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ROBUST PATTERN RECOGNITION BASED FAULT DETECTION AND ISOLATION METHOD FOR ABS SPEED SENSOR

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ABSTRACT–Anti-lock braking system (ABS) is considered an essential safety system in electric vehicles that works to grant a reliable vehicle driving experience, and it is very important to ensure the security of such an onboard safety system. This work presents a detailed analysis associated with a comparison that includes several techniques based on pattern recognition for biasing fault detection in wheel and vehicle speed sensors. These techniques are K-nearest neighbor (KNN), support vector machine (SVM) and decision tree (DT), which were selected among other pattern recognition techniques that have been studied. The MATLAB Simulink model for the ABS system was implemented, and data was extracted from healthy and unhealthy operating conditions in order to be used to train each technique individually. An offline test was applied to these trained FDI models using the same implemented ABS Simulink model to express the performance of each one. Specifically speaking, accuracy and sensitivity were used in the algorithm's efficiency comparison, with 99.9 % accuracy in the Fine KNN, 75 % accuracy in the Coarse Gaussian SVM, and 61.5 % accuracy in the Coarse Tree. From the result, and considering the ABS issues mentioned above, it can be concluded that the KNN classifier is superior to both the SVM and TREE classifiers.

KEY WORDS : Anti-lock braking system, Sensor fault, Fault detection, Pattern recognition, KNN, SVM, Decision tree

1. INTRODUCTION

Anti-lock braking system (ABS) considered one of the modern car's major factors for driving safety. Moreover, ABS offers an improvement to modern car security through the automatic control of the applied braking force in hazardous braking conditions such as panic braking or braking on wet or iced asphalt (Yadav, 2015; Ozdalyan, 2008). It works to prevent the wheels from slipping during braking, increase maneuverability, and minimize stopping distance.

The ABS is designed to regulate the longitudinal wheel-slip (λ) in order to achieve maximum friction force between the tire and the road surface and maintain lateral stability. Basically, a key control for ABS is the accuracy of the slip calculation, where consideration is taken for two output variable measurements for the slip calculation, which are vehicle velocity and wheel angular speed (Oniz *et al*., 2007). Consequently, the occurrence of faults in the vehicle velocity sensor or in the wheel speed sensor will lead to slipping regulation deterioration that results in inaccurate control, unsafe driving, and even human life threat. A fault detection and identification (FDI) method is necessary and the primary step to accommodate fault occurrence in order to keep the system performing under safe operating conditions (Isermann, 2006).

In recent decades, many sensor FDI methods have been developed. An observer-based method proposed by Zahedi and Gharaveisi (2011), where the residual response is limited to one fault occurrence, and a K number of observers, is designed to produce a K number of residuals. This approach is called "generalized observer". In this way, the isolation decision is straightforward immediately after residual generation (Widjiantoro and Indriawati, 2020). They proposed a method for sensor and actuator fault tolerant ABS control. The fault estimation is performed using a proportional-integral observer, and a special reconfiguration mechanism is used to substitute the estimated signal with the faulty signal to compensate for the control signal. In Pinandhito *et al*. (2019) designed a sliding mode observer for ABS sensor fault detection and isolation. In their work, different sensor faults were detected and isolated effectively. Also, Sun *et al*. (2017) proposed a method for residual generator based on sliding mode observer to detect the faults in wheel sensors in an aircraft ABS, and they validated their proposed diagnosis strategy in several different sensor failure cases. Luo *et al*. (2010) present an FDI method that utilizes both data based and model based methods to detect and isolate faults that may have occurred in ABS. Wang *et al*. (2010) presented an

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ABS fault diagnosis by utilizing a BP neural networks, they built up several sensors and actuators failure modes and an investigation in the effect in system variables is performed.

As a result, most of the above research is on model-based methods for ABS health monitoring and fault detection, and in general, the model-based methods require an accurate system model in order to correctly estimate the desired system state or output. In addition, for the ABS working concept, the relation between friction coefficient and slip is complex and nonlinear, which is based on the tire and road surface's various conditions, which in turn leads to large uncertainty. Therefore, in this work, an alternative method, a data-based method, is proposed for implementing the FDI method, which is based on pattern recognition. Fault detection and identification methods.

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

2. RESEARCH METHOD

2.1. ABS System Model

ABS improves vehicle safety in extreme operating conditions by preventing lateral force from approaching zero and maximizing longitudinal friction between the tire and the road via the slip regulation method.

2.1.1. Quarter-car model (QCM)

To drive an ABS model, a simple but efficient QCM is utilized. During braking, the vehicle dynamic of the QCM is given by Figure 1 below:

Which is described by the Equations (1) ~ (3) below (Tur *et al*., 2007b):

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

$$m \times \dot{V} = -F_x \tag{2}$$

I is moment inertia of the wheel, *m* is the vehicle quarter mass, T_b is the braking torque, and F_x is the road-tire contact force that given by:

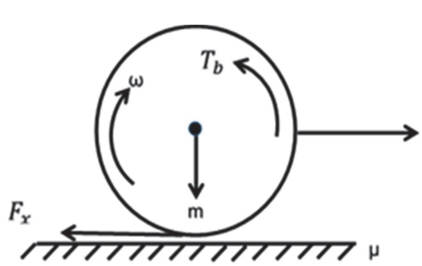


Figure 1. QCM model (Tur *et al*., 2007a).

$$F_x = m \times g \times \mu(\lambda) \tag{3}$$

Here, g is the gravitational acceleration constant, μ is the road friction coefficient that can be calculated based on the relation between it and the wheel-slip. This relation is nonlinear, complex, and varies with different vehicle speeds, tire types, and road conditions (Mirzaei *et al*., 2005). Figure 2 illustrates exemplary lateral and longitudinal friction coefficients as a function of wheel-slip for different road condition.

The wheel-slip (λ) of the wheel tire is given by (Mirzaei *et al*., 2005):

$$\lambda = \frac{V_s - \omega R}{V_s} \tag{4}$$

From Figure 2, it can be seen that the coefficient of lateral friction is maximum when the wheel slip is zero and starts to decrease when the wheel-slip increases. This coefficient offers lateral stability, as well as the ability to steer and regulate the vehicle's direction. On the other hand, the coefficient of longitudinal friction is zero when the wheel-slip is zero and, under most road conditions, it increases as the wheel-slip increases until it reaches its peak value. Then it begins to decline, where μ value begins to decrease as wheel-slip increases.

At this point, the braking force should be reduced quickly, otherwise the reduction in road force would result in a rapid increase in wheel-slip, which will result in wheel-lockup.

Anti-lock brake systems work to sense this point and lower braking force to avoid wheel-lockup and provide vehicle steerability, adequate stability, and reduced stopping distance.

As a result, any fault occurrence in vehicle speed or wheel speed sensor reading will directly affect the control operation of the ABS in particular and the vehicle' s driving safety in general.

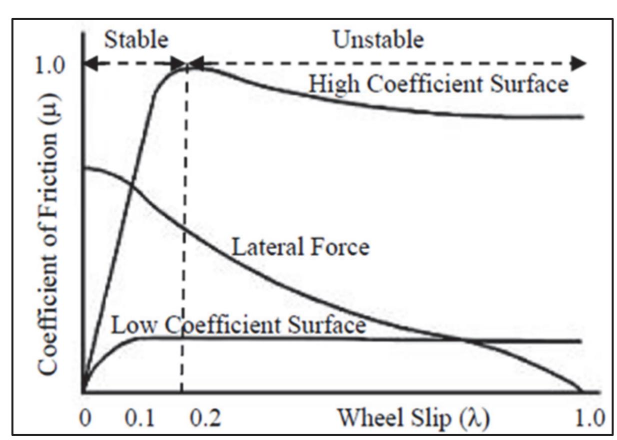


Figure 2. Coefficient of friction (μ) versus wheel slip (λ) (Mirzaei *et al*., 2005).

2.2. Pattern Recognition based Fault Detection and Identification (PR-FDI) Methods

The purpose of the FDI is to perform the following: detect the occurrence of faults in the system that it monitors, have the ability to determine their locations (whether the fault occurs in a component, sensor, or actuator); and also, provide an estimate for their severities (Tabbache *et al.*, 2014).

The pattern recognition method takes place as an FDI data-based method. This learning-based method learns about the process model from an historical input and output data set collected from the system and then utilizes its knowledge to detect fault occurrences during real time system operation. At our university, several research applications are based on pattern recognition (Abed *et al.*, 2021; Nasser *et al.*, 2020; Mahmooda *et al.*, 2021). The classification algorithms used in this study are:

2.2.1. Support vector machine (SVM)

Support vector machine (SVM) is regarded as one of the most efficient discriminating classifiers, and it is widely used in various pattern recognition activities due to its good and consistent results (Jan *et al.*, 2017). It is a familiar method for stable classification problems.

As shown in Figure 3, the principle SVM algorithm is to create a line or a hyperplane that separates the training data set into defined classes (Ramesh *et al*., 2020).

2.2.2. K-nearest neighbor

K-nearest neighbor (KNN) is considered one of the instance-based learning types. It is also called “lazy learning” because when a minimum distance is acquired, a neighbor is considered the closest. Then, KNN keeps holding all of the training examples and postpones the learning operation till new sample data is classified (Ji *et al*., 2017). Figure 4 show the general flowchart of the KNN algorithm.

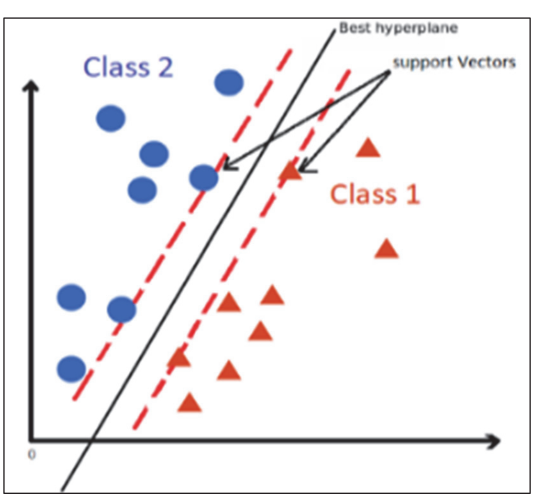


Figure 3. SVM example (Ramesh *et al*., 2020).

The KNN concept is considered one of the simplest among all machine learning algorithms, where the classification of an object is decided by a majority vote of its surrounding neighbors. In other words, the object is assigned to the class that contains the k nearest neighbors, where K is a small positive integer.

As in Figure 5, if the value of K is taken to be equal to one (K = 1), then, the object is assigned to the nearest neighbor class.

2.2.3. Decision tree

A Decision Tree (DT) is a predictive model that utilizes a combination of binary rules to compute an objective value. A decision tree can be employed for classification or

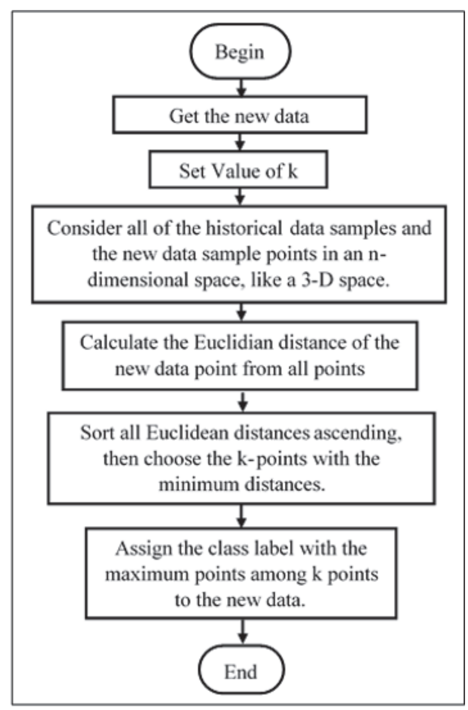


Figure 4. General KNN algorithm flowchart.

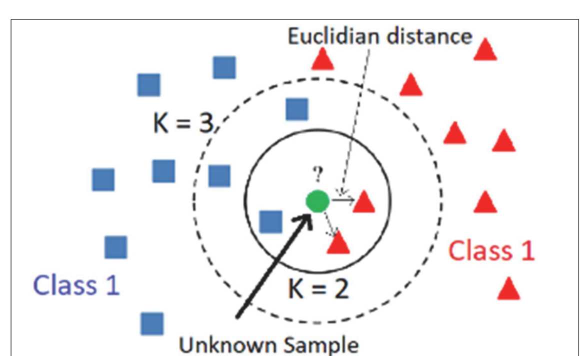


Figure 5. KNN example two-class classification.

regression applications. Some DT advantages are: simplicity in decision rule interpretation, since it's a nonparametric approach, it's easy to combine a range of numeric or classified data layers. Additionally, a decision tree is considered robust with respect to outliers among training data. Finally, fast classification ability whenever the rules are set (Yao *et al.*, 2009).

On the other hand, it's not always effective to apply splitting in a perpendicular way to feature space axes and DT does not predict outside the maximum and minimum boundaries of the training data. To build a DT classification, using training data, a tree generator is responsible for determining the variable that splits at a node, splitting value, stopping decision or continuing to split again, and finally, assigning end nodes to a specific class. The decision tree structure is shown in Figure 6.

2.3. Evaluation Metrics for Classifier

To analyze the PR algorithm ability and as a comparison criteria among selected PR algorithms, some basic related parameters are described as follows(Ouf and Hamza, 2021):

- True positives (TP): the number of samples which the trained model predicted belonged to a specific class and which actually do belong to that class.
- True negatives (TN) are the number of samples that the trained model predicted do not belong to a specific class but do not actually belong to that class.
- False positives (FP): the number of samples which the trained model predicted did belong to a specific class and which actually do not belong to that class.
- False negatives (FN) are the number of samples that the trained model predicted do not belong to a specific class but actually do.

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 (Ouf and Hamza, 2021):

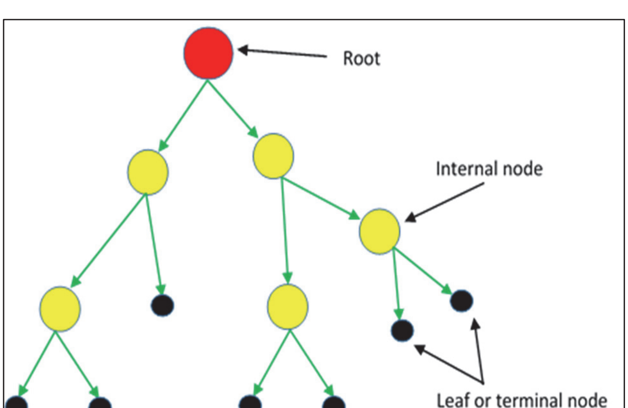


Figure 6. Decision tree structure (Yao *et al.*, 2009).

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \tag{5}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{6}$$

3. SYSTEM MODELLING AND DATA COLLECTION

The required training data is collected from the ABS model implemented within MATLAB Simulink, as shown in Figure 7. This model is built using the quarter-car model equations described in subsection 2.1., and the training data includes both fault-free and faulty data samples.

In this work, the faults of the wheel angular speed and vehicle speed sensors are assumed to be bias fault types, and through the fault injection unit, both sensors are injected with the same faults under the simulation operation conditions as described in Table 1. Fault signals $f_{vs}(t)$ and $f_{ws}(t)$ are injected into each of the vehicle speed sensors and wheel speed sensors, respectively. The equations of the injected faults can be constructed as follows:

$$\begin{aligned} f_{vs}(t) = -10 \times [(u(t-3.5) - (u(t-5.5)] + \\ 5 \times [(u(t-7.5) - (u(t-9.5)] + \\ 10 \times [(u(t-11.5) - (u(t-13.5)] \end{aligned} \tag{7}$$

$$\begin{aligned} f_{ws}(t) = 5 \times [(u(t-4.5) - (u(t-6.5)] + \\ 10 \times [(u(t-8.5) - (u(t-10.5)] + \\ 20 \times [(u(t-11) - (u(t-13)] \end{aligned} \tag{8}$$

Where $u(t)$ is a unit step function.

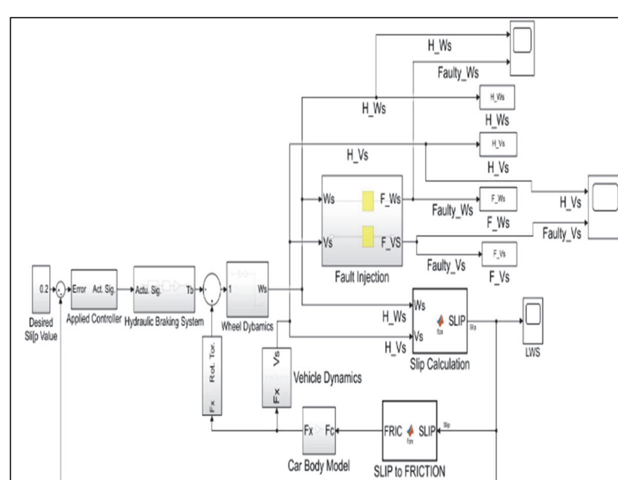


Figure 7. ABS model block diagram.

During simulation, four variables are observed: the Healthy Vehicle Speed data (H_V_s), the Faulty Vehicle Speed data (F_V_s), the Healthy Wheel Speed data (H_ω_s), and the Faulty Wheel Speed data (F_ω_s).

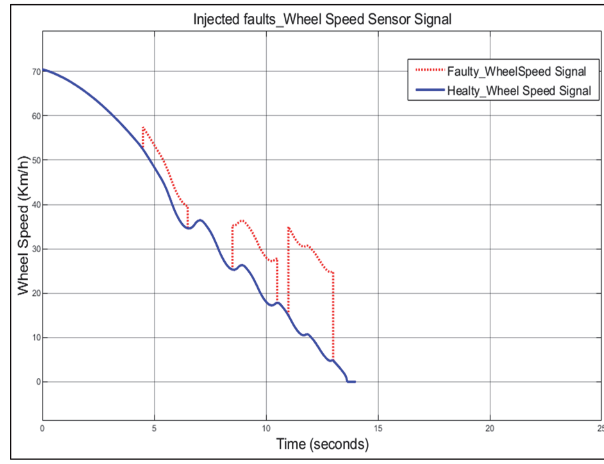
Figure 8 shows the sensors signals for both, vehicle speed and wheel angular speed with the injected faults related to Table 1. The extracted data from Simulink is arranged in suitable way to serve as a data base for training purposes. These data are categorized as faulty and fault-free. Thereby, a well-suited classification numbering is applied to distinguish between faulty and fault-free. A selected portion of these observed data samples is illustrated in Table 2. In order to evaluate each classifier model ability to detect and express severity of the occurred fault accurately, a unique class was assigned to each one of the six different injected fault, and hence, this result in an overall number of classses equal to seven in addition to healthy state class.

Table 1. Injected faults.

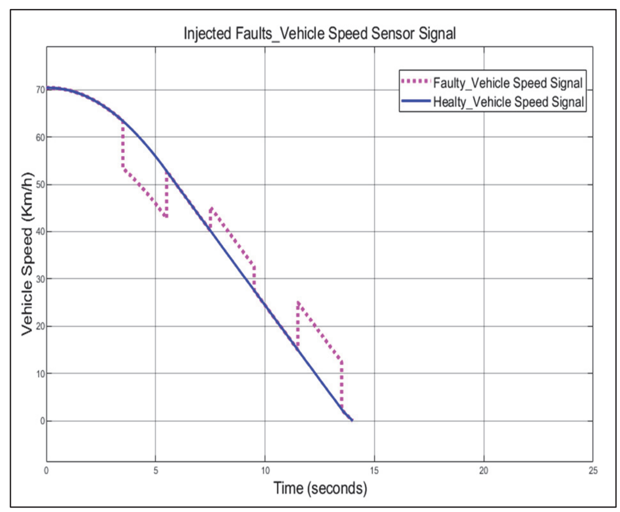
Fault location	Type	Value shifting	Time period (sec)	Assigned class
Vehicle speed sensor	Bias	-10	3.5 – 5.5	2
		+5	7.5 – 9.5	3
		+10	11.5 – 13.5	4
wheel angular speed sensor	Bias	+5	4.5 – 6.5	5
		+10	8.5 – 10.5	6
		+20	11 – 13	7

Table 2. Observed data samples (randomly selected portion).

Time (sec)	V_s (km/h)	W_s (km/h)	Class
2.8479	65.812	61.5513	1
3.0879	64.9769	60.4015	1
3.4979	63.388	58.3091	1
3.5979	52.9694	57.7747	2
3.7479	52.3185	56.9558	2
4.0379	50.9822	55.3147	2
4.2479	49.9504	54.0795	2
5.6679	51.734	46.9411	3
5.8022	50.8715	45.1013	3
5.8122	50.8075	44.968	3
5.8922	50.2966	43.9505	3



(a)



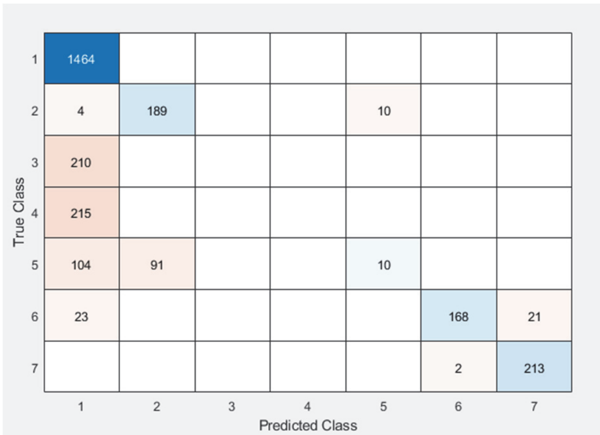
(b)

Figure 8. Injected bias fault: (a) Wheel angular speed sensor; (b) Equivalent angular vehicle speed sensor.

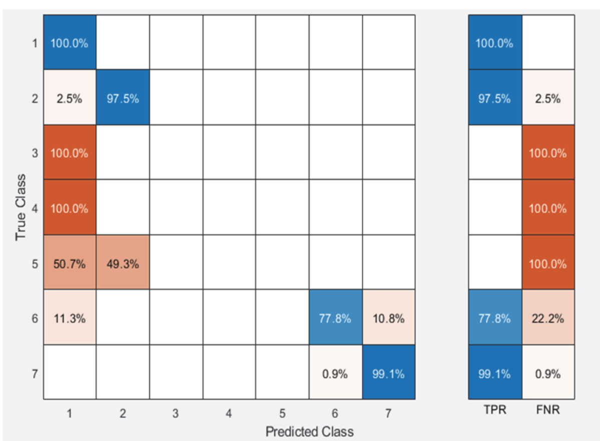
4. PR-ALGORTHIMS TRAINING AND TESTING RESEULTS

During offline, the MATLAB environment is used to perform the training process for each of the three selected PR classifiers (SVM, KNN, and NN) using the previously categorized data. Whereas the SVM model was trained based on the linear kernel function, the coarse DT was trained with a maximum number of splits of four, and finally, KNN was trained using the function K neighbors classifier with a (k = 4) number of neighbors.

Figure 9 shows the Confusion Matrix (CM) and True Positive Rate (TPR)–False Negative Rates (FNR) plots for each testing operation applied to the trained models. Table 2 shows the corresponding accuracy and sensitivity.



(a)



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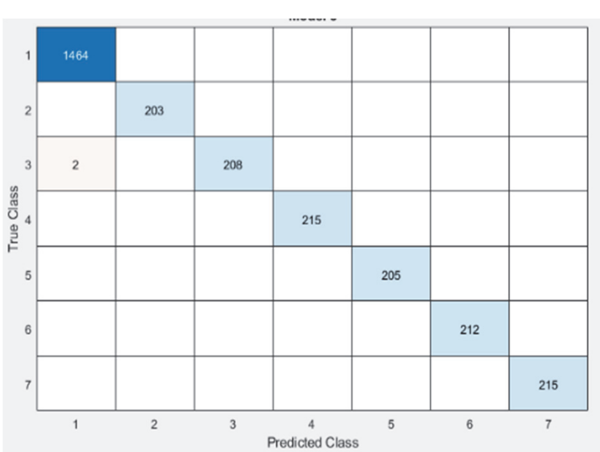
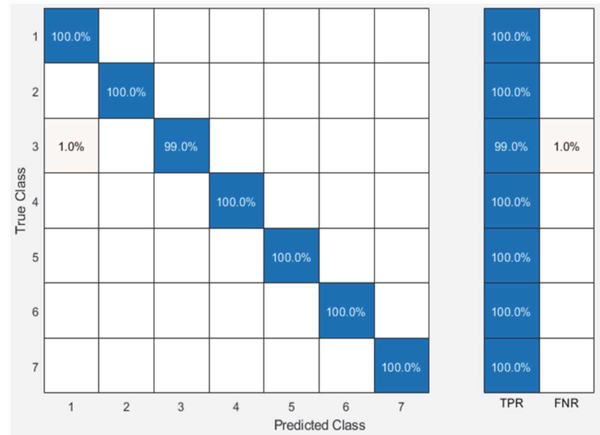
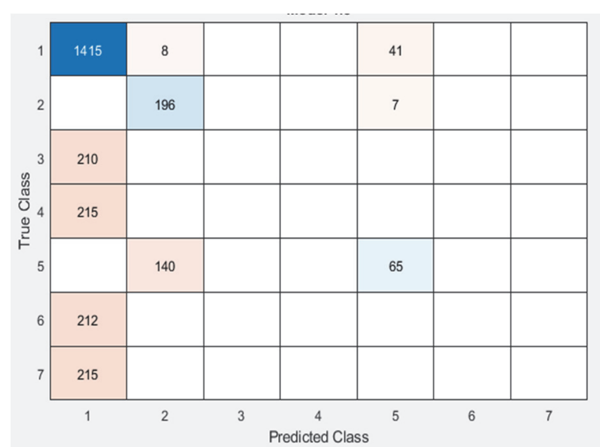


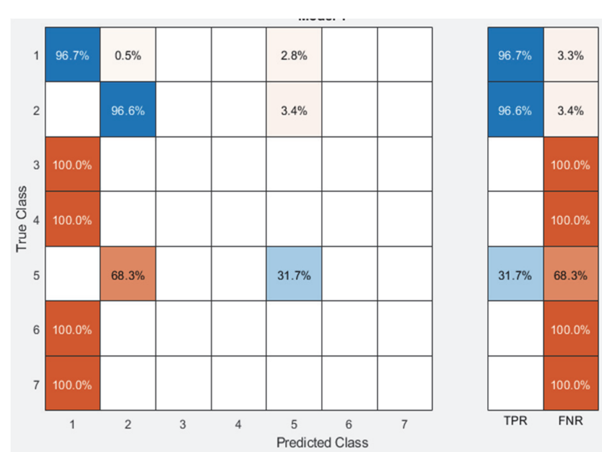
(c)



(d)



(e)



(f)

Figure 9. Algorithm training results: (a) CM for SVM classifier; (b) TPR-FNR plots for SVM classifier; (c) CM for KNN classifier; (d) TPR-FNR plots for KNN classifier; (e) CM for DT classifier; (f) TPR-FNR plots for DT classifier.

Table 3. Classifiers training performance results (Accuracy)

Method	Accuracy (%)
DT	61.5
SVM	75
KNN	99.9

Table 4. Classifiers training performance results (Sensitivity)

Method	Sensitivity (%)						
	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
DT	96.7	69.6	0	0	31.7	0	0
SVM	100	97.5	0	0	0	77.8	99.1
KNN	100	100	99	100	100	100	100

From Tables 3 and 4 above, the DT classifier has excellent and accepted sensitivity for category 1 and category 5, respectively, and poor sensitivity for the rest of the categories. These defects in performance result in an overall accuracy of 61.5 %, which makes it an undesirable choice.

Meanwhile, the SVM classifier presents a slightly better performance than the DT classifier, where the SVM's overall accuracy is equal to 75 %, where for the SVM, the sensitivity was excellent for 1, 2, 6 and 7 categories and very poor for 3, 4 and 5 categories. Finally, the Knn classifier, presents a greater accuracy of 99.9 %, which is much better performance than DT and SVM. As for the SVM, it requires a greater number of hyperparameters and less training data. When large features and less training data are present, SVM may outperforms KNN. As for DT, on the other hand, it can be non-robust despite the fact that both KNN and DT are non-parametric. For example, a slight change in the data can result in a significant difference in the final predicted tree. And that what could ouccured fault effect. Thus, KNN represents a perfect model to be employed as an FDI model for ABS speed sensors.

5. CONCLUSION

Wheel angular speed and vehicle speed sensors are key elements in ABS control operation, the malfunction or failure of theses sensors results in unsafety driving and even human life threat In this work, an FDI based on the PR approach was implemented for fault detection in the ABS wheel angular speed and vehicle speed sensors. Among the PR algorithms, three algorithms were selected for the purpose of comparison; these were the DT, SVM, and KNN classifier algorithms. After preparing the required data base for training purposes, training is performed using the MATLAB environment for the three selected algorithms, and the classifier's main performance measurements have been described by means of accuracy and sensitivity. Results demonstrate that among the three selected algorithms and as related to ABS speed sensor fault detection, KNN has much better performance than both DT and SVM.

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