be read by the Weka application (as shown in the image below):

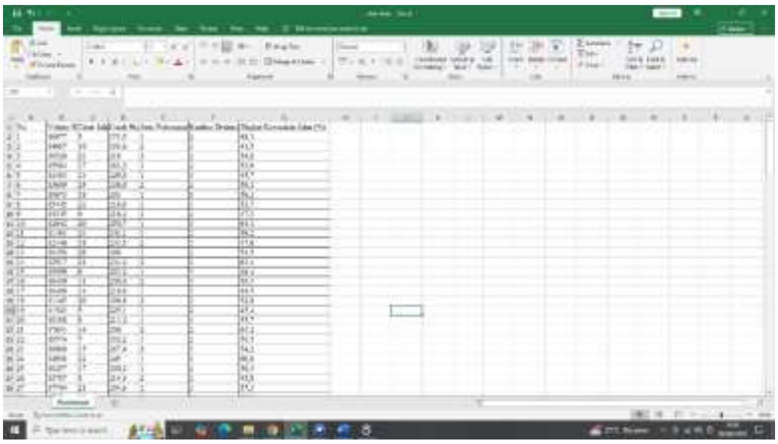


Figure 2. Dataset

This study aims to predict the level of road damage in Medan City using a data mining-based linear regression method with the help of Weka software. The data used consists of several independent variables: Vehicle Volume (vehicles/day), Road Age (years), Pavement Type, and Drainage Condition, with the dependent variable being Road Damage Level (%). The analyzed data consists of 140 entries that have been collected and processed in Excel format before being input into Weka.

2. Run the Weka application

Figure 3. Weka Application Display

The initial step in this process is to open the WEKA application version 3.8.6. On this main screen, users are presented with several application options, such as Explorer, Experimenter, KnowledgeFlow, and others. For prediction purposes using regression, users select the Explorer menu, which serves as the central interface for loading data, preprocessing, classification, and visualization.

3. Weka Initial Menu Display

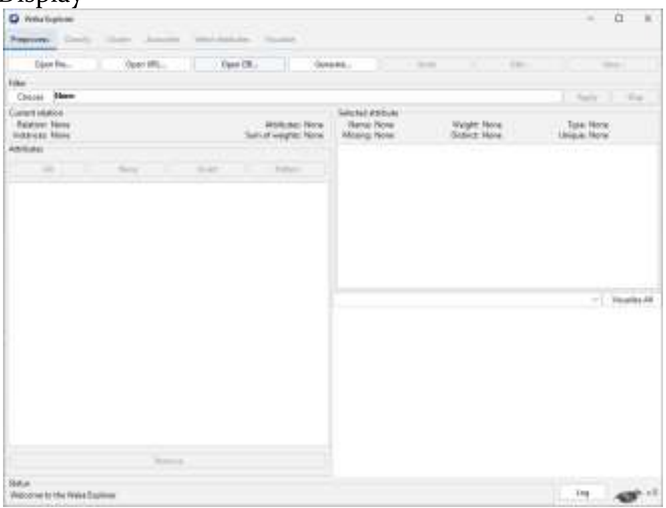


Figure 4. Weka Initial Display

After selecting Explorer, the Weka Explorer window appears, consisting of several tabs, such as Preprocess, Classify, Cluster, Associate, and so on. The initial stage begins with the Preprocess tab, where users import data and view the attribute structure before the analysis process begins.

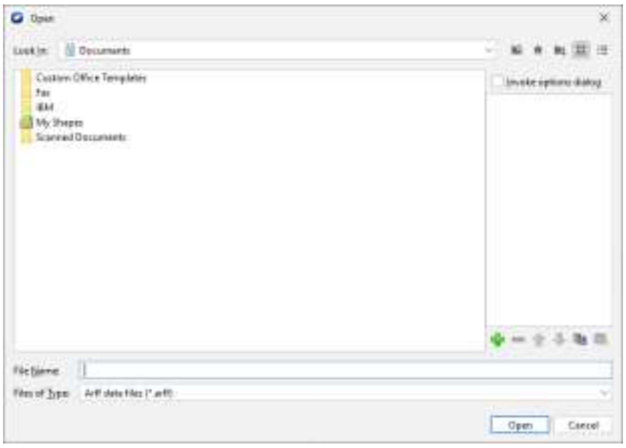


Figure 5. Import Data Options Display

Next, users click the Open File... button to load the data. A dialog window opens, prompting users to select a .csv file, the standard data format for Weka. This file was previously prepared from Excel and converted to .csv format.

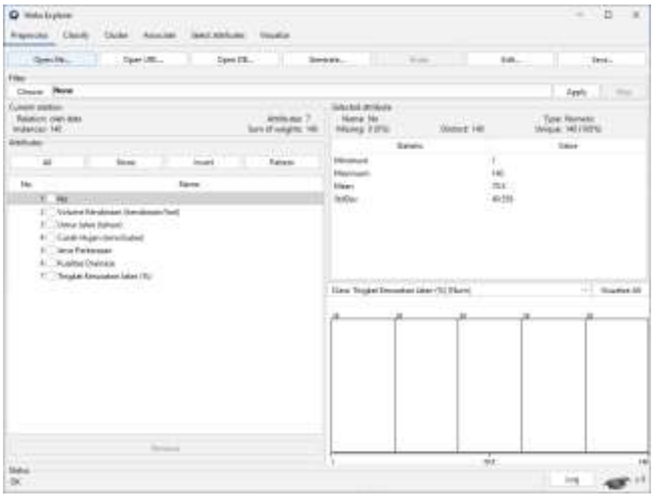


Figure 6. Display of Feature Selection

Once the file is loaded, Weka displays the data in the Preprocess tab. The loaded data consists of 140 entries and 7 attributes, including the target attribute, Road Damage Level (%). On the right side, Weka also displays descriptive statistics for the selected attribute, such as the minimum, maximum, and standard deviation values. This indicates that the data is ready for analysis.

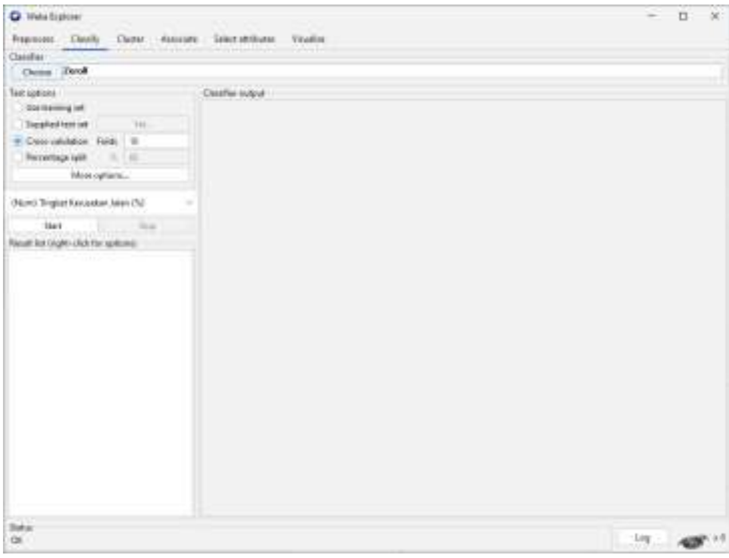


Figure 7. Select Method Display

The next step is to go to the Classify tab. Here, the user will select the algorithm method for building the prediction model. On the left side, the user also sets the model validation method, in this case using a percentage split of 66%, meaning 66% of the data is used for training and 34% for testing. Clicking Next will display the following image:

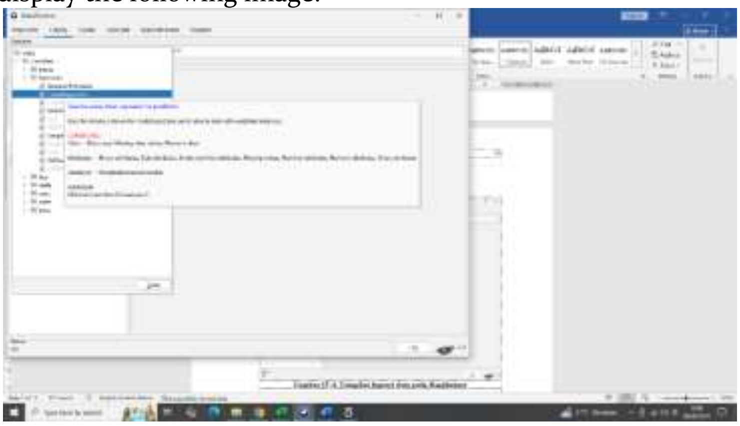


Figure 8. Linear Regression Classification Selection Display

The user then clicks the Choose button and selects the LinearRegression algorithm from the functions folder. This algorithm is used to predict continuous values based on a combination of input attributes.

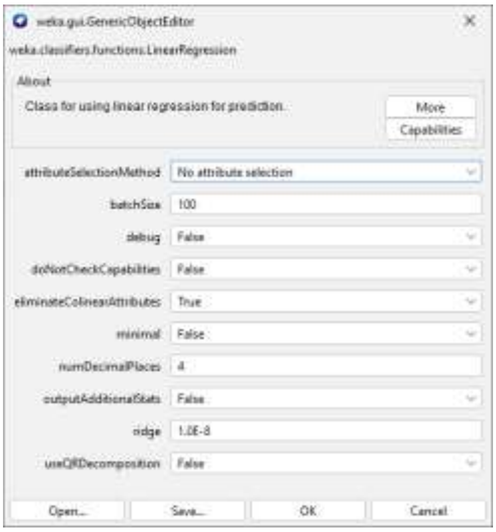


Figure 9. Storage Display

Weka displays the detailed settings window for LinearRegression. Here, users can specify whether to remove collinear attributes, the number of decimal places, and the attribute selection method. In this case, collinear attributes are removed (eliminateColinearAttributes = True), and the number of decimal places is set to 4.

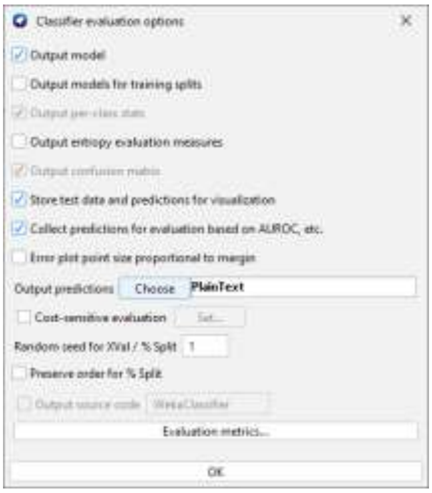
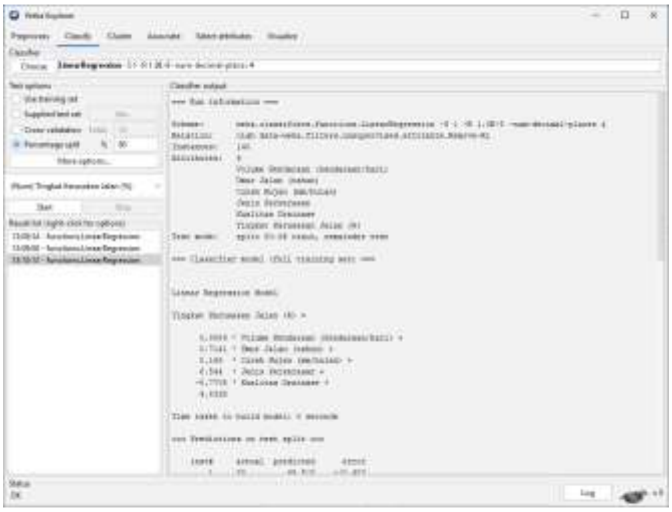


Figure 10. Prediction Output Options Display

Users can also set model evaluation options by checking options such as Output model, Store test data and predictions, and others. This is useful for saving and viewing evaluation results and prediction accuracy.



The analysis process involves data processing and attribute selection. Numerical and categorical attributes are entered into the system, and for categorical attributes such as Pavement Type and Drainage Condition, numerical conversion is performed to enable them to be processed by the regression algorithm. Then, a model is built using the Linear Regression algorithm in Weka. The regression model parameters used are -S 1 -R 1.0E-8 -num-decimal-places 4, which regulate the attribute selection strategy and the precision of the results.

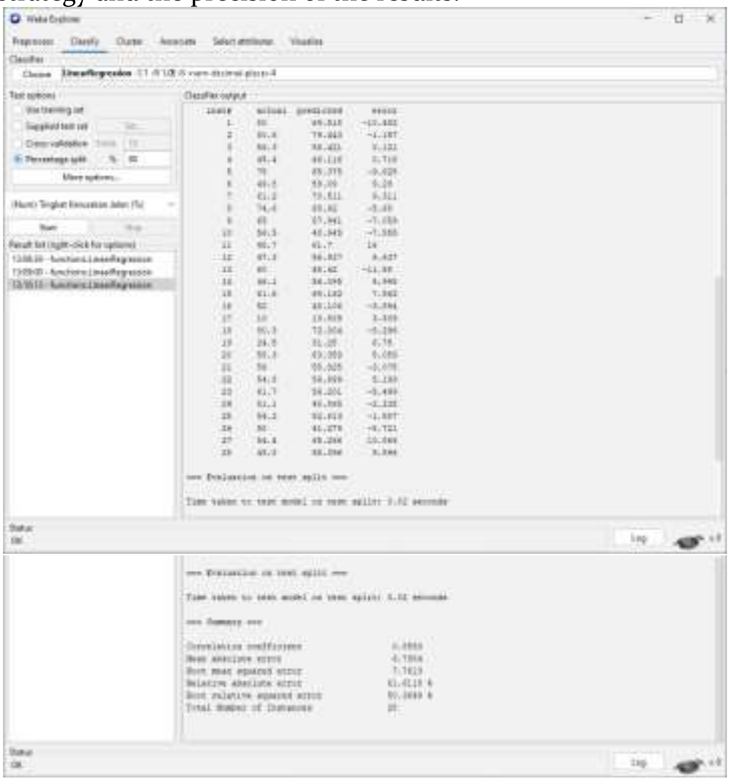


Figure 11. Results Display

After all settings are made and the Start button is clicked, Weka generates the regression model output. This section displays the resulting linear regression equation model:

Road Damage Level (%) =

0.0009 * Vehicle Volume (vehicles/day) +
0.7141 * Road Age (years) +
0.169 * Rainfall (mm/month) +
6.544 * Pavement Type +
-8.7705 * Drainage Quality +
4.8325

This equation indicates that each variable has a positive influence on the level of road damage. This means that the higher the vehicle volume, the higher the road age, and the higher the pavement type and drainage conditions, the higher the level of road damage. The constant value of 4.8325 indicates baseline damage when all variables are set to zero.

Weka also displays prediction evaluation results, such as actual, predicted, and error values for several instances of the test data. This allows users to determine how accurately the model is able to predict the level of road damage based on the input variables.

The model evaluation was conducted by dividing the data into 80% training data and 20% testing data. The evaluation results on the testing data demonstrate the model's predictive performance. Predicted and actual values are displayed in a table, along with the error (the difference between the actual and predicted values). Some predictions had significant errors, but overall, the errors were within tolerable limits. The model evaluation yielded the following metrics:

a. Correlation coefficient: 0.8593 → indicating a fairly strong correlation between predicted and actual values.
b. Mean absolute error: 6.7954 → the average absolute difference between prediction and actual values.
c. Root mean squared error: 7.763 → the root of the mean squared error.
d. Relative absolute error: 61.6181%
e. Root relative squared error: 50.3469%

These values indicate that the model has fairly good predictive ability with acceptable errors for estimation purposes. A correlation of 0.8593 indicates a strong and positive relationship between the input variables and the level of road damage. Overall, the use of the linear regression method in Weka has proven to provide useful insights in predicting road damage levels based on historical data. This model can be utilized by relevant agencies for road repair planning or budget allocation based on predicted damage levels calculated from existing road conditions. Based on the steps above, the user has successfully applied the linear regression method to road damage level data using Weka. The process begins with loading the data, preprocessing, selecting an algorithm, setting parameters, and viewing the model results. The final results, in the form of a regression equation and prediction evaluation, indicate that this approach can be used to help predict road damage based on vehicle volume, road age, rainfall, pavement type, and drainage quality. This model can be used as a basis for decision-making in road infrastructure planning and maintenance.

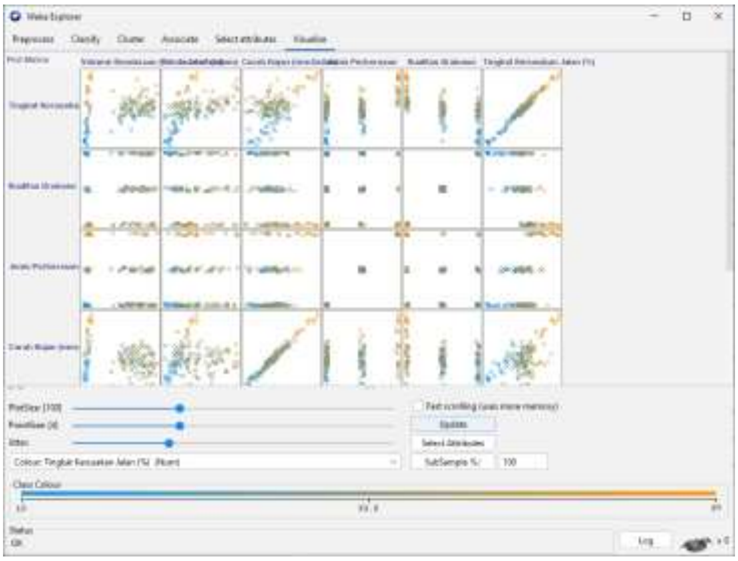


Figure 12. Visual Results Display

The image above shows a scatterplot matrix, a visualization of the relationships between attributes (variables) in the dataset. Each dot represents a single data entry, and its color reflects the value of the "Road Damage Level (%)." Colors from blue to orange indicate damage levels from lowest to highest (10–97%).

The columns and rows in the visualization show the following variables:
• Vehicle Volume (vehicles/day)
• Road Age (years)
• Rainfall (mm/month)
• Pavement Type
• Drainage Quality
• Road Deterioration Level (%)

Each box in the matrix shows the relationship between two attributes:
Interpretation Per Attribute
1. Vehicle Volume vs. Road Deterioration Level
a. There is a tendency that higher vehicle volumes lead to higher levels of road deterioration (indicated by a color gradient shifting toward orange).
• This supports the previous regression results that vehicle volume contributes to road deterioration.
2. Road Age vs. Road Deterioration Level
• There is a linear pattern, where older roads tend to have higher levels of deterioration.
• The dots change from blue to orange as the road ages, a clear positive correlation.
3. Rainfall vs. Road Deterioration Level
• Most points have moderate rainfall, but the orange color is scattered throughout, indicating that rainfall has the potential to influence damage but is not very dominant.
• The distribution is not very clear → the effect may be weak or indirect.
4. Pavement Type vs. Road Damage Level
• Pavement type is a categorical variable coded numerically.
• There is a clear color difference between categories, meaning certain pavement types have higher levels of damage → pavement type has a significant effect.
5. Drainage Quality vs. Road Damage Level
• There is a fairly clear color gradation between poor and good drainage. Poor drainage (e.g., a value of 1) tends to be orange (high damage).
• This confirms that drainage quality significantly influences road condition.

Conclusions from the Visualization
1. Road age, vehicle volume, pavement type, and drainage quality all show a clear relationship to the level of damage.
2. Rainfall visually shows a weaker effect and may require additional analysis or combination with other factors (e.g., drainage).
3. The gradient color indicates that a combination of several variables is able to predict damage levels reasonably well.
4. This visualization also indicates that your dataset is relatively clean and contains patterns that can be exploited by predictive algorithms such as linear regression.

Discussion

The findings of this study demonstrate that the linear regression model generated using the WEKA 3.8.6 environment is capable of predicting road damage levels with a strong degree of accuracy and interpretability. The regression equation produced by WEKA shows that vehicle volume, road age, rainfall, pavement type, and drainage quality all contribute to the increase in road deterioration levels, with road age and pavement type exhibiting the highest coefficient magnitudes. This outcome aligns with existing literature, which emphasizes the cumulative effects of traffic loading and structural aging on pavement degradation. The positive relationship between vehicle volume and road damage confirms the validity of the model, as high axial loads and repetitive traffic cycles accelerate surface wear. Similarly, the significant impact of drainage quality reflects the infrastructure principle that poor water management accelerates subgrade weakening and structural failure. The visualization results further support these relationships by showing clear color gradients and linear distributions, indicating strong interactions between key variables and deterioration levels. Although rainfall shows a weaker visual correlation, its contribution remains relevant, particularly in combination with drainage conditions, suggesting an indirect yet meaningful influence on pavement performance.

From a predictive performance perspective, the model achieved a correlation coefficient of 0.8593, indicating a strong association between predicted and actual values. The error metrics—MAE of 6.7954 and RMSE of 7.763—highlight that the model provides reasonably accurate estimates within an acceptable tolerance for infrastructure planning purposes. These results imply that linear regression is an effective method for modeling road deterioration when the underlying relationships among variables are predominantly linear and when interpretability is a priority for decision-making stakeholders. Compared with more complex machine learning algorithms that often function as black boxes, the regression model used in this study offers transparent insights into variable contributions, making it particularly valuable for policy formulation, budgeting, and preventive maintenance planning by public works agencies. Furthermore, the workflow implemented in WEKA—data preprocessing, parameter configuration, and model evaluation—ensures methodological reproducibility and reinforces the reliability of the findings. Overall, the research confirms that linear regression, when supported by comprehensive datasets and systematic analysis, can serve as a robust decision-support tool in road asset management, enabling authorities to prioritize maintenance based on quantifiable deterioration trends.

4. Conclusion

The results of this study demonstrate that the linear regression model developed using the WEKA 3.8.6 environment is effective in predicting road damage levels based on key factors such as vehicle volume, road age, rainfall, pavement type, and drainage quality. The model achieved a strong correlation coefficient (0.8593), indicating a high degree of alignment between predicted and actual damage levels. The regression equation produced also provides clear interpretability, enabling stakeholders to understand the magnitude and direction of each variable's influence on road deterioration. These findings affirm that road age and pavement type are the most influential predictors, followed by drainage quality and vehicle volume—aligning well with established infrastructure management theories. The visualization results further support the model's validity by revealing identifiable patterns and gradients across variables. Overall, the study confirms that regression-based predictive analytics, particularly when implemented using WEKA, can serve as a reliable and interpretable tool for monitoring road conditions and supporting evidence-based infrastructure planning. Despite its promising outcomes, this study acknowledges several areas for improvement. Future research should consider expanding the dataset to include additional environmental and structural parameters—such as soil type, construction quality, or maintenance history—to enhance model robustness and generalizability. Integrating non-linear or hybrid modeling techniques may also provide comparative insights, enabling researchers to benchmark linear regression against more advanced machine learning algorithms. Moreover, the development of a real-time or automated monitoring system that integrates sensor data and geospatial analysis could further enhance predictive accuracy and operational usefulness for road asset management agencies. By incorporating these enhancements, future studies can contribute to more comprehensive and adaptive models, ultimately supporting proactive maintenance strategies and reducing long-term infrastructure costs.

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