International Journal of Transport Development and Integration
Vol. 7, No. 4, December, 2023, pp. 321-329
Journal homepage: http://iieta.org/journals/ijtdi

AI-Enabled Assessment of Roadway Integrity: Forecasting Bitumen Deformation and Road Stability Throughout the Lifecycle Under Traffic Impact

Sabahudin Vrtagic[1*], Milan Dordevic[2], Fatih Dogan[1], Muhammed Codur[1], Mario Hoxha[1], Edis Softic[3]

[1] College of Engineering and Technology, American University of the Middle East, Egaila 54200, Kuwait
[2] Higher Colleges of Technology Sharjah, University City, Sharjah P.O. Box 7947, United Arab Emirates
[3] University of Bihac, Technical Faculty, Irfana Ljubijankića bb, Bihać 77000, Bosnia and Herzegovina

Corresponding Author Email: Sabahudin.Vrtagic@aum.edu.kw

https://doi.org/10.18280/ijtdi.070406

Received: 26 October 2023
Revised: 30 November 2023
Accepted: 7 December 2023
Available online: 28 December 2023

Keywords:
regression, modeling erosion coefficients, simulation, back propagation, lath and nail method

ABSTRACT

Asphalt-paved Road junctions frequently encounter deformation and degradation challenges due to heavy vehicular traffic and varying climatic conditions, such as temperature fluctuations and precipitation. This study employs a multifaceted approach, incorporating a Multilayer Perceptron (MLP) model, ancillary machine learning techniques, and optimization methodologies, to address these challenges effectively. The primary objectives are the prediction and analysis of pavement deformation, the optimization of maintenance strategies, and the evaluation of road effectiveness. Our findings underscore the substantial contribution of heavy vehicles to road erosion and the profound impact of vehicular retention and braking at intersections. A Multilayer Perceptron (MLP) model is utilized to simulate future pavement degradation accurately at a specific intersection, leveraging real-time traffic flow data. This approach showcases the advantages of using real-world traffic data to model the lifecycle of asphalt dependencies dynamically at the intersection level. Mitigation of road deterioration is proposed via controlled traffic flow and optimization of relevant parameters, such as minimization of intersection wait times. The integration of machine learning substantially enhances road conditions and reduces vehicular waiting times at intersections. The implementation of this study's findings in pavement design and preservation practices could enable transportation authorities to improve road safety, reduce maintenance costs, and decrease the incidence of road accidents. Overall, this paper presents a comprehensive approach towards sustainable and efficient road infrastructure management, highlighting the potential of AI in tackling pressing infrastructure challenges.

1. INTRODUCTION

Investigating the influence of traffic flow on the deformation of asphalt surfaces constitutes a significant domain within transportation engineering. Insight into the interaction between vehicles and asphalt deformation can inform the creation of more durable, cost-efficient roadways, given that road degradation is intrinsically linked to traffic flow dynamics.

Presently, road construction relies on robust calculations encompassing weather conditions and vehicular volume, with an assumed minimum lifespan of roadways spanning ten to thirty-five years. However, this study challenges these assumptions, revealing that the alteration of traffic flow at intersections significantly impacts road erosion, rendering calculations based on these assumptions potentially flawed. Particularly, the research indicates that a ten-year lifespan might not always be a realistic expectation for road segments at intersections.

To explore this phenomenon, data were extracted and processed from video footage to procure real-time vehicle movement and asphalt impact information. Subsequent analysis via computational algorithms, such as the backpropagation algorithm, unveiled patterns and correlations between traffic flow and asphalt deformation. Consequently, this analysis facilitated the identification of key factors influencing asphalt deformation and contributed to the development of predictive models for estimating asphalt lifespan. The results of this research are modeled using machine learning (ML) technique with the previously mentioned limitations.

The emphasis on road intersections in this study is justified by several factors:

- High Traffic Volume: Intersections, being convergence points of multiple roads, handle higher vehicular volume than other road segments, thereby increasing pavement strain and susceptibility to deformation.
- Complex Traffic Patterns: Intersections are characterized by intricate driving patterns, encompassing frequent acceleration, deceleration, and changes in direction.

These abrupt shifts may induce pavement wear and deformation.

- Vehicle Braking and Acceleration: Rapid stopping and acceleration at intersections exert stress on the pavement, potentially accelerating asphalt degradation.
- Safety Concerns: Deformations in asphalt at junctions can result in uneven surfaces and potholes, escalating the risk of accidents, particularly in adverse weather conditions [1].
- Maintenance Costs: Intersections' susceptibility and high traffic volume necessitate regular, intensive maintenance, thereby increasing costs for road authorities.
- Improved Intersection Design: An understanding of the impact of traffic flow on pavement deformation at intersections can inform the development of more durable and safer intersection designs.

Overall, studying the impact of traffic flow on asphalt surface deformation at road intersections provides valuable insights into optimizing road design, reducing maintenance costs, and promoting safer and more efficient transportation infrastructure [2].

Although environmental factors do contribute to asphalt degradation, their exclusion in this study is justified by the micro-scale analysis focus on a singular junction. This approach allows for a detailed exploration of the direct impact of traffic flow patterns, eliminating potentially confounding factors. This study's structure is as follows: the introduction and literature review provide a succinct overview of the current research landscape. The methodology section outlines the approaches adopted for future erosion rate calculations. The results section discusses the findings and their implications using the proposed models. The conclusion offers distinct suggestions and directions for future research.

2. MATERIALS AND METHODS

2.1 Introduction to asphalt deformation and lath and nail method

Rutting deformation, specifically in asphalt pavement, is a significant issue in the transportation sector because of its negative impact on road safety and performance. The study incorporated meteorological data implicitly into the on-site measurements performed at an actual intersection. In light of the ever-changing and unpredictable characteristics of the environment, we made the decision to exclude meteorological data as explicit input parameters in our analysis. The determination is based on the realistic difficulties that arise when striving to regulate or influence meteorological circumstances while conducting field observations. Our study relied on the real-world changes caused by the different weather conditions at the junction. The dataset utilized for research already incorporates the impact of weather on pavement conditions, accurately depicting the intersection's genuine performance under varying environmental conditions. This methodology guarantees a comprehensive and accurate comprehension of how the pavement reacts to the intricate interaction of environmental elements. This, in turn, enhances the credibility and practicality of our discoveries in real-life scenarios.

The "lath and nail method" is one fundamental technique used to comprehensively evaluate pavement erosion. It precisely measures the depth of cracks and abnormalities on asphalt surfaces. This approach entails using an aluminum lath with precise dimensions and a specified cross-section, together with accurate measurements obtained by inserting nails into the pavement.

The aluminum lath is meticulously chosen for its robustness and pliability, enabling it to effortlessly adapt to the shape of the pavement. For measurements to be consistent and accurate, its precise dimensions are vital. An unchanging point of reference for determining the depth of diverse pavement features is the cross-section of the lath.

In order to implement the "lath and nail method," scientists strategically place nails into the pavement at predefined intervals all throughout the length of the lath. These nails penetrate asphalt cracks, holes, and irregularities to indicate depth. Subsequently, the profundity of these insertions is quantified, yielding significant information regarding the degree of degradation or impairment to the pavement surface.

By utilizing this approach, scientists are capable of quantifying and analyzing the extent of erosion, thereby facilitating the identification of potential areas that require maintenance or restorations. The lath and nail method facilitates a thorough comprehension of pavement condition through the systematic measurement of crack and irregularity depths. This knowledge is crucial in the formulation of efficient maintenance strategies and in guaranteeing the durability and safety of road surfaces.

Numerous studies have been carried out in order to gain an understanding of the underlying causes and make predictions regarding the deformation that big vehicle loads will have on asphalt surfaces. One of which is a prediction model for asphalt pavement deformation using artificial neural networks. The model considered various environmental factors, such as temperature and rainfall, in addition to traffic volume. The model accurately predicted heavy vehicle load asphalt pavement deformation [3, 4]. Laboratory tests examined asphalt's rutting deformation under heavy-load vehicles [5]. Tire pressure and axle load impacted rutting. Axle load and tire pressure affected asphalt pavement rutting, according to the findings.

Similarly, the study [6] presented a prediction model for asphalt pavement deformation using an artificial neural network. Different data parameters were used to train and validate the model. Results indicated that the model was able to accurately predict the deformation of asphalt pavement under heavy vehicle loads. The support vector machine (SVM) optimized using a genetic algorithm (GA) and created by the study [7] predicts asphalt pavement rutting based on field test data and was evaluated using mean absolute error, root mean square error, and correlation coefficient. The model accurately predicted asphalt pavement rutting. Likewise, the study [8] investigated asphalt pavement deformation using a genetic algorithm optimized back-propagation neural network. Root mean square error and correlation coefficient were used to evaluate the field test-based model. The findings proved that the model accurately predicted the deformity of asphalt pavement.

Another study investigated the relationship between traffic flow and asphalt deformation using video data extraction and processing. This study analyzed the data with a back-propagation algorithm to determine the impact of traffic flow on asphalt deformation. Findings indicated that traffic flow significantly affected asphalt deformation, and the model had good accuracy in predicting the deformation [9, 10]. Finally, references [11, 12] studied the effects of vehicle speed on rutting deformation of asphalt pavement using real-time traffic data. The study used a regression analysis to identify the relationship between vehicle speed and rutting deformation. Deformation caused by rutting was found to be significantly affected by vehicle speed.

2.2 Different types of testing and mixture effects

The Yong study analyzed the effects of graphene on asphalt's performance and the effectiveness of Stone Matrix Asphalt (SMA) in pavement. Based on a Gansu Province highway project, graphene enhanced asphalt was used [13]. To prepare CRCM asphalt, which includes CRCM-SBS, CRCM-Sasobit/BRF, and CRCM-RARX, the same amount of crumb rubber and various amounts of composite additives were added [14]. Long-term road performance is assessed and predicted for self-ice-melting asphalt surfaces equipped with salt-storage materials in this lab study [15]. Employing Dynamic Mechanical Analysis, MA tested three variations of an asphalt mixture used for the surface course and six standard RIOH Track structures [16]. Zhang et al. [17] proposes a new fatigue life prediction that takes temperature load into account, which could be disregarded in inspections of steel deck welds on suspension bridges subjected to dynamic vehicle load. Liu makes use of the data that is reflective of the weather for a period of twenty-four hours during the summer [18]. Two-dimensional image technology obtains air-void data acquired from rutting sample sections with varied loading cycles (500, 1000, 1500, 2000, 2500, and 3000 times) [19]. Wu intends to conduct a comprehensive investigation to determine the law of skid resistance attenuation of SMA pavement [20]. Langa examines how high-density polyethylene (HDPE) modified asphalt binder changes in terms of its physical, rheological, and thermal properties after soybean oil is added [21].

To aid in the right decision-making processes, a long-term strategy for pavement preservation should include a thorough evaluation of the current road state. To predict flexible pavements' durability over time, the study [22] puts forward integrating Non-Destructive Testing (NDT) and ground truth data. Shaffie [23] proves RSM's statistical efficacy. Cao simulates the thermodynamic, diffusion, and adhesion effects of asphalt cement aging using molecular dynamics [24]. The study [25] carried out a model-based farm-scale exploratory study using two farms as case studies. In the study [26], researchers looked at 15 extracts from the peels of 5 different cultivars to determine their phytochemical makeup, antioxidant activity, tyrosinase influence, in vitro SPF, and cytotoxicity. As the service life increases, the actual load-carrying capacity of bridges gradually decreases due to the combined action of the environmental corrosion and repeated vehicle loads, resulting in shortened bridge service life. Nie studied fatigue reliability analysis and traffic load control of steel bridges based on artificial neural network [27]. The fatigue reliability index of a steel girder bridge over its whole life is investigated based on artificial neural networks. Hussein wants to emphasize the significance of planning marsh management, which may revitalize the marshes' natural world before drying through the Center for Marsh Revitalization in southern Iraq [28]. Cepa presents the main types of sensors and their applications in tunnels [29]. As discussed in the study [30], assessing pavement condition effectively helps making good decisions and provides longer-lasting pavement mixes.

In conclusion, the materials and methods employed in this research, particularly the lath and nail method, have proven to be instrumental in comprehensively evaluating pavement erosion. With its aluminum lath of a specific length and cross-section, the lath and nail method yield's precise measurements which demonstrate wear, structural, and instability rutting. On-site measurements inevitably incorporate weather information because environmental conditions affect pavement deterioration and rutting. Although data on weather was not explicitly used as an input parameter for machine learning (ML) instruction, it was unambiguously accounted for in the real-world metrics used in the training process. The lath and nail method and on-site measurements implicitly include weather effects, improving research reliability and leading to more accurate erosion coefficients and robust pavement management strategies.

3. METHODOLOGY

3.1 Data collection

Traffic flow's effect on road conditions is the study's main objective. Machine learning algorithms are used to analyse and simulate traffic flow data. In order to measure different types of asphalt erosion or decay, different measuring methods can be applied [31, 32]. Research results focus on the lath and nail method and future erosion coefficient will be lath and nail method related. For the lath and nail method, the changes in the pavement are measured by using an aluminium lath that is 4 meters in length. Typically, they have a rectangular cross-section and are made of solid wood or light metal, leaving no room for speculation. It is crucial that the measuring lath has no fewer than two supports. Figure 1 displays a sand patch and lath-and-nail method.

Figure 1. Visualizing data collection with sand patch and lath/nail method

Samples and data are collected at the intersection of roads M223 and R363 near Tuzla, Bosnia and Herzegovina. The data is collected at the crossing point entrance from Tuzla city side where black-top thickness layers are 7 cm and 5 cm where the 5 cm layer is the best one liable for connection with the tire while the other one is obligated for the heap pressure taking care of, also the path width given to be 2.75 m and the black-top blend qualities given as BB11s for the top layer and AGNS 22sA for the base layer with the tampon thickness given in reach from 31 to 40 cm. For this location, the traffic flow data is obtained from two different sources.

First source is a video document source using road surveillance cameras with a 15-day period, which was used for sampling. A linear support vector machine model extracts vehicle number, class, speed, heading, and time from the recorded footage [10]. The weather and temperature factors are not considered as the measurements and modelling is performed on nearby lanes. Figure 2 depicts the detection of on-road vehicles in an area of interest, a key data collection point [10]. HOG and SVM gather data in the region of interest. HOG data includes boundaries from vehicle-free and vehicle present images.

Positive set is a region of interest with identified vehicles excluded from source recordings. Likewise, the negative set is no vehicles from roads, structures, etc. 2954 images of vehicles make up the positive training set. The negative training set has 2860 vehicle-free images. A 64x64 pixel resolution is applied to these images. We count the number of directions in each square. Find more than 9 directions. Each square has 8 pixels that show us which way things are pointing. We create histograms with 2 squares for every larger square. This results in a new, smaller image that depicts the various directions in the original image. It has a size of only 16 by 16 pixels.

HOG descriptor, spatial picture vector, and situated angles histogram make up element vector. With given details, a Linear SVM can precisely identify objects of significance and those that are not. 70% and 30% of the train and test sets received the new vector. The utilized clip sets have 98-100% precision [10].

As mentioned before from the video data, we have identified breakdown of vehicle's type, time, travel direction and stopping action at the intersection for the 15-day period.

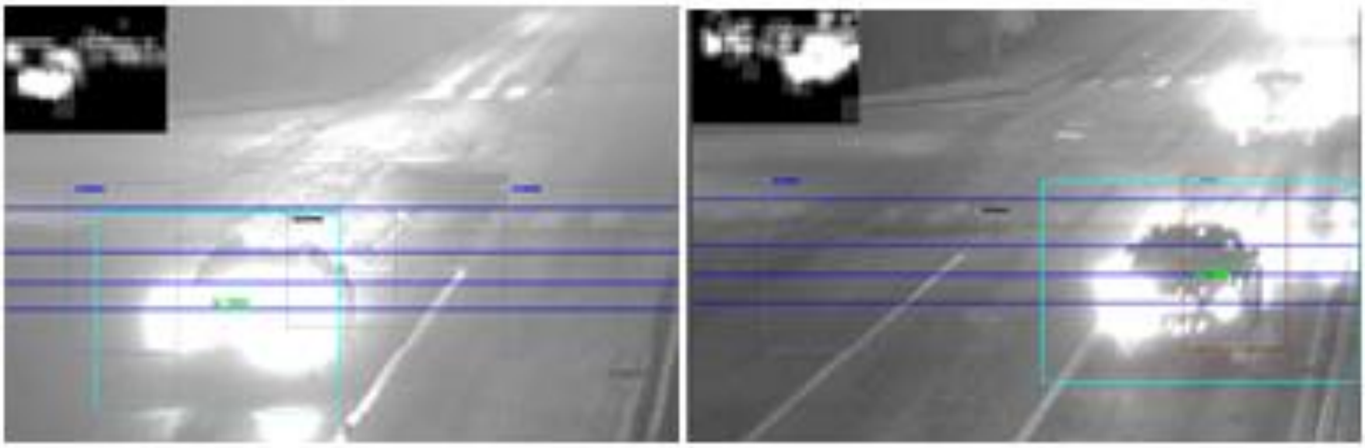

Figure 1. Linear support vector machine (Linear-SVM) vehicle detection and classification

Second source of traffic data is governmental sensor flow data between 10/26/2015-06/12/2020. The actual sensor flow measurements are taken on the main Tuzla-Sarajevo Freeway. The data contains type, number of vehicles, and direction of travel.

The input dataset is created by combining video data with traffic department sensor data and road erosion measurements as follows:

- Number of LW vehicles—The complete count of light vehicles (LW) for a given interval;
- HW vehicle count—The overall count of heavy vehicles (HW) for a particular period;
- Date range (h)—From 27.10.2015 to 12.06.2020, inclusive, to determine specified intervals;
- Time on the intersection/junction (h) for HW—Determined from footage data averages and multiplied by the total number of (HW) vehicles;
- Time on the intersection/junction (h) for LW—The total count of (LW) vehicles multiplied by the average value derived from video data;
- Number of HW that are coming to a full stop—Calculated with respect to the percentage amount;
- Road erosion (lath) Machine learning models use percentage assumptions;

Daily datasets are created for the two road intersection lanes. This study ignores weather and temperature because the lanes are adjacent. The total amount of records that comprise the final data set is 3382 days across the two lanes. Table 1 shows examples of the dataset based on daily left lane traffic flow [11].

Table 1. Overview of sample dataset (HW-Heavy vehicles, LW-Light vehicles) [10, 11]

Day	# of LW Vehicle	# of HW Vehicle	Time Period (h)	Time on Junction (h) HW	Time on Junction (h) LW	# of HW Going to a Complete Stop	Road Erosion (lath)
1	2977	225	24	0.87	9.74	51	0.021
2	6235	424	48	1.64	20.40	96	0.041
3	9423	625	72	2.42	30.83	142	0.062
4	12784	839	96	3.25	41.83	190	0.083
5	16018	996	120	3.86	52.41	225	0.103
6	18627	1069	144	4.15	60.95	242	0.124
7	21828	1251	168	4.85	71.42	283	0.145
8	24944	1437	192	5.57	81.62	325	0.166

3.2 Asphalt erosion measurement

With Lath measurement of 60 mm in 2020 used as output parameter, we have applied machine learning/ regression methods to develop a model for future erosion coefficient prediction.

3.3 Machine learning algorithms

Assuming linear decay, we have trained the model to associate the vehicle behaviour to road decay over time. We used decision tree, linear, random forest, and gradient boosting regression models [11].

Aim of research is to measure that impact by combining experimental and theoretical data sets and to apply machine learning methods (ML) or neural networks which are basic versions similar to a human brain that involve input, hidden and output layers. Our objective is to generate meaningful outputs for a provided input. After implementing different ML methods, which were tested out, results have shown that the multi-layer perceptron back propagation algorithm was able to correlate input and output data parameters [11]. The most common neural network approach is called a multi-layer perceptron (MLP). The neurons and hidden layer are arranged such that in each layer, the nodes only get inputs from the nodes in the previous layer and only send their outputs to the nodes in the next layer [33]. The input data set is traffic flow, and the output is road erosion. After running different error matrices, the MLP model was confirmed to be accurate and was used for future road erosion prediction. Throughout training, the MLP learns to recognize input-output correlations. MLP can learn a non-linear regression approximation from input variables and a target or output value. Figure 3 illustrates an MLP framework with a single concealed layer.

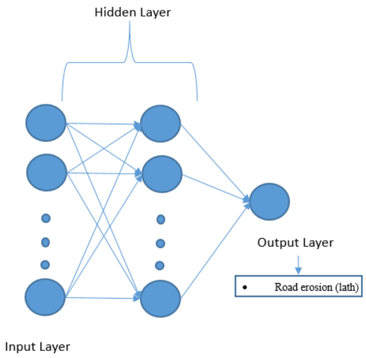

Figure 3. MLP with one hidden layer

The left side displays a set of input parameters denoted by x that are actually elements from Table 1. On-road degradation measured by lath-nail technique is the target value or Y(x). The hidden layer weights are recalibrated through the process of determining the amount by which the target values differ from the predicted values.

4. RESULTS AND DISCUSSION

Erosion of roads and how it affects the flow of traffic are discussed. The predicted "lath" measurements are put forward in this paper. Figure 4 depicts the MLP model's prediction for the "lath" dataset set compared to the actual statistical value.

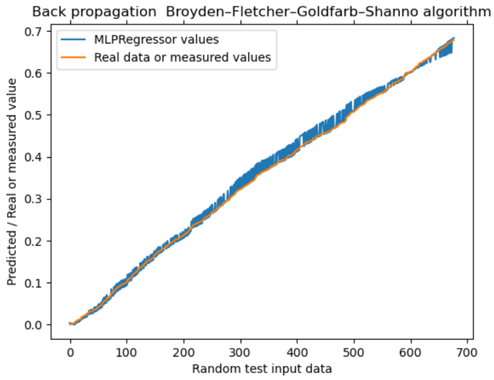

Figure 4. MLP "lath" predictions vs measured statistical value

The test stage includes 30% of the dataset, the calculation of the overall test set average absolute difference is 4.88%, $R2=0.9948$ and (Mean squared error) $MSE=0.00042$. Enhancements to the model are range and size dependent.

Figure 4 presents a prediction based on the normalized and linearized samples. The MLP projections use a dataset that has been arbitrarily divided into 70% training data and 30% testing data. Stochastic gradient descent is used for optimization, and the back-propagation algorithm is used for learning in the MLP model, with square error as the loss function. Table 2 gives a sample of test set. Last column (Predicted value) shows MLP results so we can compare to measured/statistical values Road erosion (lath). MLP takes rest of the table as input.

MLP prediction is accurate because predicted and measured values match. Heavy vehicles erode roads, as shown.

In Table 3, we show the result from right lane learned data set, meaning based on trained MLP model, we input new data points to understand the underlying impact of different inputs.

Table 2. MLP "lath" predictions by means of data normalization [10, 11]

# of LW Vehicle	# of HW Vehicle	Time Period (h)	Time on Junction (h) HW	Time on Junction (h) LW	# of HW Going to a Full Stop	Road Erosion (lath)	Predicted Value
11551382	1144688	40584	57.51	9787.6	10064	16	16
11551382	1144688	40584	100	19000	20000	30	30

Table 3. MLP "lath" predictions with right lane data [10, 11]

# of LW Vehicle	# of HW Vehicle	Time Period (h)	Time on Junction (h) HW	Time on Junction (h) LW	# of HW Going to a Full Stop	Predicted Value
0	0	0	0	0	0	0.021
1000000	100000	10000	400	100	100	0.41
1000000	100000	10000	4000	100	1000	7.18
1157278	156707	8544	575	4057	35385	13.5

After 4.6 years since the road was completed, the actual measurement of road erosion (lath) is 60 mm. The limitations are related to the dataset as only data from one intersection was used for modeling. Traffic can drastically alter street conditions. Using AI, we can predict the erosion and significantly improve control of the traffic flow to optimize road erosion due to the traffic. The real test uses measurements from the 2nd intersection. The introduction to a new intersection data is the next step before the model is applied. The "Lath" measurement can be seen in Figure 5.

With the "Lath" standard reading equal to 16 mm, procedure on how the "Lath" standard reading is done can be seen from the Figure 5.

In Figure 6, intersections sketch is provided with indicated points of observations.

Figure 2. "Lath" with measurements taken 75m from the intersection

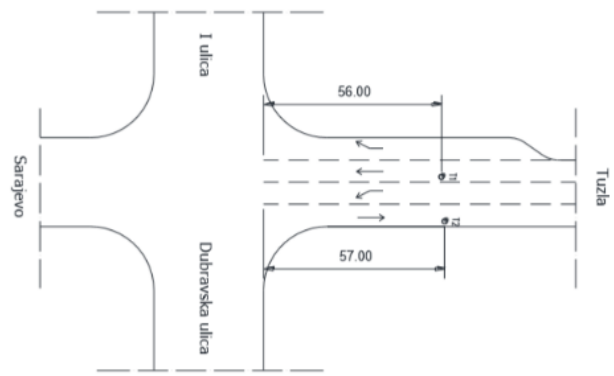

Figure 6. Intersection two sketch with indicated points of observations as T1 and T2 (meter)

All the measurements are summarized in Table 4, and all of them are for T1 location.

Both Table 4 input parameters are derived from traffic/statistical data, and the time interval is identical to that of the initial intersection. Table 4's first two parameters, determine the next three parameters. Since the first intersection was observed at 25 m and the second at 75 m, the values have to be considerably smaller than those from the first intersection. MLP Road erosion (lath) model prediction is 16.62 mm.

Finally, MLP that learned from right lane is used to predict the behavior in the left lane (shown in Figure 7 as T2 point). This impact is shown in Table 5 and Figure 8.

Table 4. The dataset derived from the new junction, with measurements taken 75 meters away [10, 11]

# of LW Vehicle	# of HW Vehicle	Time Period (h)	Time on Junction (h) HW	Time on Junction (h) LW	# of HW Going to a Full Stop	Road Erosion (lath)	Road Erosion (sand)	Road Erosion (SRT)
11551382	1144688	40584	4206	5049	40000	16.62	60	40

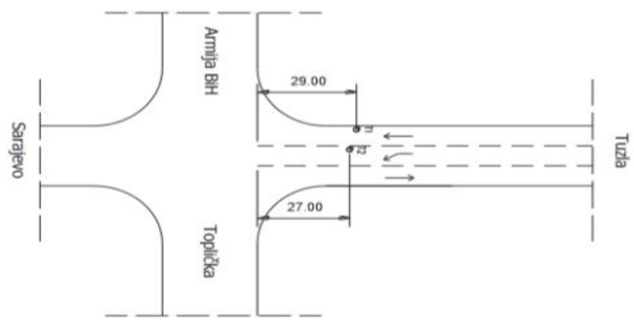

Figure 3. A visual representation of the intersection used. T1 lane is used to teach AI the erosion and T2 is used for prediction

The following inputs for heavy and light vehicles are calculated by applying the known spectrum of past years which is later used to calculate the number of vehicles in the future. Other input variables are calculated with respect to the average and percentage values for the left lane which is explained in detail before.

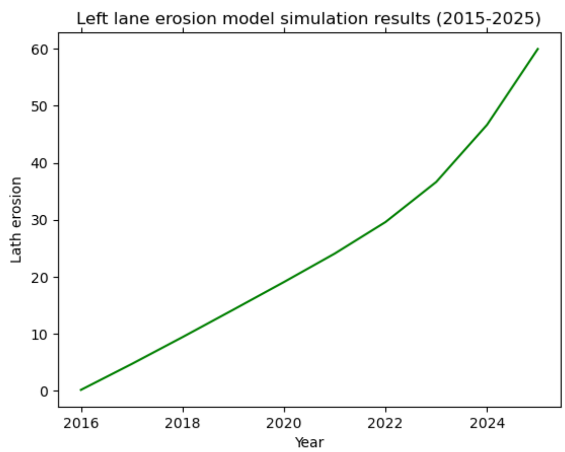

Figure 8. Model based visualization for the 10-year road erosion (lath)

Figure 8 is a visual representation of Table 5. After 7-8 years, asphalt characteristics are decaying much faster. With this result we can say that focusing on the road intersection segment quality and traffic fluidity is a higher priority than the other road segments.

Table 5. Road erosion (lath) value predictions for the left lane

Year	# of LW Vehicle	# of HW Vehicle	Time Period (h)	Time on Junction (h) HW	Time on Junction (h) LW	# of HW Going to a Full Stop	Road Erosion (lath)
2016	1260235	59554	8760	231.0	4123.6	9410	0.19
2017	2466064	116648	17520	452.4	8069.1	18431	4.73
2018	3703982	176937	26280	686.2	12119.7	27957	9.44
2019	4973366	242763	35040	941.5	16273.2	38357	14.25
2020	6244993	307140	43800	1191.1	20434.0	48529	19.10
2021	7544905	375202	52560	1455.1	24687.4	59282	24.10
2022	8873103	446951	61320	1733.3	29033.3	70619	29.63
2023	10229586	522386	70080	2025.9	33471.8	82538	36.66
2024	11614355	601507	78840	2332.7	38002.9	95039	46.68
2025	13027410	684314	87600	2653.8	42626.5	108122	59.98

The predicted outcomes that have been provided possess considerable importance within the domains of road maintenance and traffic management. Gaining insight into the relationship between traffic patterns and road erosion enables the implementation of proactive strategies to enhance road quality and durability. The MLP model possesses predictive capabilities that empower stakeholders, including transportation authorities and urban planners, to foresee forthcoming road deterioration and execute focused interventions. The scope of these interventions may encompass strategic road maintenance schedules and the optimization of traffic flow patterns, both of which ultimately contribute to the sustainability of infrastructure. Furthermore, an in-depth examination of the economic ramifications of these projections could assist policymakers in the judicious allocation of resources and the prioritization of high-impact areas. Fundamentally, a more comprehensive examination of the pragmatic implementations and ramifications of the outcomes of the MLP model would augment the research's worth in the domains of infrastructure management and transportation engineering.

Taking advantage of projected values enables the evaluation of pavement surface flatness by identifying areas of elevation or hollow that require grinding or filling. The High-Low Detector or Rolling Straight Edge gauges vertical deviations in increments of 0.125" (1 mm), with magnified readings spanning up to 0.25" (6.4 mm), indicating high or low areas. In accordance with these measurements, our methodology initially recorded a significantly elevated reading for low areas (60 mm) at the training intersection. The acceptable discrepancy between the predicted and actual values is clearly illustrated in Figure 4, where the mean absolute difference is recorded as 4.88%. Moreover, by including a wider range of intersections and fluctuating traffic flows, a more diverse dataset could potentially strengthen the model's ability to adapt to data fluctuations.

5. CONCLUSIONS

The progress made in artificial intelligence and image processing has created novel opportunities for engineering investigation, providing significant data for the assessment of road infrastructure and safety. The primary objective of this research endeavor was to evaluate the influence of heavy vehicles on the degradation of a particular intersection in Bosnia and Herzegovina. The study recognized the significant impact that vehicle retention and braking have on roadway conditions. Nevertheless, the research acknowledged certain constraints, such as its dependence on a restricted dataset, absence of meteorological data, and utilization of civil engineering measurements.

The research effectively utilized traffic data to develop a MLP model that predicted road erosion with remarkable precision, specifically in identifying heavy vehicles as substantial contributors to the erosion process. Recognizing the necessity for data originating from various intersections, the study put forth suggestions for future research avenues.

Assessment of newly collected intersection data from a distance of 75 meters yielded road erosion predictions. Placing considerable emphasis on the pragmatic implications for road maintenance and traffic management, the research underscored the model's capability to evaluate pavement surface flatness and pinpoint regions necessitating repair and maintenance.

It was emphasized that a diverse dataset is crucial for the robustness of a model, which suggests directions for future research. Looking into the future, it is imperative to thoroughly examine the effects of traffic flow management on road conditions while also integrating intelligent solutions to mitigate road erosion and improve safety. Additionally, for the benefit of a more sustainable future, research should investigate how climate conditions and vehicle fuel consumption affect road development strategies.

Further developments in AI and image processing technologies may enable future studies to analyze road deterioration and pavement deformation using larger datasets. By embracing state-of-the-art research and innovation, the engineering community possesses the capacity to make a positive impact on society and commuters alike by developing roads that are more intelligent, secure, and durable.

REFERENCES

[1] Gururaj, H.L., Janhavi, V., Tanuja, U., Flamini, F., Soundarya, B.C., Ravi, V.K. (2022). Predicting traffic accidents and their injury severities using machine learning techniques available online. International Journal of Transport Development and Integration, 6(4): 363-377. https://doi.org/10.2495/tdi-v6-n4-363-377

[2] Pratelli, A., Sordi, L., Fariña, A. (2021). Methods to generate an expected turning traffic flows matrix for road junction analysis available online. International Journal of Transport Development and Integration, 5(1): 1-14. https://doi.org/10.2495/tdi-v5-n1-1-14

[3] Keskin, M., Karacasu, M. (2022). Artificial neural network modelling for asphalt concrete samples with

boron waste modification. Journal of Engineering Researc, 10(4B). https://doi.org/10.36909/jer.8124

[4] Zhang, Q.S., Chen, Y.L., Li, X.L. (2009) Rutting in asphalt pavement under heavy load and high temperature. In Asphalt Material Char-acterization, Accelerated Testing, and Highway Management: Selected Papers from the 2009 GeoHunan International Conference. https://doi.org/10.1061/41042(349)6

[5] Nian, T.F., Li, J.G., Li, P., Liu, Z.C., Guo, R., Ge, J.G., Wang, M. (2022). Method to predict the interlayer shear strength of asphalt pavement based on improved back propagation neural network. Construction and Building Materials, 351: 128969. https://doi.org/10.1016/j.conbuildmat.2022.128969

[6] Issa, A., Samaneh, H., Ghanim, M. (2022). Predicting pavement condition index using artificial neural networks approach. Ain Shams Engineering Journal, 13(1): 101490. https://doi.org/10.1016/j.asej.2021.04.033

[7] Nguyen, H.L., Le, T.H., Pham, C.T., Le, T.T., Ho, L.S., Le, V.M., Pham, B.T., Ly, H.B. (2019). Development of hybrid artificial intelligence approaches and a support vector machine algorithm for predicting the marshall parameters of stone matrix asphalt. Applied Sciences, 9(15): 3172. https://doi.org/10.3390/app9153172

[8] Reza K.K., Amiri, N., Ghorbani, S., Souri, K. (2022). Prediction of concrete compressive strength using a back-propagation neural network optimized by a genetic algorithm and response surface analysis considering the ap-pearance of aggregates and curing conditions. Buildings, 12(4): 438, https://doi.org/10.3390/buildings12040438

[9] Chang, Y.L., Wang, Y.J., Sun, C., Zhang, P., Xu, W.Q. (2023). Day-to-day dynamic traffic flow assignment model under mixed travel modes considering customized buses. Sustainability, 15(6): 5440. https://doi.org/10.3390/su15065440

[10] Vrtagić, S., Softić, E., Ponjavić, M., Stević, Ž., Subotić, M., Gmanjunath, A., Kevric, J. (2020). Video data extraction and processing for investigation of vehicles' impact on the asphalt deformation through the prism of computational algorithms. Traitement du Signal, 37(6): 899-906. https://doi.org/10.18280/ts.370603

[11] Vrtagić, S., Ademović, N., Mujčić, E., Akšamija, Z., Kevrić, J., Avdaković, S., Volić, I. (2022). Traffic flow influence on the bitumen distortion through the back propagation algorithm based on the real on road formed dataset parameters. In Advanced Technologies, Systems, and Applications VI. IAT 2021, Lecture Notes in Networks and Systems, Springer, Cham, p. 316. https://doi.org/10.1007/978-3-030-90055-7_13

[12] Khan, M.I., Ullah, H., Khan, K.M., Khan, K., Arifuzzaman, Md. (2015). Evaluation of speed effect of vehicles on asphalt pavement. Implementing Innovative Ideas in Structural Engineering and Project Management, pp. 376-380. https://doi.org/10.14455/ISEC.res.2015.88

[13] Kotek, P., Kováč, M. (2015). Comparison of valuation of skid resistance of pavements by two device with standard methods. Pro-cedia Engineering, 111: 436-443. https://doi.org/10.1016/j.proeng.2015.07.113

[14] Yong, P., Tang, J.H., Zhou, F., Guo, R., Yan, J., Yang, T. (2022). Performance analysis of graphene modified asphalt and pavement performance of SMA mixture. PLOS ONE, 17(5): e0267225. https://doi.org/10.1371/journal.pone.0267225

[15] Gong, F.Y., Lin, W.J., Chen, Z.K., Shen, T., Hu, C.C. (2022). High-temperature rheological properties of crumb rubber composite modified asphalt. Sustainability, 14(15): 8999. https://doi.org/10.3390/su14158999

[16] Ansar, M., Sikandar, M.A., Althoey, F., Tariq, M.A.U.R., Alyami, S.H., Elsayed Elkhatib, S. (2022). Rheological, aging, and micro-structural properties of polycarbonate and polytetrafluoroethylene modified bitumen. Polymers, 14(16): 3283. https://doi.org/10.3390/polym14163283

[17] Zhang, H.H., Guo, R.H. (2022). Investigation of long-term performance and deicing longevity prediction of self-ice-melting asphalt pavement. Materials, 15(17): 6026. https://doi.org/10.3390/ma15176026

[18] Ma, Z.M., Wang, X.D., Wang, Y.Z., Zhou, X.Y., Wu, Y. (2022). Long-term performance evolution of RIOHTrack pavement surface layer based on DMA method. Materials, 15(18): 6461. https://doi.org/10.3390/ma15186461

[19] Xiao, X.H., Zhang, H.P., Li, Z.C., Chen, F.H. (2022). Effect of temperature on the fatigue life assessment of suspension bridge steel deck welds under dynamic vehicle loading. Mathematical Problems in Engineering, 2022: 1-14. https://doi.org/10.1155/2022/7034588

[20] Liu, P.F., Kong, X.R., Du, C., Wang, C.H., Wang, D., Oeser, M. (2022). Numerical investigation of the temperature field effect on the mechanical responses of conventional and cool pavements. Materials, 15(19): 6813. https://doi.org/10.3390/ma15196813

[21] Zhao, K., Yang, H.L., Wang, W.T., Wang, L.B. (2022). Characterization of rutting damage by the change of air-void characteristics in the asphalt mixture based on two-dimensional image analysis. Materials, 15(20): 7190. https://doi.org/10.3390/ma15207190

[22] Gkyrtis, K., Plati, C., Loizos, A. (2022). Mechanistic analysis of asphalt pavements in support of pavement preservation decision-making. Infrastructures, 7(5): 61. https://doi.org/10.3390/infrastructures7050061

[23] Shaffie, E., Jaya, R.P., Ahmad, J., Arshad, A.K., Zihan, M.A., Shiong, F. (2022). Prediction model of the coring asphalt pavement performance through response surface methodology. Advances in Materials Science and Engineering, 2022: 1-17. https://doi.org/10.1155/2022/6723396

[24] Cao, W., Fini, E. (2022). A molecular dynamics approach to the impacts of oxidative aging on the engineering characteristics of asphalt. Polymers, 14(14): 2916. https://doi.org/10.3390/polym14142916

[25] Aguerre, V., Chilibroste, P., Casagrande, M., Dogliotti, S. (2022). Exploring alternatives for sustainable development of mixed vegetable beef-cattle family farm systems in southern Uruguay. Agrociencia Uruguay, 26. https://doi.org/10.31285/agro.26.1098

[26] Ansar, M., Sikandar, M.A., Althoey, F., Tariq, M.A.U.R., Alyami, S.H., Elsayed Elkhatib, S. (2022). Rheological, aging, and microstructural properties of polycarbonate and polytetrafluoroethylene modified bitumen. Polymers, 14(16): 3283. https://doi.org/10.3390/polym14163283

[27] Gaweł-Bęben, K., Czech, K., Strzępek-Gomółka, M., Czop, M., Szczepanik, M., Lichtarska, A., Kukula-Koch, W. (2022). Assessment of Cucurbita spp. peel extracts as

potential sources of active substances for skin care and dermatology. Molecules, 27(21): 7618. https://doi.org/10.3390/molecules27217618

[28] Czarnecki, A.A., Nowak, A.S. (2008). Time-variant reliability profiles for steel girder bridges. Structural Safety, 30(1): 49-64. https://doi.org/10.1016/j.strusafe.2006.05.002

[29] Moharekpour, M., Liu, P., Oeser, M. (2022). Evaluation and improvement of the current CRCP pavement design method. Materials, 16(1): 358. https://doi.org/10.3390/ma16010358

[30] Hussein, A.A.K., Asal, A.A. (2023). Drying water and its impact on the vital system in the marshes of southern Iraq. In IOP Conference Series: Earth and Environmental Science, 1129(1): 012032. https://doi.org/10.1088/1755-1315/1129/1/012032

[31] Ergun, M., Iyinam, S., Iyinam, A.F. (2005). Prediction of road surface friction coefficient using only macro- and microtexture measurements. Journal of Transportation Engineering, 131(4): 311-319. https://doi.org/10.1061/(asce)0733-947x(2005)131:4(311)

[32] Bánhalmi, A., Bilicki, V., Megyeri, I., Majó-Petri, Z., Csirik, J. (2021). Extracting information from Wi-Fi traffic on public transport. International Journal of Transport Development and Integration, 5(1): 15-27. https://doi.org/10.2495/tdi-v5-n1-15-27

[33] Pedregosa, F., et al. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12: 2825-2830. https://doi.org/10.48550/arXiv.1201.0490