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Road Surface Analysis through Machine Learning Techniques

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** Regular Paper*

***Abstract*:** Roads are an important part of transporting goods and products from one place to another. In developing countries, the main challenge is to maintain road conditions regularly. Roads can deteriorate from time to time. Monitoring the conditions of the roads, which may degrade with time, is very difficult, resulting in a delay in transportation and damage to the vehicles moving on the roads. Poor road conditions cause road accidents. A model is being proposed to monitor the conditions of the road surface by smartphone sensors. Accelerometer, gyroscope, and GPS sensors are deployed in the mobile phones, which will help to collect data on the road conditions. After collecting the data about the road conditions, various machine learning approaches, such as supervised, multi-layered, and multiclass, are applied to data filtration. Road conditions are divided into three categories to achieve this methodology: potholes, deep traverse cracks, and smooth roads. This categorization helped in analyzing the road surface condition through smartphone sensors over all three axes instead of taking it over a single axis. Neural networks helped analyze data or road conditions more accurately than Decision Tree and SVM.

***Keywords*:** GPS based tracking, Mobile based application, Accelerometer, Gyroscope

1. Introduction

In the field of transportation infrastructure, monitoring road conditions is the most challenging task on a worldwide scale because, without proper maintenance, the maintenance and repair costs of the roads significantly increase vehicle damage and road accidents. Major road accidents occur because of the poor conditions of the road surface [1-3].

The major focus while maintaining good quality roads is to support an efficient road network and reduce traffic accidents. Nevertheless, road maintenance must face various daily challenges, such as weather conditions, heavy manpower and heavy traffic loads.

An efficient and low-latency road surface monitoring system is needed to meet the demands of frequently repairing the deteriorating road surface. Thus far, traditional systems use equipment that is too expensive, such as LIDAR and GPR, which makes it less efficient for deploying at a very large scale [5, 6].

The major anomaly that comes as distress in the roads is as follows:

- Rutting
- Patching
- Cracking
- Alligator
- Block
- Traverse
- Longitudinal
- Raveling
- Potholes [4]

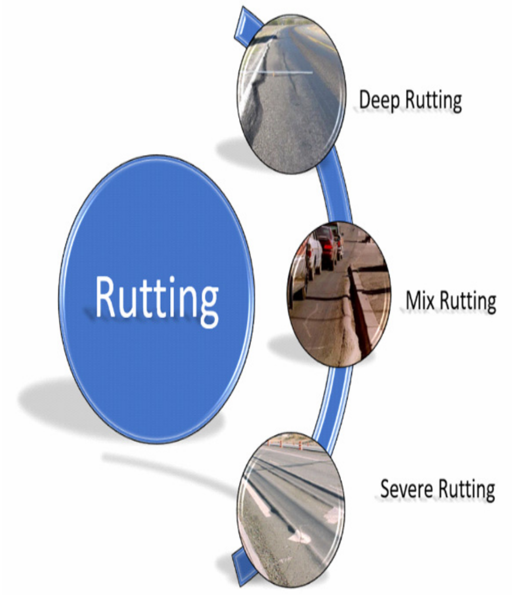

Fig. 1. Cracking and its types.

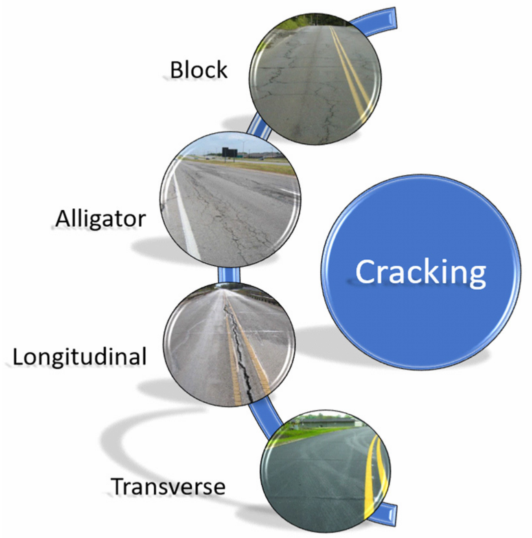

Fig. 2. Rutting and its types.

Therefore, this methodology was used to focus on these anomalies and analyze them using machine-learning methodology.

2. Methods

The goal of this study was to design a low latency efficient road monitoring system using a machine learning methodology to classify various conditions of road surfaces using the data collected using smartphones. The results over a single axis were compared with the three axes system and performances of neural networks to classify the conditions of road surfaces. The proposed system was divided into various steps for a better evaluation of the data, which are as follows (Fig. 3):

- **Data Collection**
  - GPS location system
  - Gyro meter
  - Accelerometer
- **Data processing**
  - Labeling
  - Filtering
  - Extraction of features
- **Machine learning designing and training**
  - Support Vector Machine
  - Decision Tree
  - Neural Networks
  - Design Model Evacuation
  - Classification

A. Data Collection

The data collection stage is the stage that handles the situation of collecting and recording data according to the requirements of the present system. Different sensors of smartphones, such as GPS sensors, gyrostat, and accelerometer, were used.

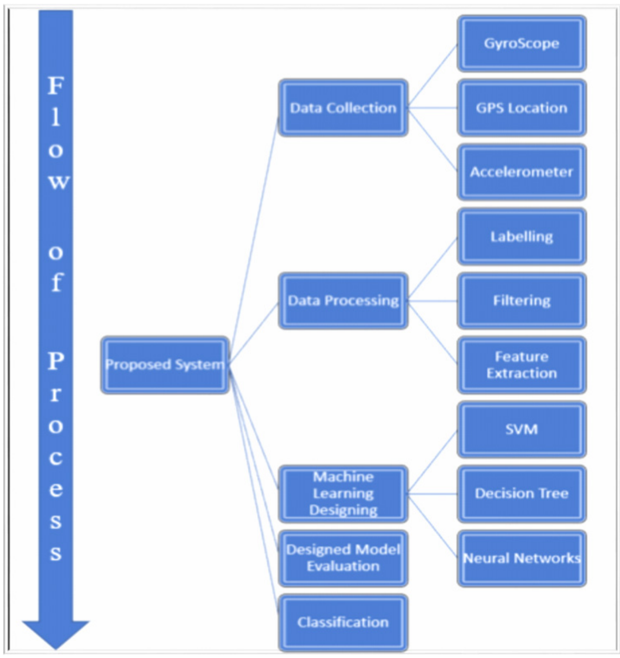

Fig. 3. Block Diagram of Proposed System.

As expected, the calculations might differ with different vehicles because of their features and suspension quality. Therefore, the data were collected from two types of vehicles by stabilizing smartphones and mounting. These vehicles were a car and motorcycles [8, 9].

The figure shows one of the collected data samples with readings as a sample. The latitude and longitude records of the vehicle using GPS technology were used to detect its location at every point in time. The rotation around all three axes is taken through a gyro meter, and acceleration is obtained from all three axes using an accelerometer.

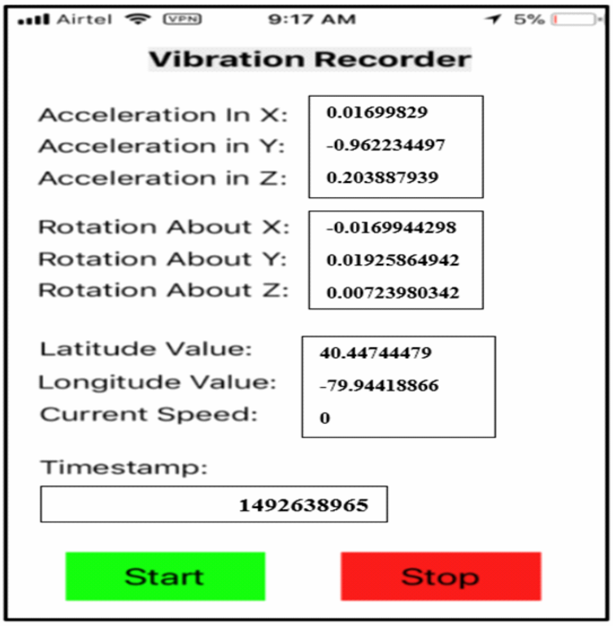

Fig. 4. Sample Data acquired during data collection [38].

B. Data Processing

After collection, the data quality is deficient because it contains too many fluctuations, which must be processed for analyzing and classifying the road surface quality. The readings were taken using an accelerometer and gyro meter to determine the speed and locations. The data were collected under different frames of reference on the same device, as shown in Fig. 5.

The coordinate axis reference frame needs to be reoriented to the global reference frame that can become common with a redefined and reprocessed frame of reference of the Gyro meter. The reorientation algorithm was used to reorient the data set obtained using an accelerometer through Eyler's angles.

The condition in which vehicles are at resting position on a horizontal surface was taken because the ideal acceleration value is mentioned below:

$A_x = 0$ m/s^2
$A_y = 9.81$ m/s^2 (Gravitational pull)
$A_z = 0$ m/s^2

The following equations were used to convert the accelerometer reference frame to the Global reference frame by calculating two of the three Euler angles [30]

$$A'x = \cos(\beta)Ax + \sin(\beta)\sin(\alpha)Ay + \cos(\alpha)\sin(\beta)Az$$

$$A'y = \cos(\alpha)Ay - \sin(\alpha)Az$$

$$A'z = -\sin(\beta)Ax + \cos(\beta)\sin(\alpha)Ay + \cos(\alpha)\cos(\beta)Az$$

The road surface condition needs to be labeled in various parts for proper operation on the ground level of the supervised machine learning algorithm. The conditions in various road pavements could be labeled using the video recorded by the specialized developed application [7, 10].

Subsequently, the data collected regarding the speed and location coordinates are being trained to detect the exact position of the road surface anomalies because of the spline interpolation of GPS data, location, and speed calculation because of the variance in the sampler rate of the Gyro meter or accelerometer. On the other hand, the driving conditions, such as accelerating, decelerating, turning, and changing lanes, which are unrelated to the road surface condition, are also considered. The 11th order of high pass filters, attenuation of 80db, and a cut-off frequency of 3Hz for filtering it out are needed to remove such disturbances in X' and Z' of acceleration data. This results in the omission of low-frequency bands and the saving of high-frequency bandwidth of the data.

- *Feature extraction*

While driving, many road vibrations occur, which has various features. Nevertheless, this study focused mainly on three broad domain categories: frequency, time, and wavelet domain features.

✔ *Time Domain Features*

Through the analysis done according to Gandelmawla et al. on various domains in his present and previous literature, the following were used to calculate from time domain signals and their channels, crests, and packets of the signal: maximum, minimum, and mean values; RMS; Peak to Peak; Ten-Point Average values [11].

✔ *Frequency Domain Features*

Focusing on the vibrational signals, the power spectral density would provide information to distinguish between road surface conditions [12, 13]. The signals were calculated for the windowed system, and the bandwidth was divided into various signals of small bands of 5Hz each, of which average, maximum, and RMS band values are considered frequency domain features.

✔ *Wavelet Domain Features*

Through the extensive analysis and study of Griffith's studies, the RMS points and ten-point averages of the studied scales were used to consider the wavelet domain features [14-16].

The last task in features extraction is to extract the features from the dataset evaluated of the accelerometer, in which the analysis found that the Y' axis is just used to distinguish road surface anomalies and the X' and Z' axes analysis that is affected by every change in the road surface and provides information that can be used to distinguish cracks and potholes.

Therefore, 54 features were considered using an accelerometer, and 162 feature values for every feature vector were used.

C. Machine Learning Designing and Training

The research and methodology should have the self-capacity to learn and improve. AI (Artificial Intelligence)

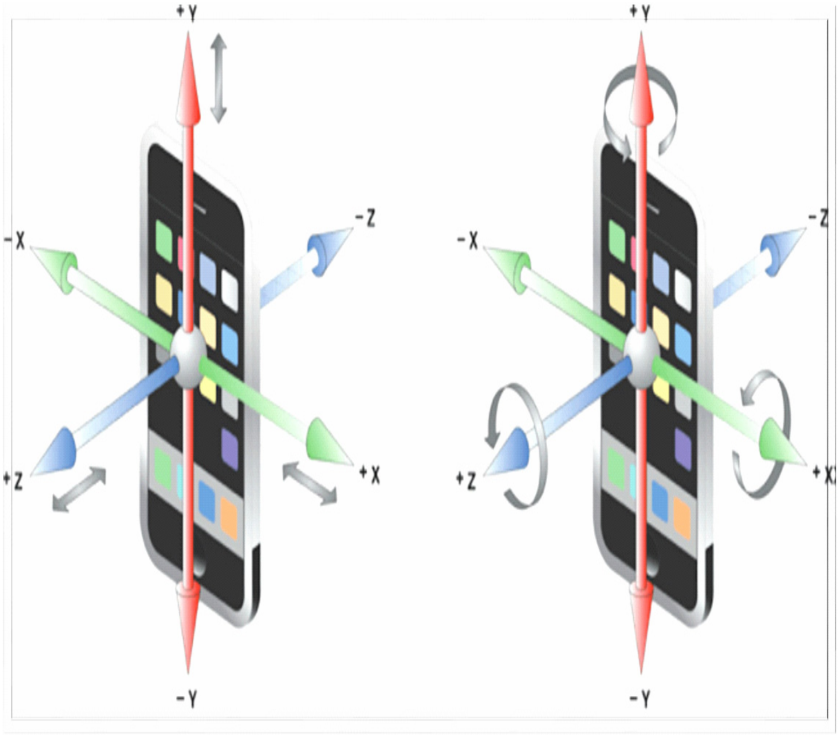

Fig. 5. Frame of references of Accelerometer and Gyro meter on the same Cartesian Plane [38].

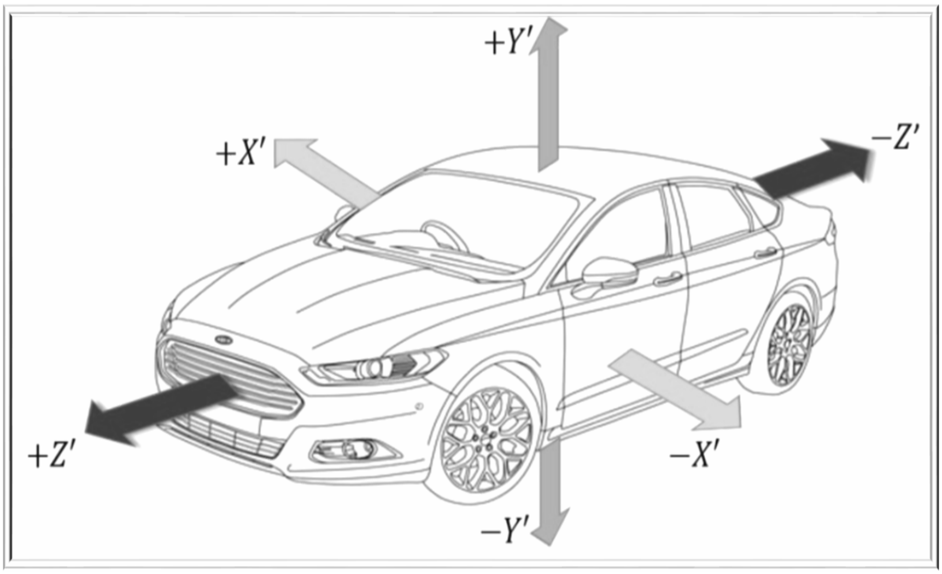

Fig. 6. Global frame of references common to both gyro-meter and accelerometer [38].

was used for machine learning to improve with experience. After training the system, the algorithm uses the relationship learned to solve the same type of previously solved problems. For implementation, it is important to understand the workflow diagram used (Fig. 7).

No standard nomenclature exists for implementing machine learning algorithms. Hence, selecting classifiers becomes difficult. Seven Machine Learning Classifiers were applied from MATLAB and its incorporation of The Statistics and Machine Learning Toolbox [17-19]:

- Classification introduced by Naïve Bayes
- Analysis based on Discriminants
- Classifier based on Ensemble
- Decision Tree Induction
- Nearest Neighbours Tree
- SVM (Support Vector Machine)
- NN (Neural Networks)

Further analysis of their results revealed the three most popular and reliable techniques to work on the data set of the processed road surface conditions:

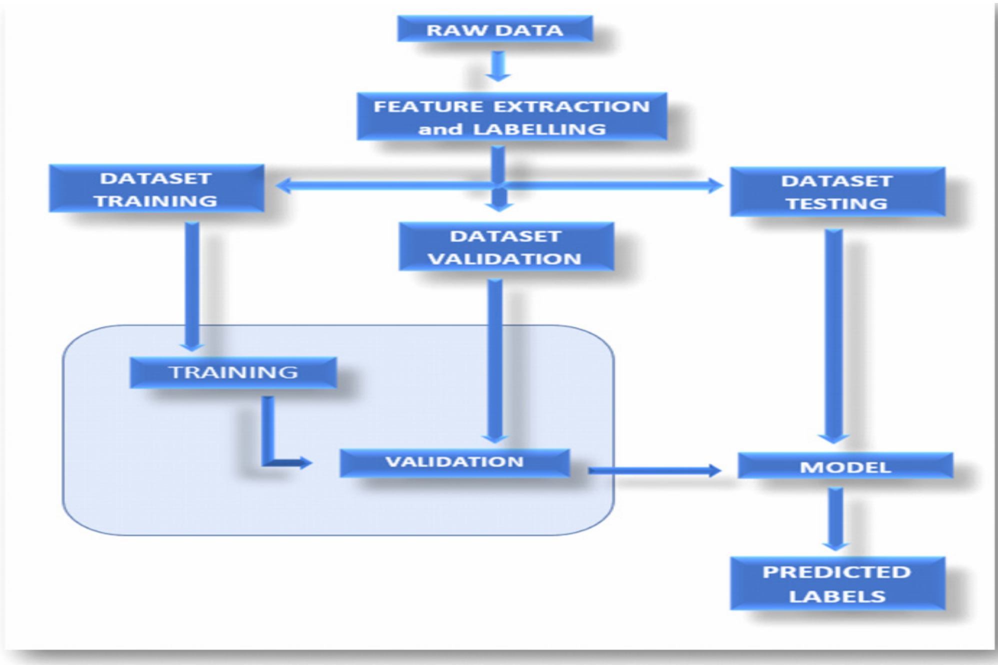

Fig. 7. Workflow diagram of Machine Learning Algorithms.

- SVM
- Decision Trees
- Neural networks

Randomization and division of data sets in the ratio of 80:20 were used for training and testing for the system. This data set was used in the three selected classifiers.

I) Support Vector Machine (SVM)

SVM works on the pattern recognition methodology for classifying and regression analysis by evaluating input datasets as a supervised machine learning methodology. SVM uses the hyperplane for classification because a hyperplane is the maximum margin between the data point clusters of various classes [20]. Versatility, memory efficiency, and efficiency in high-dimensional spaces are needed.

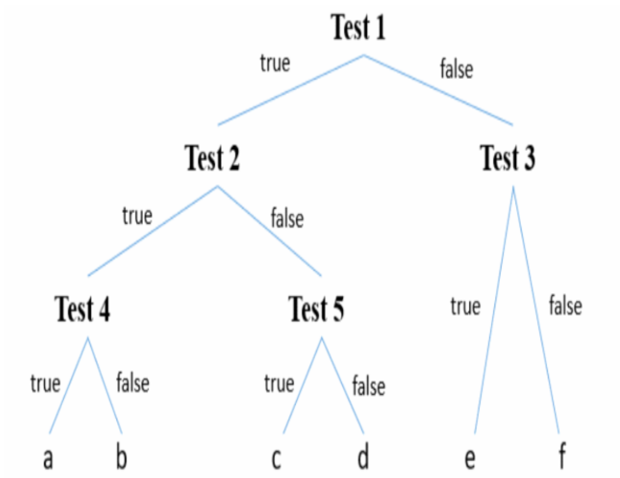

Fig. 8. Decision Tree Diagram [38].

II) Decision Trees

Classification or regression trees are decision trees that predict the output using the input responses. Moving from the root node to the leaf node provides the output based on the input values and decisions made in the path [21]. Fig. 8 shows the decision tree algorithm that categorizes the data using a series of arithmetical tests.

III) Neural Networks

Neural networks are a set of algorithms that are designed to recognize patterns and modeled loosely after the human brain. They use machine perception, labeling, or clustering of raw input to interpret the sensory data. The patterns they recognize are numerical and contained in vectors, into which all real-world data, images, sound, text, or time series must be translated [34-36].

Neural network algorithms are used to connect the class labels (output layer) to the feature vectors (input layer) using another multi-layered network layer called hidden layers by the neural network algorithms (depicted in diagram 9). The total count of hidden layers needed can be determined by measuring the complexity of the classification problem [22-24].

The neural network helps cluster and classify the data. Therefore, this layer can be taken as a clustering and classification layer on top of the data that needs to be stored and managed. They group the unlabelled data according to the similarities found among the example inputs, and the labeled dataset is then classified to train on [39]. Although neural networks are extremely powerful and high-accuracy algorithms, they require a large dataset to train them, which increases as the number of hidden layers increase.

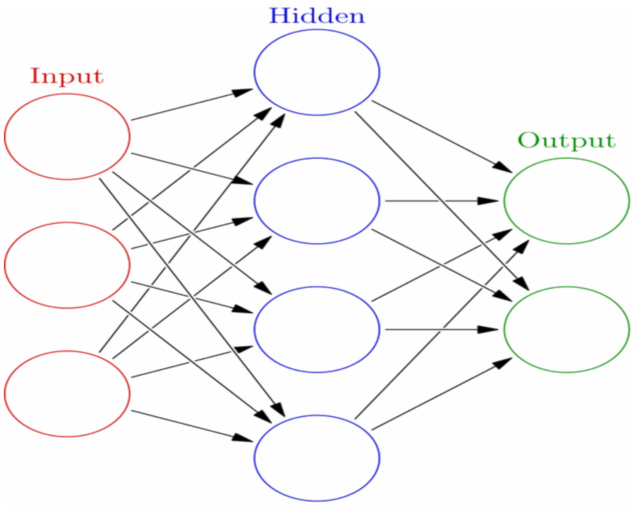

Fig. 9. Structure of the Neural Network with one hidden layer.

D. Designed Model Evaluation

As mentioned earlier about the classifiers, different performance assessment methodologies are used in machine learning models to evaluate the classifier performance because some parameters are used to measure their performance efficiently. For efficient analysis and classification methodology, they are derivative of the confusion matrix, which shows the working of a supervised machine-learning algorithm in tabular form based on the true negatives (TN), true positives (TP), false negatives (FN), and false positives (FP) in the following equation:

$$Accuracy = \frac{(TN + TP)}{(FN + FP + TN + TP)}$$

$$Precision = 1 - \frac{FP}{(FP + FP)}$$

$$Recall = 1 - \frac{FN}{(FN + TP)}$$

The performances of the simple decision tree and the SVM classifiers were assessed using average test accuracy and average training loss on the trained classifier, where the accuracy of the average test is the average of the correctness for the n-iterations dataset during classification. In contrast, the average training loss is the average in the sample loss of the skilled classifier model using a working-out dataset. In addition, the average recall and average precision are recorded for three different modules projected by the model for analyzing them and finding which portion of identification is correct and which portion of actual positives are identified correctly.

Table 1 lists the results of the time requirement comparison, which are required to evaluate the significance of the time requirement for feature extraction. It compares three axes with one axis (Y-axis).

Table 1. Average Time Requirements for Feature Extraction.

Parameter	All Axis (ms)	Y axis (ms)
Filtering Using HIGH PASS FILTER	.158	.0211
Extraction of Feature using TIME DOMAIN	16.43	5.56
Feature Extraction using Frequency Domain	1.75	1.105
Feature Extraction using Wavelet Domain	53.41	19.65
Total	71.748	26.336

Table 2. Implemented Results of Simple SVM.

Parameter (AVG)	all Axis (ms)	Y axis (ms)
Training Loss	.0153	.0582
5-fold Loss	.079	.0891
7-fold Loss	.075	.0956
10-fold loss	.0821	.089
Leave one out loss	.071	.082

Table 3. Implemented Results of Cross-Validated SVM.

Parameter (AVG)	all Axis (ms)			Y axis (ms)		
Training Loss	.0312			.0942		
Test Accuracy	.754			.895		
	Crack	Pothole	Smooth	Crack	Pothole	Smooth
Precision	.521	.6724	.892	.412	.668	.883
Recall	.323	.5149	.8762	.321	.521	.815

3. Results

This study analyzed and evaluated the results of the machine learning models to know their capabilities in detecting road surface anomalies. The algorithm was run on a Lenovo Idea Pad 310 on Microsoft Windows 10 Home OS with an Intel core of i5-7200 processor, 2.30 GHz CPU, and 8GB RAM.

A. SVM – Support Vector Machine

The simple SVM was implemented with one hundred iterations, where every iteration use different groupings of occurrences for the testing and training. The machine also maintains the same ratio every time for all classes. The generalized performance of the algorithm was evaluated using the average values of evaluation parameters. Table 2 lists the calculated training loss, accuracy of testing, correctness, and recall rates.

An analysis of Table 2 showed that the SVM classifier was trained using structures with lower loss and performed better on all three axes than only one axis. Table 3 lists the data calculated on a cross-validated SVM over both cases of considering all three axes and considering only one axis,

Table 4. Implemented Results of the Decision Tree.

Parameter (AVG)	all Axis (ms)			Y axis (ms)		
Training Loss	0.036			0.0613		
Test Accuracy	0.886			0.816		
	Crack	Pothole	Smooth	Crack	Pothole	Smooth
Precision	.516	.642	.944	.379	.825	.851
Recall	.437	.554	.868	.121	.746	.816

Table 5. Cross-Validated Implemented Results of Decision Tree.

Parameter (AVG)	all Axis (ms)	Y axis (ms)
Training Loss	.0214	.0653
5-fold Loss	.079	.0981
7-fold Loss	.086	.0841
10-fold loss	.0821	.089
Leave one out loss	.089	.081

Y. Considering all three axes in a classifier has less training loss and fewer loss cross-validated errors.

B. Decision Tree

The decision tree was produced using a highly varying set of hyperparameters with each iteration with the number of nodes and node thresholds, which is easier and faster for training. The process can be implemented just like SVM, and 500 iterations can be used using an exclusive collection of training data sets for implementation in SVM. Table 4 lists the training loss, precision, recall, and test accuracy of the decision tree implementation.

The classifier Decision Tress trained with features had lower loss and performed better on all three axes than on only one axis (Table 4). The features were calculated on a cross-validated model over both cases, considering all three axes and considering only one axis, Y (Table 5). Considering all three axes in the classifier also gave less training loss and fewer loss cross-validated errors.

C. Neural Networks

The introductory examination phase of implementing an MLP neural network classifier includes the assessment of test precision, accuracy, and recall for the different parametric groupings selected earlier. The result is tabulated in Tables 6 and 7. Different numbers of hidden layers were used to compare the effects of the number of hidden layers in the analysis. The average test precision, recall rates, and accuracy of the MLP model were relatively greater for all three axes as related to one axis. Tanh was used as the activation function because the models are trained through features from one axis only, which provides higher recall rates and precision among the three classes. Nevertheless, high recall and precision rates for crashes were obtained using ReLU and taking all three axes. The recall rates and accuracy for potholes and plane roads did not change between the two activation functions [37].

Table 6. Execution Results with the Tanh-Results for MLP.

Hidden Layers	Features of all axes			Features of Y' Axis only		
Accuracy of Test						
7	.752			.821		
8	.891			.749		
9	.781			.814		
10	.823			.715		
Accuracy Rates						
	Crack	Pothole	Smooth	Crack	Pothole	Smooth
7	.641	.632	.876	.42	.512	.875
8	.612	.641	.824	.216	.532	.87
9	.53	.658	.743	.43	.542	.89
10	.521	.617	.813	.41	.69	.991
Recall Rates						
	Crack	Pothole	Smooth	Crack	Pothole	Smooth
7	.68	.419	.97	.312	.62	.85
8	.59	.82	.98	.343	.68	.875
9	.58	.69	.99	.39	.574	.83
10	.52	.75	.94	.41	.661	.84

Table 7. Implementation results using the Re LU-Results for MLP.

MLP Hidden Layers Count	Features of all axes			Features of Y' Axis only		
Accuracy of Test						
7	.711			.8525		
8	.989			.7865		
9	.823			.8642		
10	.8023			.7643		
Accuracy Rates						
	Crack	Pothole	Smooth	Crack	Pothole	Smooth
7	.532	.625	.876	.42	.772	.882
8	.424	.698	.789	.415	.634	.89
9	.51	.786	.943	.39	.692	.98
10	.456	.721	.912	.39	.79	.912
Recall Rates						
	Crack	Pothole	Smooth	Crack	Pothole	Smooth
7	.98	.679	.92	.265	.69	.87
8	.424	.69	.912	.282	.81	.812
9	.56	.786	.885	.48	.734	.86
10	.521	.79	.934	.41	.751	.89

Table 8 lists the average time acquired to categorize a single data set of data features from all three axes for diverse ML algorithms and classifiers.

Table 8. Testing Time – Classifier Performance.

Classifier	Average Time to Categorize one Window (micro-seconds)
SVM	30.12
Decision Trees	5.113
MLP	38.134

4. Discussion & Future Work

Machine Learning approaches are quite effective for potholes and cracks. In addition, implementing all three axes to consider the feature use is more accurate and precise than only a single axis. This approach was novel for extracting many features from all three axes in training multiclass ML classifiers. On the other hand, there were some limitations that will be addressed in future works:

a) Loss in accuracy and precision because of the small number of data sets.
b) Errors in individual precision and recall rates because the distribution of instances was disproportional in potholes, cracks, and smooth areas.
c) Possibilities of better results as the study focused on specific architectures only in neural networks.
d) Impacts on the data acquired in data acquisition because of the condition of vehicles, smartphones, and other devices.
e) Possibilities of larger scale implementation because of the self-learning methodology of ML technologies.

5. Conclusion

Machine Learning techniques based on the collected data produced acceptable results. Smartphone sensors were used to collect the data, which is feasible and cost-effective, and monitor the road surface conditions. Machine learning models used parameters mined from all three coordinate axes. This method improved accuracy, precision, and recall rates compared to the models trained with only one axis perpendicular to the ground. This behavior will be followed by all three machine-learning methods discovered in this paper. The results prove the initial hypothesis of the road present in data collected with respect to all three axes (x, y, and z). With the rise of self-driving cars and smart cars, which have several sensors, and the current development rate, data collected from them could be used to improve safety and infrastructure quality and assess the road surface.

References

[1] J. Eriksson, L. Girod and B. Hull, etc. “The Pothole Patrol: Using a Mobile Sensor Network for Road Surface Monitoring”, 6th International Conference on Mobile Systems, Application, and Services (MobiSys 2008), Breckenridge, USA, June, 2008, pp. 29-39. Article (CrossRef Link)

[2] R. Bishop, “A Survey of Intelligent Vehicle Application Worldwide”, IEEE Intelligent Vehicles Symposium (IV 2000), Dearborn, MI, USA, May 2000, pp. 25-30.

[3] U.S. Department of Transportation, Traffic Safety Facts – Crash Stats, June 2015. Article (CrossRef Link)

[4] Pothole (2002). Article (CrossRef Link)

[5] Roadscanners. Roadscanners oy (1998). Article (CrossRef Link)

[6] J. Budras, A synopsis on the current equipment used for measuring pavement smoothness. Article (CrossRef Link)

[7] Texas DOT Pavement Management Information System (PMIS) Rater’s Manual. Retrieved from Texas State Department of Transporation: Article (CrossRef Link)

[8] V. Douangphachanh and H. Oneyama, “A Model For The Estimation Of Road Roughness Condition From Sensor Data Collected By Android Smartphones,” *Journal of Japan Society of Civil Engineers, Ser. D3 (Infrastructure Planning and Management)*, vol. 70, no. 5, 2014. Article (CrossRef Link)

[9] V. Douangphachanh and H. Oneyama, “Formulation of a simple model to estimate road surface roughness condition from Android smartphone sensors,” 2014 IEEE Ninth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), 2014. Article (CrossRef Link)

[10] Pavement Manual, Texas Department of Transportation. (online) Article (CrossRef Link)

[11] E. Gadelmawla, M. Koura, T. Maksoud, I. Elewa, and H. Soliman, “Roughness parameters,” Journal of Materials Processing Technology, vol. 123, no. 1, pp. 133-145, 2002. Article (CrossRef Link)

[12] L. Sun, “Simulation of Pavement Roughness and IRI Based on Power Spectral Density”, Mathematics and Computers in Simulation, 2003, vol. 61, pp. 77-88. Article (CrossRef Link)

[13] D. Xu, A. Mohamed, and R. Yong, etc. “Development of a criterion for road surface roughness based on power spectral density function”, Journal of Terramechanics, 1992, vol. 29, pp. 477-486.

[14] W. Staszewski, K. Giacomin, “Application of the Wavelet based FRFs to the Analysis of Nonstationary Vehicle Data,” Proceedings- SPIE the International Society for Optical Engineering, pp. 425-431, 1997

[15] K.R. Griffiths, “An Improved Method for Simulation of Vehicle Vibration Using a Journey Database and Wavelet Analysis for the Pre-Distribution Testing of Packaging,” Ph.D. Dissertation, Univ. of Bath, Bath, UK, 2012

[16] L. Wei, T. F. Fwa, and Z. Zhe, “Wavelet Analysis and Interpretation of Road Roughness,” Journal of Transportation Engineering, vol. 131, no. 2, pp. 120-130, 2005.

[17] “Statistics and Machine Learning Toolbox,”

MATLAB. [Online]. Available: Article (CrossRef Link)

[18] S. Shalev-Shwartz and S. Ben-David, *Understanding machine learning: from theory to algorithms*. New York: Cambridge University Press, 2016. Article (CrossRef Link)

[19] V. S. Cherkassky and F. Mulier, *Learning from data: concepts, theory, and methods*. Hoboken, NJ: IEEE Press, 2007. Article (CrossRef Link)

[20] Multiclass Model for Support Vector Machines or Other Classifiers - MATLAB. Article (CrossRef Link)

[21] Gordon, A., Breiman, L., Friedman, J., Olshen, R. and Stone, C. (1984). Classification and Regression Trees. Biometrics, 40(3), p. 874.

[22] F. Rosenblatt, Principles of neurodynamics; perceptrons and the theory of brain mechanisms. Washington, D.C.: Spartan Books, 1962. Article (CrossRef Link)

[23] Rumelhart, David E., Geoffrey E. Hinton, and R. J. Williams. "Learning Internal Representations by Error Propagation". David E. Rumelhart, James L. McClelland, and the PDP research group. (editors), Parallel distributed processing: Explorations in the microstructure of cognition, Volume 1: Foundation. MIT Press, 1986. Article (CrossRef Link)

[24] Fabian Pedregosa; Gaël Varoquaux; Alexandre Gramfort; Vincent Michel; Bertrand Thirion; Olivier Grisel; Mathieu Blondel; Peter Prettenhofer; Ron Weiss; Vincent Dubourg; Jake Vanderplas; Alexandre Passos; David Cournapeau; Matthieu Perrot; Édouard Duchesnay (2011). "Scikit-learn: Machine Learning in Python". Journal of Machine Learning Research. 12: 2825-2830. Article (CrossRef Link)

[25] Ranyal, E., Sadhu, A., & Jain, K. (2022). Road condition monitoring using smart sensing and artificial intelligence: A review. *Sensors*, *22*(8), 3044. Article (CrossRef Link)

[26] Chhabra, R., & Singh, S. (2021). A survey on smart phone-based road condition detection systems. *IEEE Access*. Article (CrossRef Link)

[27] Raslan, E., Alrahmawy, M. F., Mohammed, Y. A., & Tolba, A. S. (2022). IoT for measuring road network quality index. *Neural Computing and Applications*, 1-18. Article (CrossRef Link)

[28] Dey, M. R., Satapathy, U., Bhanse, P., Mohanta, B. K., & Jena, D. (2019, October). MagTrack: detecting road surface condition using smartphone sensors and machine learning. In *TENCON 2019-2019 IEEE Region 10 Conference (TENCON)* (pp. 2485-2489). IEEE. Article (CrossRef Link)

[29] Lee, T., Chun, C., & Ryu, S. K. (2021). Detection of road-surface anomalies using a smartphone camera and accelerometer. *Sensors*, *21*(2), 561. Article (CrossRef Link)

[30] Martinez-Ríos, E. A., Bustamante-Bello, M. R., & Arce-Sáenz, L. A. (2022). A Review of Road Surface Anomaly Detection and Classification Systems Based on Vibration-Based Techniques. *Applied Sciences*, *12*(19), 9413. Article (CrossRef Link)

[31] Martinelli, A., Meocci, M., Dolfi, M., Branzi, V., Morosi, S., Argenti, F., ... & Consumi, T. (2022). Road surface anomaly assessment using low-cost accelerometers: a machine learning approach. *Sensors*, *22*(10), 3788. Article (CrossRef Link)

[32] Varona, B., Monteserin, A., & Teyseyre, A. (2020). A deep learning approach to automatic road surface monitoring and pothole detection. *Personal and Ubiquitous Computing*, *24*(4), 519-534. Article (CrossRef Link)

[33] Kumar, M., Srivastava, S., & Uddin, N. (2019). Forgery detection using multiple light sources for synthetic images. *Australian Journal of Forensic Sciences*, *51*(3), 243-250. Article (CrossRef Link)

[34] Alsharef, A., Aggarwal, K., Sonia, Kumar, M., & Mishra, A. (2022). Review of ML and AutoML solutions to forecast time-series data. *Archives of Computational Methods in Engineering*, *29*(7), 5297-5311. Article (CrossRef Link)

[35] Madhu, G., Govardhan, A., Ravi, V., Kautish, S., Srinivas, B. S., Chaudhary, T., & Kumar, M. (2022). DSCN-net: a deep Siamese capsule neural network model for automatic diagnosis of malaria parasites detection. *Multimedia Tools and Applications*, *81*(23), 34105-34127. Article (CrossRef Link)

[36] Rana, A., Vaidya, P., Kautish, S., Kumar, M., & Khaitan, S. An application for the earthquake spectral and source parameters and prediction using adaptive neuro fuzzy inference system and machine learning. *Journal of Intelligent & Fuzzy Systems*, (Preprint), 1-16. Article (CrossRef Link)

[37] Choudhary, C., Singh, I., & Kumar, M. (2023). SARWAS: Deep ensemble learning techniques for sentiment based recommendation system. *Expert Systems with Applications*, *216*, 119420. Article (CrossRef Link)

[38] Basavaraju, A., Du, J., Zhou, F., & Ji, J. (2019). A machine learning approach to road surface anomaly assessment using smartphone sensors. IEEE Sensors Journal, 20(5), 2635-2647. Article (CrossRef Link)

[39] https://oaktrust.library.tamu.edu/handle/1969.1/174107

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