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A Data Based Method Road Surface Parameters Estimation for Anti-Lock Braking System

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ABSTRACT

Accurate road surface parameter identification is considered essential for selecting the appropriate controlling threshold in the Anti-lock Braking System (ABS) utilized in modern vehicles. This paper presents a data-based method for road surface parameter estimation. The proposed method utilizes a pattern recognition technique that works to estimate the road type during braking. A detailed analysis and related comparison is provided for several pattern recognition techniques such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Tree (DT), which were chosen among previously studied pattern recognition techniques. A model for the ABS system is implemented with MATLAB Simulink, and the required data is extracted to be utilized to train each model individually. After training is complete, a test has been applied in order to obtain the performance of each trained model. In particular, accuracy and sensitivity are utilized to compare the effectiveness of these models, with 96% for the SVM, 95.2% for the DT model, and 94% for the KNN model. Although the SVM classifier accuracy was better than both the KNN and DT classifiers, all classifiers presented a high-performance accuracy that proves the possibility of utilizing a data-based method for road surface parameter identification that increases the reliability of safety systems like the ABS.

1. Introduction

The Anti-Lock Braking System (ABS) is one of the modern ground vehicle's main factors for safe driving. Additionally, ABS provides an enhancement to vehicles security by controlling automatically exerted braking force in hazard braking like emergency braking or braking on wet or icy roads [1][2]. ABS works, during braking, to keep maneuverability, reduces stopping distance and prevent wheel from skidding. The ABS has been designed to control the wheel-slip (λ) to obtain the maximum amount of friction between the wheel tire and the surface of the road and, therefore, ensure lateral stability.

Basically, accuracy core for ABS is the slip rate calculation, which takes into account two main variable measurements, namely, Wheel angular speed (Ws) and Vehicle linear velocity (Vs), and is calculated as [3]. Where, the Electronic Control Unit (ECU), located inside ABS, receives the data values of both (Ws) and (Vs) from the respective sensors and applies required calculation to provide the current road-tire slip. Then, the calculated slip is evaluated in accordance with the optimal slip value. Then a decision is made to either hold, reduce or terminate wheel brake pressure in order to keep the operation at the desired optimal slip value[4].

However, in most modern vehicles, only wheel speed sensors are utilized, and the ECU works to estimate the current vehicle speed in order to calculate the wheel slip [5]. The vehicle

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speed estimation operation is related to Newton's second law of motion and is mainly based on nonlinear relationship between the wheel slip (λ) and the road's friction coefficient (μ). The $\mu - \lambda$ relationship is determined by road surface parameters that vary from one another[6].

In recent years, many researchers have dedicated their efforts to developing the performance of the ABS. N. Raesian, N. Khajehpour, and M. Yaghoobi (2011)[7], developed an intelligent fuzzy control method for ABS in order to reduce the wheel's tendency to lock-up. The tire friction model used is the Burckhardt model, and the desired slip value for all road types is considered to be 0.2. This assumption may be accepted by a large number of researchers. However, it’s still necessary to obtain the desired slip value for each road in order to obtain more efficient results.

S. Ko, C. Song, J. Park, J. Ko, I. Yang, and H. Kim,(2013)[8], proposes an algorithm for slip control of ABS used in an in-wheel braking system for electric vehicles. In their method, the desired slip value is assumed to be fixed for all selected road types without defining its value.

D. K. Yadav ,(2015), [1] proposes an intelligent controller to improve the ABS behavior. His work includes a fuzzy logic controller, a bang-bang controller, and a PID controller, and a comparison among the three different strategies was presented, but no technique for road identification was presented.

L. Xiao, L. Hongqin, and W. Jianzhen,(2016),[9] presented a fuzzy logic controller to improve the ABS response. A dugoff model is used as a tire model, and this method has a drawback. That is, the shape of the friction force in the non-linear region is totally inaccurate since there is a consideration for vertical load distribution and coefficient of friction to be both constant within that region.

B. L. Widjiantoro and K. Indriawati ,(2020), [10], introduced a fault tolerant method for ABS. The proposed method is observer based and works to tolerate the faults that may occur in both the actuator and the speed sensor. In their work, they utilized a Pacejka and Bakker tire model, and their results are built for only one road surface type, which is dry asphalt, and no consideration for other roads has been taken.

In this work, a data-based technique is proposed to estimate the road surface parameters accurately. Then, the desired optimal slip is set for the ABS controller that results in an accurate control response. The estimation process is based on Pattern Recognition (PR) techniques. PR techniques are a type of data analysis technique that employs machine learning algorithms to find regularities and patterns in data automatically. PR has the ability to solve classification problems easily, such as fault detection or detected signal reorganization. Moreover, it is widely used in robots and in the medical field.

In sequel, Section two presents the research methodology for ABS modelling and selected PR algorithms. Section three provide training and testing results are followed by discussion and, finally, a conclusion is presented in section four.

2. Research Methodology

This section will explain the system model analysis and analysis methods that are utilized in this work.

2.1 Anti-lock braking system Mathematical Model

The quarter car model (QCM) is widely utilized in the design of slip control for ABS [4][11][12], [13]. Figure 1. Shows the representation of a quarter-car.

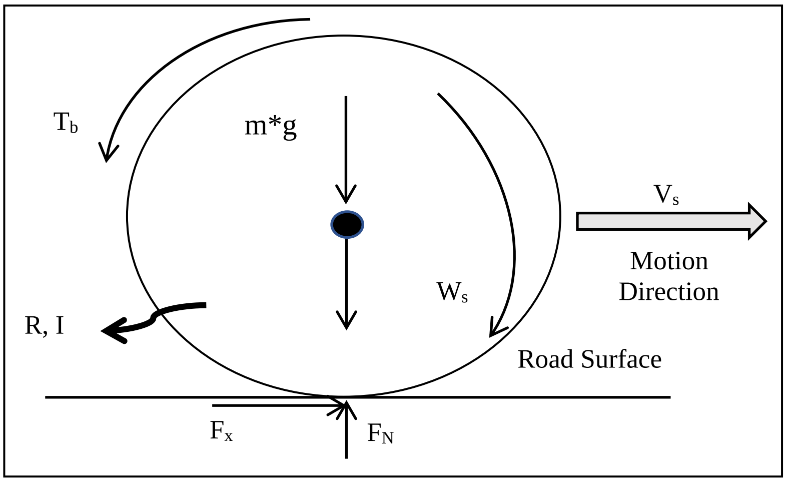


Figure 1. Quarter Car Model [4]

Which can be described by the equations; the dynamic equation of the rotating wheel [4]:

$$I \times \dot{\omega} = R \times F_x - T_b \tag{1}$$

$$\dot{\omega} = \frac{R \times F_x - T_b}{I} \tag{2}$$

Where, I is wheel moment of inertia, T_b is the braking torque, and F_x is the road-tire contact force, and R is the Wheel radius.

From Newton's second law of motion, the vehicle linear velocity during braking is given by [4]:

$$m \times \dot{V} = -F_x \tag{3}$$

$$\dot{V} = \frac{-F_x}{m} \tag{4}$$

m is the vehicle quarter mass, simple formula to calculate the slip ratio is [4]:

$$\lambda = \frac{V_s - \omega_s * R}{V_s} \tag{5}$$

$$\lambda = \frac{\int \frac{-F_x}{m} - \int((R \times F\_x - T\_b)/I) * R}{\int \frac{-F_x}{m}} \tag{6}$$

Based on the slip rate λ value, the ABS interfere the braking operation to ensure safe operation.

The road friction force F_x is calculated by [4]:

$$F_x = m \times g \times \mu(\lambda) \tag{7}$$

Here, the μ is calculated based on nonlinear relationship between the wheel slip (λ) and the road's friction coefficient (μ). One of the most empirical models utilized to calculate the friction coefficient friction for some selected standard road surface is the Burkhardt model[6].

$$\mu = C_1\left(1 - e^{C_2\lambda}\right) - C_3\,\lambda \tag{8}$$

In this work and regarding the streets of our capitol city, Baghdad, three roads are selected among different standard roads whose $C_1, C_2, and\ C_3$ values are illustrated in Table 1 below:

Table 1: Parameters of various standard road surfaces[6]

Surface Road	C_1	C_2	C_3
Dry Asphalt	1.28	23.99	0.52
Wet Asphalt	0.857	33.82	0.35
Wet pebbles	0.4	33.71	0.12

And the corresponding $\mu - \lambda$ curve is presented in figure 2.

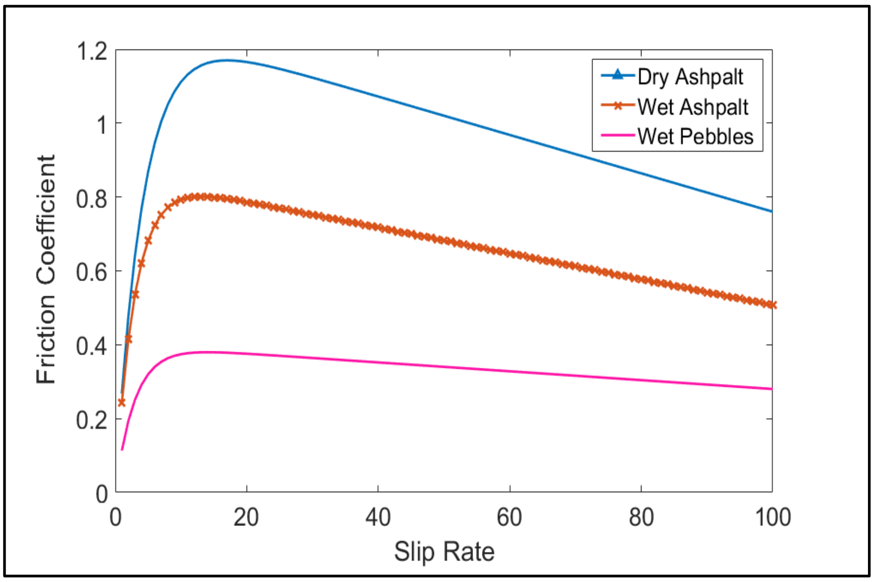


Figure 2. Burkhardt model based $\mu - \lambda$ Curve for selected Roads[6]

If a derivative is applied to equation 8 and makes it equal to zero:

$$\frac{d\mu}{d\lambda} = -C_1\, C_2\, e^{C_2\lambda} - C_3 \quad (9)$$

$$0 = -C_1\, C_2\, e^{C_2\lambda_{optimal}} - C_3 \quad (10)$$

$$C_1\, C_2\, e^{C_2\lambda_{optimal}} = -C_3 \quad (11)$$

$$e^{C_2\lambda_{optimal}} = \frac{-C_3}{C_1\, C_2} \quad (12)$$

$$C_2\lambda_{optimal} = \ln\frac{C_1\, C_2}{C_3} \quad (13)$$

Then the optimal slip value equation is:

$$\lambda_{optimal} = \frac{1}{C_2}\ln\frac{C_1\, C_2}{C_3} \quad (14)$$

The coefficients values related to different selected road types of Table 1 are substituted within equation (14) to get the optimal slip value for each road surface as illustrated in Table 2.

Table 2: The optimal slip ratio of selected standard road surfaces.

Surface Road	λ_optimal
Dry Asphalt	0.17
Wet Asphalt	0.13
Wet pebbles	0.14

So, once the type of road has been determined, the optimal slip value for that road should be set as the desired slip input to the ABS controller.

2.2. Classifier models-based PR techniques

Pattern recognition is one of the most significant and frequently searched characteristics or areas of artificial intelligence. The goal of science is to create machines that are as clever as people in terms of pattern recognition and reliable classification into the appropriate categories.

A PR system model design basically includes:

- Data collecting and pre-processing: acquisition the data from surrounding environment and set as input to the PR system. This data may be subjected to a pre-processing in order to remove noise or extracting pattern of interest in order to make the input system-readable

- Feature extraction: The appropriate features are extracted from the processed data. These features work together to create an identifiable or categorizable object.
- Decision making: The descriptor of the extracted features is used to perform the necessary classification or recognition operation.

Pattern Recognition provides the solution to a lot of problems that fall under the category of either recognition or classification, such as speech recognition, face recognition, classification of handwritten characters, medical diagnosis etc. Several research applications are based on pattern recognition [14][15][16]. The classification techniques used in this work are:

2.2.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) is considered an efficient discriminating classifiers, and it is commonly used in different PR activities because of its consistent and good outcomes. [17]. It is a well-known method for stable classification issues.

The principle SVM technique is to assign a line or a hyperplane that breaks up the set of training data into defined categories, as shown in Figure 3. [18].

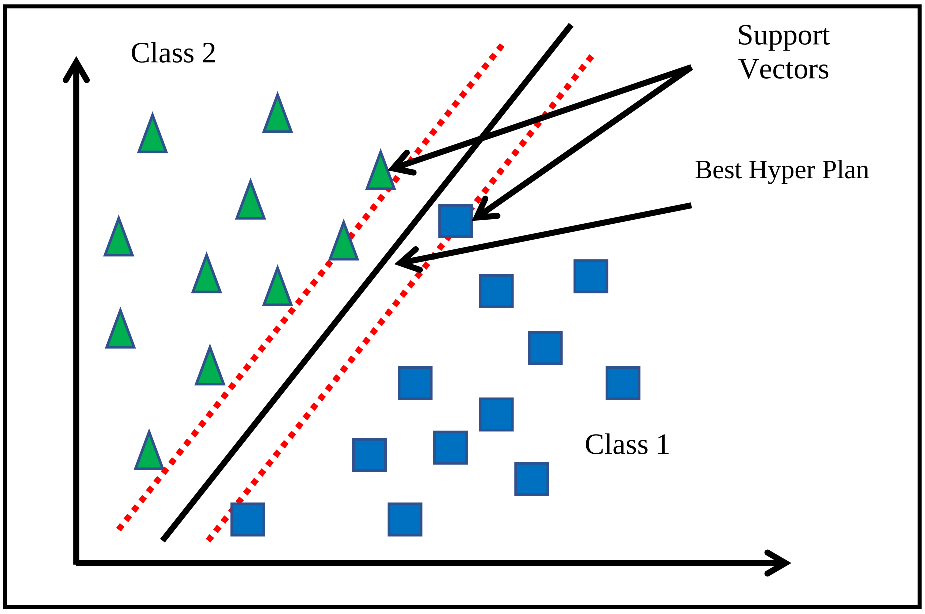


Figure 3. SVM example [18]

2.2.2 K-Nearest Neighbor

K-Nearest Neighbour (KNN) is an instance-based learning technique utilized in network security [19], deep learning [20], face recognition[21], fault diagnosis [22], and Plant disease [23]. It is called also “lazy learning" and considered one of the simplest machines learning algorithms Where a majority of an object's neighbours vote to determine the object's classification. By other words, The object is placed in the class that includes its k nearest neighbours, where K is a small positive number classified [24]. As shown in Figure 4. When k is set to one (K=1), then, the new sample is assigned to the same class of nearest neighbour.

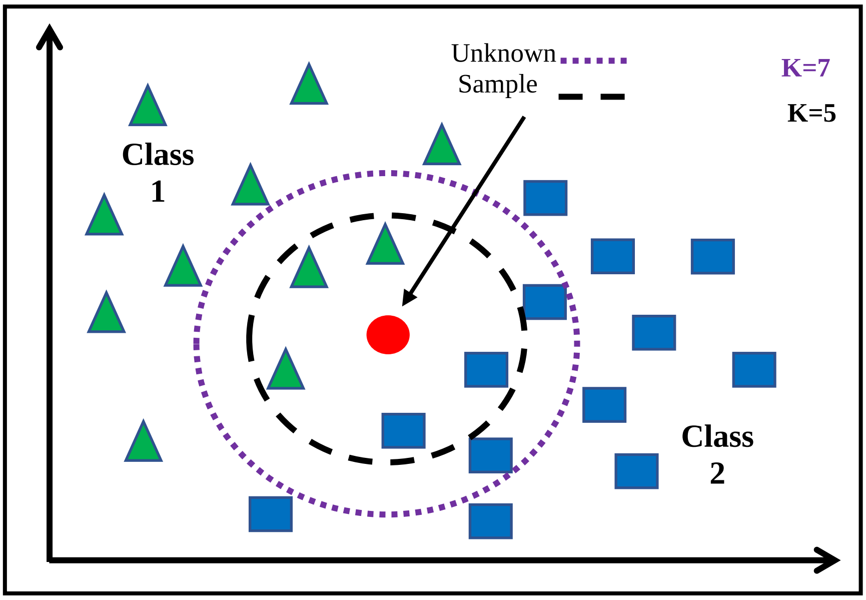


Figure 4. KNN example two-class classification[25].

2.2.3 Decision tree

It is a predictive model where the category of an object is determined by a group of binary rules. It can be used in either regression or classification applications. One of its benefits is that it is a nonparametric method that makes it simple to combine a variety of numeric or categorized data layers. Also, a decision tree is regarded as robust with regard to outliers in training data. Finally, it has the ability to classify quickly once the rules have been established [26]. The decision tree topology is shown in Figure 5.

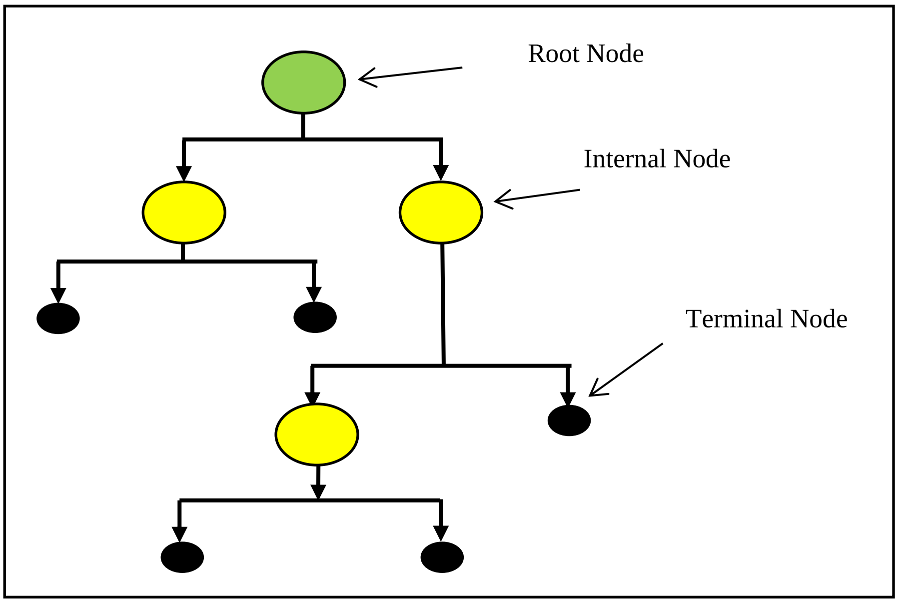


Figure 5. Decision tree structure [26]

However, applying splitting perpendicular to feature space axes is not always effective. Also, no prediction can be made beyond the maximum and minimum limits of the training data.

2.3 Classifier's Evaluation Metrics

In order to evaluate the ability of the PR algorithm and as a comparison between classifier techniques and a description of some related terms are given below [27]:

- True positives (TP): represent the sample number that the classifier model predicted to belong to a particular category, and they indeed do belong to that category.
- The True Negatives (TN): represent sample number that the classifier model predicted do not belong to a particular category, and they indeed do not belong to that category.
- False positives (FP): represent sample number that the classifier model predicted to belong to a particular category, but in fact, they do not belong to that category.
- False negatives (FN) represent sample number that the classifier model predicted did not belong to a particular category, but in fact, they do belong to that category.

Then, the ratio of the correct estimates to all estimates performed by the classifier is called Accuracy. While the ratio of samples that is predicted as a positive value of samples that are actually positive is called Sensitivity [27]:

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \quad (15)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (16)$$

3. System modelling and data collection

A MATLAB Simulink is utilized to implement the ABS model based on QCM described in subsection (2.1) in order to collect the training required data. As shown in Figure 6.

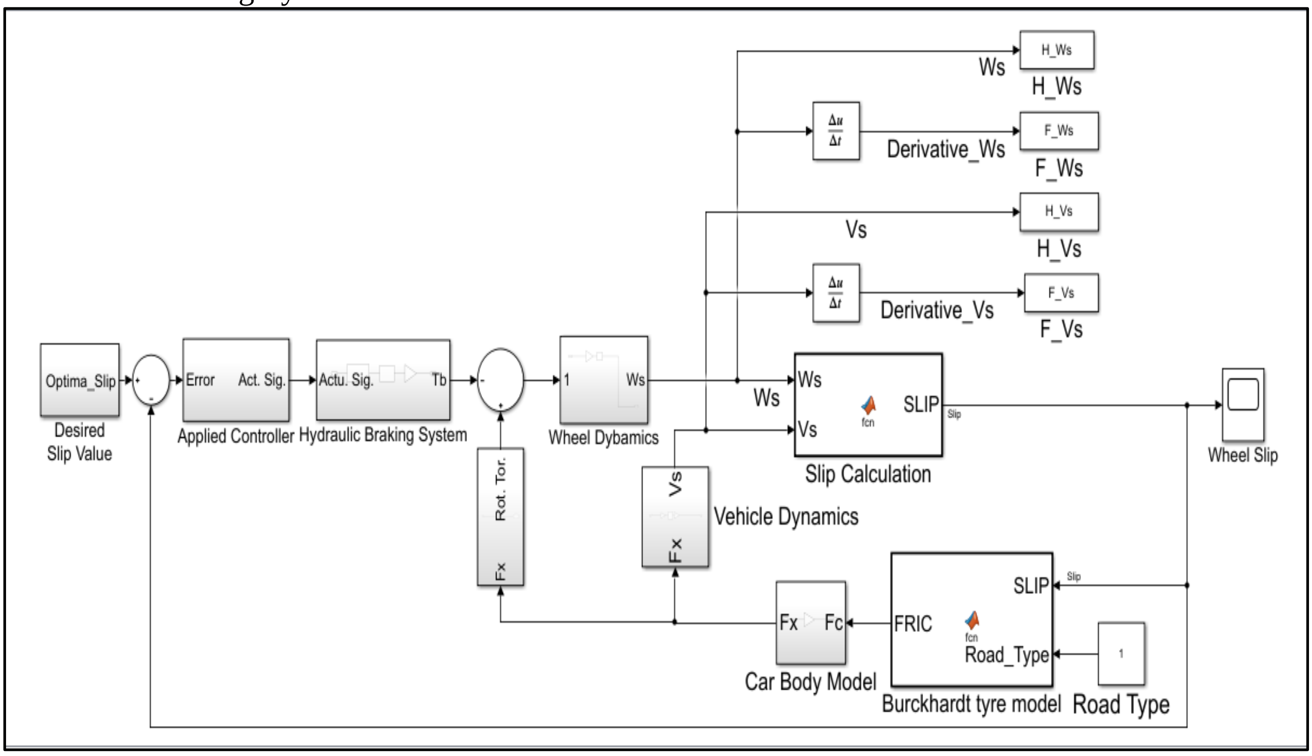


Figure 6. ABS Model Block Diagram

During simulation, the three selected standard road surfaces illustrated in table 1 are selected one after another, and for each selected road surface type, the range of examined initial velocities is set from [50-120 km/h] with a stepsize of 10km/h.

At each selected operation, four variables are observed: Wheel speed data (Ws), Wheel Speed change ration (Ws), Vehicle Speed data

(Vs), and Vehicle Speed change ration (Vs). These variables are considered the required features to train the classifier models.

These extracted data is organized in a way that will be useful as a training data base. they are categorized as related to the pre-selected road surface and by using an appropriate categorization numbering system, where, unique class number was assigned to each one of the selected three roads, class 1 assigned to dry asphalt road type, class 2 assigned to wet asphalt road type and, class 3 assigned to wet pebbles road type. Table 3 illustrate a selected portion of these catogrized samples.

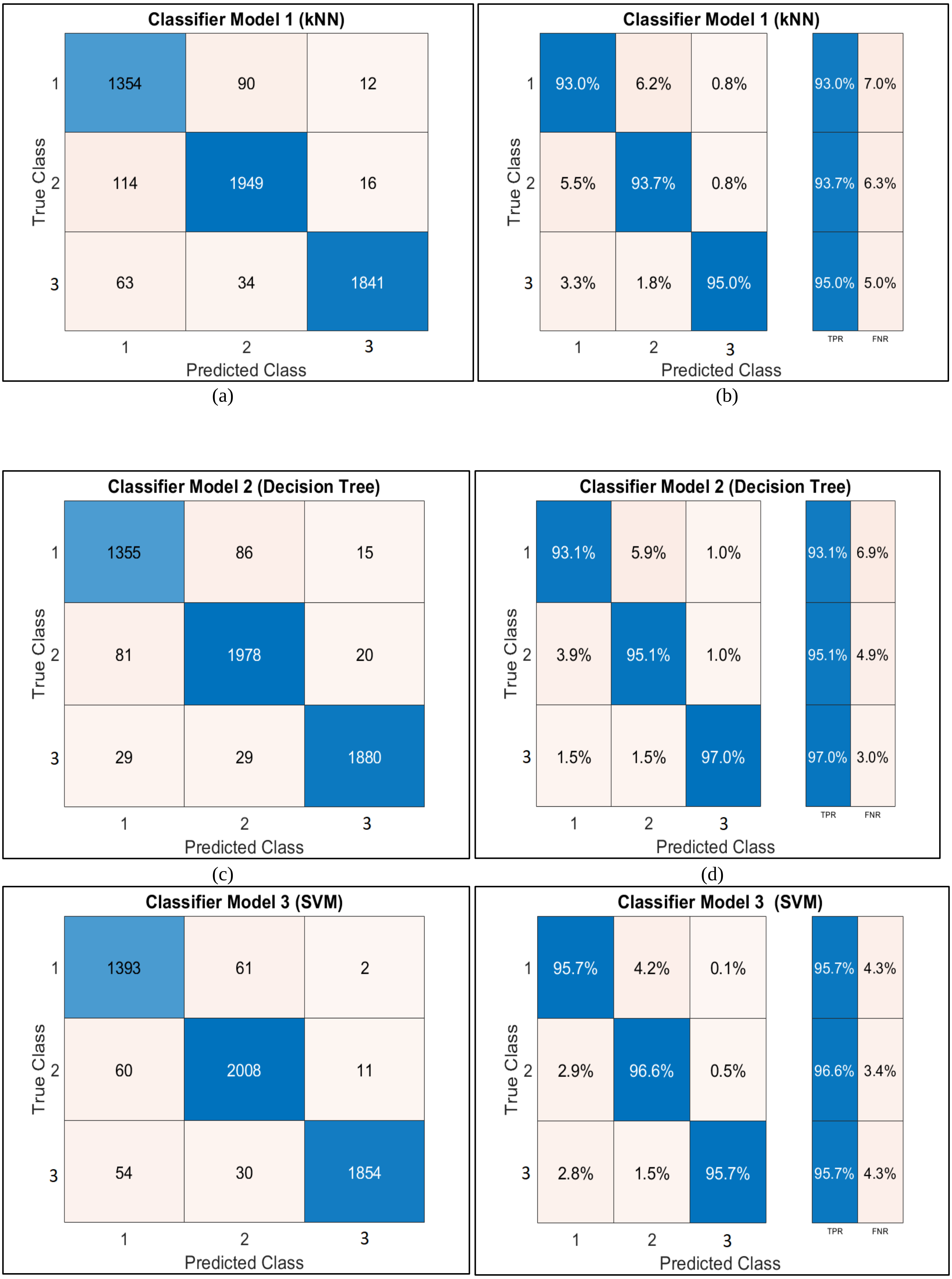
Table 3: A selected portion of these catogrized samples

Ws	$\mathrm{d}W_s/\mathrm{dt}$	V_s	$\mathrm{d}V_s/\mathrm{dt}$	$Class$
25.9837	-5.8445	32.9345	-7.4796	1
25.2240	-5.8441	31.9621	-7.4801	1
15.9282	-4.0085	20.0000	-5.0514	2
44.9934	-1.9086	56.3641	-2.4157	3
51.5483	-3.9205	64.9551	-5.0456	2
48.9747	-5.7639	62.0582	-7.4801	1
14.7729	-1.9324	18.4701	-2.4168	3
14.5410	-1.9324	18.1800	-2.4168	3
32.2901	-3.9931	40.5465	-5.0513	2
31.8907	-3.9945	40.0413	-5.0515	2

4. PR-Classifiers models training and testing results

The three PR classifiers (SVM, KNN, and NN) are trained individually using the previously categorized data in the MATLAB environment. Whereas, the SVM models were trained using a linear kernel function, coarse DT models were trained using a maximum of four splits, and KNN models were trained using a function K neighbors classifier that uses a single neighbor (k = 1) .

After training process has compeleted an appiled test is performd in order to evaluate each trained model. Figures (7-a) to (7-f) illustrate the plots of the Confusion Matrix (CM) and True Positive Rate (TPR)–False Negative Rates (FNR) that related to the applied test for each one of the trained models. while the corresponding accuracy and sensitivity are shown in table (4) and Table (5), respectively.



(a) (b) (c) (d) (e) (f)

Figure 7. Algorithm Training results (a) CM for KNN Classifier, (b) TPR-FNR plots for KNN Classifier, (c) CM for DT Classifier, (d) TPR-FNR plots for DT Classifier, (e) CM for DT Classifier, and (f) TPR-FNR plots for SVM Classifier

Table 4: Classifiers Training performance Results (Accuracy)

Method	Accuracy (%)
KNN	94.0 %
DT	95.2 %
SVM	96.0 %

Table 5: Classifiers Training Performance Results (Sensitivity)

Method	Class 1 Dry Asphalt	Class 2 Wet Asphalt	Class 3 Wet pebbles
KNN	93.0 %	93.7 %	95.0 %
DT	93.1 %	95.1 %	97.0 %
SVM	95.7 %	96.6 %	95.7 %

According to tables (4) and (5) above, the KNN classifier has a high sensitivity for class 3 and almost equal sensitivity for both class 2 and class 3, the overall accuracy of 94.0%. Meanwhile, a slightly better performance than KNN is presented by DT classifier with an overall accuracy is equal to 95.2%. where, the sensitivity for DT model was higher for all classes and lead to an overall accuracy of 95.2%. Finally, the SVM classifier, introdecs the highest accuracy of 96 % as compared to the kNN and DT classifier. althoutg the three models has some topological and working principles deferences. all of them presened a high accuracy regarding the main purpose requiremnet. These lead that the utilization of data based method is feasible for road surface parameter identification that improve the reliability and control accuracy of safety systems such as the ABS.

5. Conclusion

In this work, a data-based method for road surface parameter identification was proposed and evaluated. The proposed method is based on the PR technique and evaluated for ABS utilized in modern ground vehicles, and the results are obtained for three road types only, which are dry asphalt, wet asphalt, and wet pebble road types. Three PR algorithms were chosen for the purpose of comparison and evaluation of the proposed method. The selected techniques were the kNN, DT, and SVM classifier algorithms.

After the required data has been prepared using the implemented QCM model, the MATLAB environment is used to train and test each selected classifier model, and the performance accuracy was 94.0%, 95.2%, and 96.0% for kNN, DT, and SVM, respectively. Regardless of whether SVM has the highest accuracy, all of the selected classifiers accuracy results were high, confirming that the proposed data-based pattern recognition method is feasible and well suited for identifying road surface parameters that ensure secure ABS working and eliminate the need for any additional hardware redundancy.

References

[1] D. K. Yadav, “Modeling an intelligent controller for anti-lock braking system,” *Int. J. Tech. Res. Appl.*, vol. 3, no. 4, pp. 122–126, 2015.

[2] B. Ozdalyan, “Development of a slip control anti-lock braking system model,” *Int. J. Automot. Technol.*, vol. 9, no. 1, pp. 71–80, 2008, doi: 10.1007/s12239-008-0009-6.

[3] A. Mirzaei, M. Moallem, and B. Mirzaeian, “Designing a genetic-fuzzy anti-lock brake system controller,” *Int. J. Eng. Trans. B Appl.*, vol. 18, no. 2, pp. 197–205, 2005.

[4] O. Tur, O. Ustun, and R. N. Tuncay, “An introduction to regenerative braking of electric vehicles as anti-lock braking system,” *IEEE Intell. Veh. Symp. Proc.*, no. 5, pp. 944–948, 2007, doi: 10.1109/ivs.2007.4290238.

[5] M. Tanelli, L. Piroddi, and S. M. Savaresi, “Real-time identification of tire-road friction conditions,” *IET Control Theory Appl.*, vol. 3, no.

7, pp. 891–906, 2009, doi: 10.1049/iet-cta.2008.0287.

[6] R. Bhandari, S. Patil, and R. K. Singh, “Surface prediction and control algorithms for anti-lock brake system,” *Transp. Res. Part C Emerg. Technol.*, vol. 21, no. 1, pp. 181–195, 2012, doi: 10.1016/j.trc.2011.09.004.

[7] N. Raesian, N. Khajehpour, and M. Yaghoobi, “A new approach in Anti-lock Braking System (ABS) based on adaptive neuro-fuzzy self-tuning PID controller,” *Proc. - 2011 2nd Int. Conf. Control. Instrum. Autom. ICCIA 2011*, pp. 530–535, 2011, doi: 10.1109/ICCIAutom.2011.6356714.

[8] S. Ko, C. Song, J. Park, J. Ko, I. Yang, and H. Kim, “Comparison of braking performance by electro-hydraulic ABS and motor torque control for in-wheel electric vehicle,” *World Electr. Veh. J.*, vol. 6, no. 1, pp. 186–191, 2013, doi: 10.3390/wevj6010186.

[9] L. Xiao, L. Hongqin, and W. Jianzhen, “Modeling and Simulation of Anti-lock Braking System based on Fuzzy Control,” *Iarjset*, vol. 3, no. 10, pp. 110–113, 2016, doi: 10.17148/iarjset.2016.31021.

[10] B. L. Widjiantoro and K. Indriawati, “Sensor/actuator fault tolerant sliding mode control for anti-lock braking in a quarter electric vehicle,” *Int. J. Power Electron. Drive Syst.*, vol. 11, no. 3, pp. 1220–1229, 2020, doi: 10.11591/ijpeds.v11.i3.pp1220-1229.

[11] I. D. De Carvalho Dantas Maia, “Modeling and control of anti-lock braking systems considering different representations for tire-road interaction,” *2019 23rd Int. Conf. Syst. Theory, Control Comput. ICSTCC 2019 - Proc.*, pp. 344–349, 2019, doi: 10.1109/ICSTCC.2019.8885694.

[12] W. Zhang and X. Guo, “An ABS control strategy for commercial vehicle,” *IEEE/ASME Trans. Mechatronics*, vol. 20, no. 1, pp. 384–392, 2015, doi: 10.1109/TMECH.2014.2322629.

[13] S. John, J. O. Pedro, and C. R. Pozna, “Enhanced slip control performance using nonlinear passive suspension system,” *IEEE/ASME Int. Conf. Adv. Intell. Mechatronics, AIM*, pp. 277–282, 2011, doi: 10.1109/AIM.2011.6027054.

[14] A. Abed, S. Gitaffa, and A. Issa, “Quadratic Support Vector Machine and K-Nearest Neighbor Based Robust Sensor Fault Detection and Isolation,” *Eng. Technol. J.*, vol. 39, no. 5A, pp. 859–869, 2021, doi: 10.30684/etj.v39i5a.2002.

[15] S. Nasser, I. Hashim, and W. Ali, “Visual Depression Diagnosis From Face Based on Various Classification Algorithms,” *Eng. Technol. J.*, vol. 38, no. 11, pp. 1717–1729, 2020, doi: 10.30684/etj.v38i11a.1714.

[16] N. T. Mahmooda, M. H. Al-Muifraje, S. K. Salih, and T. R. Saeed, “Pattern Recognition of Composite Motions based on EMG Signal via Machine Learning,” *Eng. Technol. J.*, vol. 39, no. 2A, pp. 295–305, 2021, doi: 10.30684/etj.v39i2a.1743.

[17] S. U. Jan, Y. D. Lee, J. Shin, and I. Koo, “Sensor Fault Classification Based on Support Vector Machine and Statistical Time-Domain Features,” *IEEE Access*, vol. 5, no. c, pp. 8682–8690, 2017, doi: 10.1109/ACCESS.2017.2705644.

[18] G. Ramesh, N. Sandeep Kumar, and N. Champa, “Recognition of Kannada Handwritten Words using SVM Classifier with Convolutional Neural Network,” *2020 IEEE Reg. 10 Symp. TENSYMP 2020*, no. June, pp. 1114–1117, 2020, doi: 10.1109/TENSYMP50017.2020.9231003.

[19] M. Y. Su, “Real-time anomaly detection systems for Denial-of-Service attacks by weighted k-nearest-neighbor classifiers,” *Expert Syst. Appl.*, vol. 38, no. 4, pp. 3492–3498, 2011, doi: 10.1016/j.eswa.2010.08.137.

[20] C. Yuan, “Deep Learning of the SSL Luminaire Spectral Power Distribution under Multiple Degradation Mechanisms by Hybrid kNN algorithm,” *2021 22nd Int. Conf. Therm. Mech. Multi-Physics Simul. Exp. Microelectron. Microsystems, EuroSimE 2021*, pp. 2–5, 2021, doi: 10.1109/EuroSimE52062.2021.9410872.

[21] F. Liu, S. Yang, Y. Ding, and F. Xu, “Single sample face recognition via BoF using multistage KNN collaborative coding,” *Multimed. Tools Appl.*, vol. 78, no. 10, pp. 13297–13311, 2019, doi: 10.1007/s11042-018-7002-5.

[22] S. Ji, X. Xu, and C. Wen, “A kind of K - Nearest neighbor fault diagnosis method based on MIV data transformation,” *Proc. - 2017 Chinese Autom. Congr. CAC 2017*, vol. 2017-January, pp. 6306–6310, 2017, doi: 10.1109/CAC.2017.8243914.

[23] E. Hossain, M. F. Hossain, and M. A. Rahaman, “A Color and Texture Based Approach for the Detection and Classification of Plant Leaf Disease Using KNN Classifier,” *2nd Int. Conf. Electr. Comput. Commun. Eng. ECCE 2019*, pp. 1–6, 2019, doi: 10.1109/ECACE.2019.8679247.

[24] S. Ji, X. Xu, and C. Wen, “A kind of K - Nearest neighbor fault diagnosis method based on MIV data transformation,” *Proc. - 2017 Chinese Autom. Congr. CAC 2017*, vol. 2017-Janua, pp. 6306–6310, 2017, doi: 10.1109/CAC.2017.8243914.

[25] S. R. Madeti and S. N. Singh, “Modeling of PV system based on experimental data for fault

detection using kNN method," *Sol. Energy*, vol. 173, no. June, pp. 139–151, 2018, doi: 10.1016/j.solener.2018.07.038.

[26] Y. Yao, Z. L. Fu, X. H. Zhao, and W. F. Cheng, "Combining classifier based on decision tree," *2009 WASE Int. Conf. Inf. Eng. ICIE 2009*, vol. 2, pp. 37–40, 2009, doi: 10.1109/ICIE.2009.12.

[27] S. Ouf and N. Hamza, "The Role of Machine Learning to Fight COVID-19," *Int. J. Intell. Eng. Syst.*, vol. 14, no. 2, pp. 121–135, 2021, doi: 10.22266/ijies2021.0430.11.