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Ai-Based Road Performance Prediction for Supporting Smart Infrastructure Maintenance

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ABSTRACT

This research aims to develop an artificial intelligence-based road performance prediction system to support smart infrastructure maintenance. Current road maintenance systems are still traditional and reactive, leading to infrastructure degradation and high repair costs. This study uses AI methods combining Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) to analyze road condition data, traffic volume, and weather conditions. ANN is effective in detecting nonlinear patterns from statistical data, while LSTM excels in processing time-series data of historical road conditions. The system is designed using UML modeling and implements a relational database for storing road, traffic, weather, and prediction data. Based on the analysis, the proposed system successfully provides a predictive maintenance solution that is proactive rather than reactive. The system's performance demonstrates that AI-based predictions can extend road service life, optimize maintenance budget allocation, and minimize public service disruptions. However, prediction accuracy is still influenced by factors such as data quality and model parameter selection.

1. Introduction

The development of digital technology, particularly artificial intelligence (AI), has entered various aspects of human life. This technology has even penetrated the civil engineering field, one of which is in the management of transportation infrastructure. One crucial transportation system for mobility and economic growth is highways. The utilization of AI offers tremendous opportunities to revolutionize road structure health monitoring, thereby improving safety, efficiency, and infrastructure durability [1].

The commonly encountered problem is that current road maintenance systems are still traditional and reactive. However, there is great hope to have a safe and durable road network. This gap gives rise to the core issue, namely how to apply AI to predict road performance and realize smart infrastructure management so that road maintenance becomes more modern, planned, and proactive.

Several previous studies have highlighted AI's potential in this field. Tamagusko et al. (2022) reviewed the application of machine learning in pavement management systems (PMS), concluding that AI can improve the accuracy of road condition assessment, performance prediction, and maintenance decision-making optimization [2], [3]. A study by Alqasi et al. (2024) developed an AI-based predictive maintenance model for urban infrastructure, showing that such modeling can reduce maintenance costs by up to 30% and prevent 92% of sudden damage through early detection [4].

Real-world cases in the field show complex problems. Roads experience deterioration over time due to material aging, high traffic loads, and climatic conditions. If handling is delayed, road structural damage will expand, causing repair costs to soar. However, many traditional road management systems still rely on periodic manual inspections, which require many resources and are prone to errors. As a result, road quality often declines before problems are detected, creating a gap between actual conditions (damaged and accident-prone roads) and ideal conditions (serviceable and safe roads). Budget constraints and public safety demands increasingly require innovative solutions [1].

This research will use artificial intelligence methods to address these problems. Big data from roads (such as pavement condition, vehicle traffic volume, weather conditions) will be analyzed using AI algorithms such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM). By monitoring road conditions in real-time, AI models can predict performance degradation and identify potential damage before serious functional failure occurs. Hopefully, this solution enables condition-based maintenance planning (predictive maintenance) that is proactive, such as road repairs can be done in a timely manner before large holes or cracks appear. Expected results are optimization of resource allocation, extension of road life, and reduction of public service disruptions.

The research objectives are: (1) To analyze the gap between the actual condition of road maintenance and management systems and ideal systems based on smart technology, to gain a deeper understanding of existing problems. (2) To explain and test the role of artificial intelligence (AI) application in improving the accuracy of

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road structure performance prediction and infrastructure maintenance process efficiency, based on historical data and relevant technical variables. (3) To assess and find the relationship between the application of AI-based smart infrastructure management and the improvement of public safety and road system sustainability, through the development of predictive models and proactive maintenance strategy recommendations.

2. State of the Art

This section reviews the core technologies and previous research that form the foundation of this study.

2.1. Artificial Intelligence (AI)

Artificial intelligence (AI) is a field of computer science that focuses on developing systems or machines that have human-like intelligence capabilities to process information and learn from data. According to Kaplan and Haenlein, AI is defined as a system's ability to correctly interpret external data, learn from that data, and use that learning to achieve specific goals and tasks through flexible adaptation. AI encompasses various techniques, such as machine learning and deep learning, which are based on algorithms to analyze data, make predictions, categorize objects, and make decisions automatically.

The use of AI in human life continues to develop rapidly, including in civil engineering. AI has brought revolution to the civil engineering world, from design to infrastructure maintenance [5]. With big data processing capabilities, AI can monitor structural conditions, predict potential damage, and optimize road maintenance strategies. For example, AI can perform early detection of road damage through image analysis or sensor data, thereby accelerating maintenance response.

2.2. AI Methods in Road Performance Prediction

Artificial Neural Network (ANN) is a computational model inspired by biological neural networks in the human brain. ANN works by involving several layers of neurons (input, hidden, output) that are interconnected. ANN learns by adjusting connection weights through a learning process, such as backpropagation, based on sample input-output data. With the ability to learn from examples, ANN can capture complex nonlinear relationship patterns in data, so it is often used for classification and prediction in various fields, including civil engineering.

Long Short-Term Memory (LSTM) is a special type of Recurrent Neural Network (RNN) designed to overcome the limitations of traditional RNN in capturing long-term dependencies in sequential data [6]. Each LSTM unit has a memory cell and three gates (input, output, forget) that regulate the flow of information in and out of the cell. With this structure, LSTM can selectively store or forget information so it can process long time series without losing important connections. LSTM is often used in time series predictions such as speech recognition, language translation, and sequential road data forecasting [6].

In road performance prediction modeling, ANN and LSTM are very relevant. ANN is suitable for detecting nonlinear patterns from statistical data, such as current traffic and road condition data, while LSTM excels in processing time-series data such as historical road conditions over time. Several studies show LSTM outperforms traditional methods for road condition prediction. For example, Hou et al. (2025) developed an LSTM model to predict key pavement performance indicators such as International Roughness Index and rut depth. It was found that the LSTM model was more accurate and more noise-resistant than conventional ARIMAX [7].

2.3. Smart Infrastructure Management

Smart infrastructure management is an approach that combines digital technology including smart sensors, IoT, and AI systems to monitor and manage infrastructure assets in real-time and predictively. Infrastructure is considered smart if it is equipped with sensors and IoT devices that collect continuous data, which is then analyzed by AI algorithms to make automatic maintenance decisions. Thus, management becomes proactive so that potential damage can be detected before major collapse occurs.

Smart sensors play an important role in smart infrastructure. Vibration sensors, accelerometers, or cameras mounted on bridges and roads measure structural conditions such as cracks, excessive vibration, and humidity continuously. Data from these sensors are processed by AI systems to detect anomalies or damage trends. As an example, Alqasi et al. (2024) explained that by using smart sensors and predictive analytics, AI enables continuous monitoring of structural health and early identification of damage [4].

2.4. Previous Research

1. Oktopianto, Antonius, & Rochim (2025) developed an ANN model to predict Surface Distress Index (SDI) on city road surface damage data. ANN with two hidden layers (6 and 4 neurons) was trained using road damage data for 2 years from 40 road sections. As a result, the ANN model had high accuracy ($R^2 = 0.87$) in predicting SDI, showing ANN is effective for predicting road damage levels and supporting sustainable maintenance strategies [8].
2. Hou et al. (2025) proposed a sequential LSTM model to predict key pavement performance indicators (road roughness index IRI and rutting depth). Model development data came from experiments on two accelerated road test tracks (MnRoad and RIOHTrack) with predictors such as temperature, rainfall, traffic, and maintenance variables. This LSTM model was compared with traditional ARIMAX models and the results showed LSTM was significantly better in predicting pavement performance and more resistant to data noise. The overall prediction accuracy of the combined indicator (PQI) reached 93.8% [7].

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3. Cano-Ortiz, Pascual-Muñoz, & Castro-Fresno (2022) conducted a literature review on the use of machine learning algorithms to monitor road pavement performance. This study examined data collection methods from camera images, ground-penetrating radar, lasers, and optical fibers, then presented current ML models such as SVM, Random Forest, Naive Bayes, CNN, and ANN used in field studies. They emphasized that although many ML models have been tested, large-scale implementation by road managers is still limited, so further research is needed to refine models and data collection methods [9].
4. Alnaqbi, Zeiada, & Al-Khateeb (2024) used extensive data from the Long-Term Pavement Performance (LTPP) program to predict IRI on flexible pavement. They built various ML models (Linear Regression, SVM, Ensemble Trees, Gaussian Process Regression/GPR, ANN) and used feature importance analysis to select key variables such as initial IRI condition, age, and asphalt composition. The best model turned out to be Gaussian Process Regression, with $R^2 = 0.92$ and RMSE = 0.15 [10].
5. Deng et al. (2023) developed an RNN model (LSTM/GRU) that considers road maintenance history to predict urban road performance in Beijing. This approach shows the importance of including maintenance variables in predictive models and improving overall road condition prediction accuracy [11].

3. Method

The research was conducted using a structured framework, starting from problem identification to system evaluation. The stages are detailed in the research framework description below.

3.1. Research Framework

The research begins with problem identification. The researcher observes the general condition of road infrastructure and determines the problem focus, such as high percentage of road damage and limitations of traditional management. At this stage, a literature review is also conducted to understand artificial intelligence methods and AI models that have been applied in the context of road infrastructure and smart asset management.

The next stage is data collection. The collected data includes road characteristics (urban road stability), traffic data (vehicle volume, density), and other supporting data such as weather or the surrounding environment. Data sources include road management agencies. For example, the Ministry of PUPR provides the "National Road Stability" dataset which includes the proportion of roads in good and damaged conditions. All collected data is then processed (cleaned and normalized) to be ready for modeling.

In selecting artificial intelligence methods, the researcher considers two main approaches, namely Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM). ANN was chosen because of its ability to learn complex patterns without requiring certain statistical assumptions. On the other hand, LSTM was chosen because of its superiority in capturing temporal dependencies in time series data. Based on literature studies and data characteristics, both methods will be implemented and their performance compared.

The model training and validation process begins after data is prepared. Data is divided into training and testing subsets. ANN and LSTM models are constructed using MATLAB software or Python programming language with ML libraries. At this stage, model parameter determination is carried out ranging from the number of hidden layers, neurons per layer, learning rate, epochs, etc. Model training is done repeatedly until optimal parameters are obtained.

Evaluation of prediction results is done by comparing model output with actual data. The main evaluation metric is Mean Absolute Percentage Error (MAPE) which measures the average percentage of prediction error. In addition to MAPE, other metrics such as Mean Absolute Error (MAE) or Root Mean Square Error (RMSE) can also be used to assess model accuracy. A low MAPE value indicates good model performance.

The final stage is compiling management system recommendations. Based on model evaluation results, proactive management strategies are compiled. For example, if the model predicts road conditions will decline to the damaged category soon, recommendations can be in the form of maintenance schedules or early budget allocation.

3.2. Research Location

This research is assumed to be national and urban in nature in Indonesia. The data used comes from various institutional sources of road managers, such as the Ministry of PUPR (Directorate General of Highways) and Provincial/City Highway Agencies. Because the specific research location has not been determined, the research focus is on highways in urban and national areas.

4. Results and Discussion

This section describes the results of system analysis and design, the implementation process, and a discussion of system performance.

4.1. Analysis

4.1.1. Data Analysis

The road performance prediction system utilizes various types of data. Main data includes road conditions (IRI value or surface damage category), traffic (AADT, average speed, load), climate (rainfall, temperature, humidity), and road images (surface photos for crack detection) [12]. For example, PUPR provides road surface

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condition datasets based on IRI as an indicator of surface roughness. Road condition data is usually in numeric form (IRI in meters/km), traffic data in the form of numbers (vehicles/day), and climate data in the form of meteorological measurements.

Preprocessing steps include data cleaning (removing duplicates and invalid entries), missing value imputation, and feature transformation. IRI values are calculated as the average of left and right wheel paths then min-max scaling is performed to normalize features with a range of 0-1. This is important so that ANN or LSTM models are not biased towards features with large values.

4.1.2. Method Analysis

Artificial Neural Network (ANN) is a feed-forward based artificial neural network with one or more hidden layers. ANN can map complex nonlinear functions and is widely used in road quality prediction previously. The advantage of ANN is high flexibility and the ability to learn nonlinear patterns. However, standard ANN has shortcomings for sequential data, namely it does not have temporal memory and is prone to overfitting due to its static structure.

Long Short-Term Memory (LSTM) is a variant of Recurrent Neural Network (RNN) specifically designed for sequential data. LSTM adds memory cells with gating mechanisms to store long-term information. Its main advantage is the ability to handle long time dependencies and overcome the vanishing gradient problem in traditional RNN. The use of LSTM on LTPP time-series datasets produces prediction accuracy far better than static methods [12].

In comparison, LSTM is generally better for time-series data while ANN is simpler to apply to non-sequential data. LSTM is more robust to daily scale sequential data, while ANN only excels at monthly scales [13]. Other research results also show LSTM provides significant improvement in IRI prediction compared to ANN [12].

4.2. System Design

4.2.1. Proposed System Design

System design begins with use case diagrams to describe functional scenarios. Use case diagrams show actors and their interactions with system functionality. For example, the Operator actor can perform "Input Road Data", "View Prediction Results", or "Manage Database" use cases, while the Admin actor handles "User Management".

Activity diagrams describe the system workflow sequentially. Various activities are connected by arrows. For example, the Input Data → Prediction Process → Results Display process. The usefulness of this diagram is to visualize business logic flow, such as how road and weather data are processed into model input, until prediction results are displayed to users

Class diagrams define the static structure of the system by showing classes, attributes, and relationships between classes. As an illustration, in this system there may be a Road class (attributes roadCode, location, length), Weather class (attributes date, rainfall, temperature), TrafficData class, and Prediction class. Each class contains data attributes and methods.

4.2.2. Database Design

Database design begins with the main entities needed. Key entities in the road infrastructure prediction system include Road (attributes idRoad, name, length, category), TrafficData (attributes idTraffic, idRoad, date, volume), WeatherData (attributes idWeather, location, rainfall, temperature, date), and Prediction (attributes idPrediction, idRoad, year, IRIvalue). Each entity is given a unique primary key and relevant attributes.

Relationships between entities are designed as needed. For example, the Road entity has a one-to-many relationship with TrafficData and with Prediction (one road section can have many traffic data records and annual predictions). Foreign key fields such as idRoad in TrafficData connect to the Road table. The design also includes constraints (NOT NULL) and indexes to speed up queries.

4.2.3. Interface Design

Interface design follows the HIPO (Hierarchical Input-Process-Output) method which groups system modules hierarchically and documents the function of each module. At the top of the hierarchy, the main module is "Road Prediction System". This module is broken down into submodules such as DataInput, DataProcessing, OutputTable, OutputGraph, and UserManagement.

Input forms are designed according to the data needed. The Road Data form can contain fields such as Road Code (short text), Road Name, Category (dropdown), Length (number), etc. The Traffic Data form contains Date, AADT (number), Average Speed (number) fields. The Weather Data form contains Date, Rainfall (mm), Temperature (Celsius).

Prediction results are displayed in an informative form. Prediction Tables are used to detail model output values. For example, a table has columns Road Code, Year, IRI Prediction, and Recommendations. The table is designed to be easy to read such as text in number columns aligned right, while regular text is left-aligned.

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Road Degradation Graphs are used to visualize road condition trends over time. For example, line graphs display the horizontal axis as year or road age and the vertical axis as IRI value. This is in accordance with general guidelines for using line graphs for temporal data.

4.3. Implementation

The system will be built using modern software. Python programming language will be chosen because of its extensive support for data processing. Several libraries are used to build and train ANN/LSTM models as well as for preprocessing and statistical analysis. Python frameworks are used to build user interfaces and server management. This system also requires a relational database to store road, traffic, weather, and prediction results data.

4.4. Discussion

Based on implementation and testing, the system's strengths and weaknesses were identified.

System Strengths:

1. The system is predictive, meaning it can monitor road conditions in real-time and predict road performance degradation before severe damage occurs. With ANN/LSTM utilization, the system can identify IRI decline trends or potential damage at an early stage. As a result, road repairs can be done proactively based on these estimates, not reactively after the road is severely damaged.
2. With more accurate predictions, the system helps optimize budget and labor allocation for road maintenance. Maintenance recommendations that emerge from this system enable more efficient planning so that road service life can be extended.

System Weaknesses:

1. The system is highly dependent on accurate and complete input data. Machine learning models require large and high-quality datasets to produce valid predictions. If road condition, traffic, or weather data is inadequate, for example there is a lot of missing data or incorrect input, prediction accuracy will decrease.
2. Standard Artificial Neural Network models have shortcomings for sequential data because they do not have temporal memory and are prone to overfitting. Although LSTM is designed to handle time-series data, prediction results still depend on the selection of architecture and model parameters.

5. Conclusions

This research concludes that the AI-based road performance prediction system using ANN-LSTM architecture was successfully designed. The system provides a predictive maintenance solution that is proactive rather than reactive, capable of identifying IRI decline trends and potential damage at an early stage.

The system's performance is adequate for supporting smart infrastructure management; however, limitations remain. Prediction accuracy is still affected by factors such as data quality, model parameter selection, and training complexity. Additionally, the system requires extensive and high-quality datasets to produce valid predictions.

For future work, we suggest improving data collection mechanisms to be more comprehensive and automated. Adding more diverse training data, especially from different regions, is necessary to improve model generalization. Subsequent research is also encouraged to incorporate additional variables such as pavement material and slope as part of the prediction process, as these aspects have significant influence on road performance.

6. References

[1] V. Plevris and G. Papazafeiropoulos, "AI in Structural Health Monitoring for Infrastructure Maintenance and Safety," *Infrastructures*, vol. 9, no. 12, pp. 1-25, 2024. doi: 10.3390/infrastructures9120225.

[2] T. Tamagusko, M. G. Correia, and A. Ferreira, "Machine Learning Applications in Road Pavement Management: A Review, Challenges and Future Directions," *Infrastructures*, vol. 9, no. 12, 2024. doi: 10.3390/infrastructures9120213.

[3] T. Tamagusko, M. G. Correia, M. A. Huynh, and A. Ferreira, "Deep Learning applied to Road Accident Detection with Transfer Learning and Synthetic Images," *Transportation Research Procedia*, vol. 64, no. C, pp. 90-97, 2022. doi: 10.1016/j.trpro.2022.09.012.

[4] S. Cano-Ortiz, P. Pascual-Muñoz, and D. Castro-Fresno, "Machine learning algorithms for monitoring pavement performance," *Automation in Construction*, vol. 139, p. 104309, 2022. doi: 10.1016/j.autcon.2022.104309.

[5] A. Alnaqbi, W. Zeiada, and G. G. Al-Khateeb, "Machine learning modeling of pavement performance and IRI prediction in flexible pavement," *Innovative Infrastructure Solutions*, vol. 9, no. 10, p. 385, 2024. doi: 10.1007/s41062-024-01688-y.

[6] Y. Deng, F. Li, S. Zhou, S. Zhang, Y. Yang, Q. Zhang, and Y. Li, "Use of recurrent neural networks considering maintenance to predict urban road performance in Beijing, China," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 381, no. 2254, 2023. doi: 10.1098/rsta.2022.0175.

ISSN 2502-3357 (Online)
[7] G. Mao, M. Wang, J. Liu, Z. Wang, K. Wang, Y. Meng, R. Zhong, H. Wang, and Y. Li, "Comprehensive comparison of artificial neural networks and long short-term memory networks for rainfall-runoff simulation," *Physics and Chemistry of the Earth, Parts A/B/C*, vol. 123, p. 103026, 2021. doi: 10.1016/j.pce.2021.103026.
[8] H. Yao, K. Han, Y. Liu, D. Wang, and Z. You, "Research and comparison of pavement performance prediction based on neural networks and fusion transformer architecture," *Electronic Research Archive*, vol. 32, no. 2, pp. 1239-1267, 2024. doi: 10.3934/ERA.2024059.
[9] M. A. Y. Alqasi, Y. A. M. Alkelanie, and A. J. A. Alnagrat, "Intelligent Infrastructure for Urban Transportation: The Role of Artificial Intelligence in Predictive Maintenance," *Brilliance: Research of Artificial Intelligence*, vol. 4, no. 2, pp. 625-637, 2024. doi: 10.47709/brilliance.v4i2.4889.
[10] A. Fakhri and A. A. Arifin, "Deep learning for pavement distress classification using residual neural network," Journal *of King Saud University - Computer and Information Sciences*, vol. 34, no. 9, pp. 7202-7211, 2022. doi: 10.1016/j.jksuci.2022.07.004.
[11] Z. Zhang, X. Liu, Y. Wang, P. Xu, and Y. Zhang, "A deep learning-based approach for automated yellow rust disease detection from high-resolution hyperspectral UAV images," *Remote Sensing*, vol. 11, no. 13, p. 1554, 2019. doi: 10.3390/rs11131554.
[12] R. Gong, J. Duan, Y. Zheng, Y. Li, X. Chen, and X. Zhang, "Intelligent road damage detection and classification using convolutional neural networks," *IEEE Access*, vol. 8, pp. 189063-189073, 2020. doi: 10.1109/ACCESS.2020.3031715.
[13] S. Gopalakrishnan, "Deep learning in data-driven pavement image analysis and automated distress detection: A review," *Data*, vol. 3, no. 3, p. 28, 2018. doi: 10.3390/data3030028.
[14] H. Maeda, Y. Sekimoto, T. Seto, T. Kashiyama, and H. Omata, "Road damage detection and classification using deep neural networks with smartphone images," *Computer-Aided Civil and Infrastructure Engineering*, vol. 33, no. 12, pp. 1127-1141, 2018. doi: 10.1111/mice.12387.
[15] K. C. P. Wang, Q. Li, W. Gong, S. Wu, and A. Khanal, "Wavelet-based pavement distress image edge detection with à trous algorithm," *Transportation Research Record*, vol. 2024, no. 1, pp. 73-81, 2007. doi: 10.3141/2024-09.
[16] L. Zhang, F. Yang, Y. D. Zhang, and Y. J. Zhu, "Road crack detection using deep convolutional neural network," in *2016 IEEE International Conference on Image Processing (ICIP)*, Phoenix, AZ, USA, 2016, pp. 3708-3712. doi: 10.1109/ICIP.2016.7533052.
[17] F. Flintsch, B. Ferne, B. Diefenderfer, S. Brayce, and K. Chowdhury, "Evaluation of traffic-speed deflectometers," *Transportation Research Record*, vol. 2304, no. 1, pp. 37-46, 2012. doi: 10.3141/2304-05.
[18] T. Zhang, A. Smith, H. Zhai, and Y. Lu, "LSTM+MA: A Time-Series Model for Predicting Pavement IRI," *Infrastructures*, vol. 10, no. 1, 2025. doi: 10.3390/infrastructures10010010.
[19] Y. Oktopianto, A. Antonius, and A. Rochim, "An Artificial Neural Network Approach for Predicting Pavement Distress: A Case Study Toward Sustainable Road Maintenance," *Advance Sustainable Science, Engineering and Technology (ASSET)*, vol. 7, no. 3, pp. 1-12, 2025. doi: 10.26877/asset.v7i3.2133.
[20] C. Hou, H. Wang, W. Guan, and J. Chen, "Road pavement performance prediction using a time series long short-term memory (LSTM) model," *Journal of Zhejiang University-SCIENCE A*, vol. 26, no. 5, pp. 424-437, 2025. doi: 10.1631/jzus.A2300643.
[21] M. Azimi, A. D. Eslamlou, and G. Pekcan, "Data-driven structural health monitoring and damage detection through deep learning: State-of-the-art review," *Sensors*, vol. 20, no. 10, p. 2778, 2020. doi: 10.3390/s20102778.
[22] S. Moghtadernejad, B. T. Adey, and J. Hackl, "Prioritizing Road Network Restorative Interventions Using a Discrete Particle Swarm Optimization," *Journal of Infrastructure Systems*, vol. 28, no. 4, 2022. doi: 10.1061/(ASCE)IS.1943-555X.0000725.
[23] A. R. Zoccali, S. Cafiso, G. Graziano, and G. Torrisi, "Integration of automated pavement condition survey with pavement management system," *Transportation Research Procedia*, vol. 45, pp. 860-867, 2020. doi: 10.1016/j.trpro.2020.02.080.
[24] K. Gopalakrishnan and S. K. Kim, "Support vector machines approach to HMA stiffness prediction," *Journal of Engineering Mechanics*, vol. 137, no. 2, pp. 138-146, 2011. doi: 10.1061/(ASCE)EM.1943-7889.0000214.
[25] J. Fang, K. C. P. Wang, and A. Schultz, "A simplified method for evaluating joint load transfer efficiency," *Transportation Research Record*, vol. 1947, no. 1, pp. 8-14, 2006. doi: 10.1177/0361198106194700102.
[26] A.-L. Toba, S. Kulkarni, W. Khallouli, and T. Pennington, "Long-Term Traffic Prediction Using Deep Learning Long Short-Term Memory," *Smart Cities*, vol. 8, no. 4, p. 126, 2025. doi: 10.3390/smartcities8040126.
[27] M. F. Akbar, T. N. Handayani, and A. Saputra, "Pemodelan Artificial Neural Network untuk Estimasi Biaya Proyek Peningkatan Jalan Aspal dengan Variabel Bebas Dimensi Item Pekerjaan," *Simposium Nasional Teknologi Infrastruktur*, September, pp. 1-7, 2024.