Health Monitoring of Automotive Suspension System using Machine Learning

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Abstract: This paper investigates Knowledge-based condition monitoring of automotive suspension dampers by implementing a quarter car model (QCM). The sprung mass acceleration - frequency power spectral density curves, for different cases of performance degradation in suspension damping and different operational conditions, is provided in response to the random road disturbance of different road classes. Training and testing acceleration response data are generated by Mtalb/simulink and fed to different classification algorithms that are trained and tested to distinguish between the different damping degradation values, in order to assess their performance in terms of classification accuracy as well as their confusion matrix. In addition, the worthiness of applying Principal Component Analysis (PCA), as a dimensional reduction technique, to increase all candidate classification algorithms is explored. Finally, the results of Quadratic Support Vector Machine showed the best performance in terms of accuracy and confusion matrix, while using dimensional reduction turned to be inefficient.

1 INTRODUCTION

It is inevitable for suspension system or any other structure to gradually show signs of damage like reduction in performance due to many causes such as inadequate maintenance, and material aging. Suspension system needs to be monitored frequently so that if any damage detected, it could be fixed as soon as possible in order to avoid unsafe or unreliable service because of its partial or full failure. Recently, automotive suspension health monitoring has been drawing more interest as a potential application of the current promising machine learning techniques (Jayasundara et al., 2020).

Historically, providers of on-board monitoring systems, installed on railway vehicles, were confined to track defects and did not show any concern to the suspension systems of the vehicle which could lead to serious failures. On-board health monitoring systems provide continuous monitoring with real-time detection of defects and early warning of any defect that might happen on the future or even if there is a defect now that will indeed help in saving money or even in saving lives. Sensors, typically including accelerometers, gyros, noise sensors (e.g. microphones) and (GPS), used to be installed in a railway vehicle to identify track irregularities, vehicle dynamic behaviour, vehicle precise location and velocity. Smart algorithms like machine learning have been developed to analyse the data from sensor networks to offer a precise real-time state estimation and for Fault Detection and Isolation (FDI) (Ngigi et al., 2012).

Health monitoring can be classified into three different categories; model based, signal based, and knowledge based systems. In model based approach ,the system dynamic behaviour is modelled by mathematical equations which relate the system response to the input excitation. The main idea behind the model based approach is to monitor the change in the system dynamic behavior, using measured real-time system response, which could be traced back to the degradation of system properties by the aid of the equations of motion. (Peng et al., 2010).

Instead, signal based methods use only the measured output signals, which are further analyzed using feature extraction methods. Signal-based feature extraction methods are mainly classified into three different types which are time domain, frequency domain and time-frequency domain (Gao et al., 2015). It does not matter which method is used, the idea is that different faults in the system gives a totally different combination of values in the extracted features,

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which enables the classifier to distinguish between faulty and non-faulty condition,and also between different types of faults(Dai and Gao, 2013). In signal based methods the relationship between the features and the system current state, is extracted from the data set without any human interference. It requires the identification of signal patterns without having predefined examples(Karlsson, 2019).

On the other hand, the core idea of Knowledge based methods is to create a connection from feature to system condition autonomously, Which means that the classifier will be trained by examining a huge amount of examples and it learns the pattern necessary for fault classification on its own. Therefore, this method requires much more training data compared to those required in signal based and model based techniques.Knowledge based method also have different types based on the fault detection and diagnosis (FDD) method utilized in them.

Hybrid technique is mainly a combination of two of the above techniques or even all of them which is the most common Fault Detection Technique (Cecati, 2015)(Gao et al., 2015) and hereinafter, some of the previous research work of this topic will be cited. In the process of developing a data-driven health monitoring system, two major tasks have to be solved for improving prediction accuracy and computation efficiency: proper feature extraction from large-scale sensory data and an accurate data analysis model. The goal of a good health monitoring of a suspension system is high prediction accuracy and low computation time.

Luo et al.(Luo et al., 2018) proposed a novel method is proposed to develop a health monitoring system by integrating a multi- Gaussian fitting feature extraction method with a long short-term memory (LSTM) Convolutional Neural Network (CNN) based damage identification method. Firstly, a multi-Gaussian fitting method is devised to obtain comprehensive frequency-domain information of each subsequence of the available vibration signals in order to represent data of vibration signals and reduce the input data size for data analysis purposes. Then this data is feed to CNN model in order to obtain a nonlinear relation between the frequency domain features and real time partial damage level.

In addition, Luo et al(Luo et al., 2019) introduced another method of health monitor by using Dual-Tree Complex Wavelet enhanced (DTCWT), to obtain multi scale characteristics information of measured signals. A deep convolutional neural networks (DCNN) model is then employed to automatically extract useful damage features.The proposed method proved efficient in eliminating noise from the measured vibration signals.Finally a Contextual long short-term memory (CLSTM) is built to capture the nonlinear relationship between the preprocessed vibration signals and corresponding partial damage values. Chen et al.(Chen et al., 2019) introduced another approach to achieve the same goal by using Extreme Learning Machine (ELM) along side with convolutional neural networks. Time series vibration signals were measured using accelerometers, while good representative features were obtained using Wavelet Transform (WT) to convert the one-dimensional time signals into two-dimensional time-frequency images. In CNN-ELM, the training samples are firstly fed into the CNN architecture to obtain the feature maps, then all the features are combined together and regarded as the input of the ELM model which can be efficiently trained by a generalized inverse operation. At the testing phase, the testing samples are fed into the trained CNN-ELM model to obtain the final diagnosis result.

Hong et al.(Hong et al., 2019) presented Multi-Output Support vector regression (MSVR) method for health monitoring of trains suspension system. The main idea was to monitor the stiffness and damping coefficients the suspension system using vibration signals measured on trains in real time. First, a simple suspension system dynamics model is built to generate a training data set. Furthermore, key features are extracted from frequency response curves to reflect the impact of spring and damper degradation. Subsequently, a supervised learning model based on the (MSVR) is built to predict the stiffness and damping coefficients of suspension systems from features extracted in the second module Once the model is built, real time monitoring can be achieved.

KARLSSON (Karlsson, 2019) developed a model, based on frequency response functions,to simulate the response of the four corner suspensions and the goal was to detect which suspension is the faulty one without quantifying the degradation value itself. Hong et al. (Hong et al., 2019) provided different approach based on the bode plot of the vertical acceleration alongside with multi-output support vector regression. The current paper presents an extension to the above mentioned work, by introducing acceleration frequency response analysis along side with a classification technique, in order to identify and quantify the degradation percentage of the faulty suspension. A Knowledge-based condition monitoring, of automotive suspension dampers, is developed by implementing a quarter car model (QCM). The sprung mass acceleration - frequency power spectral density curves, for different cases of performance degradation in suspension damping and different operational conditions, is provided in response to the random

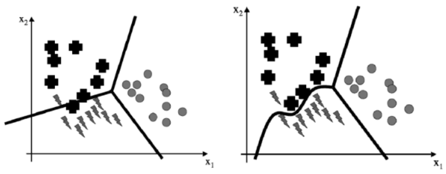

Figure 1: Machine Learning Classification Algorithm.

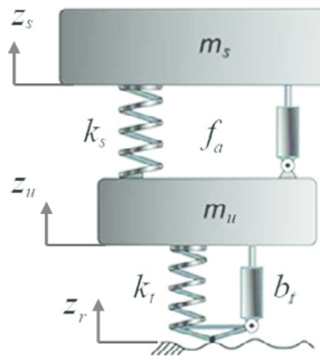

Figure 2: Quarter Car Model.

Table 1: List of parameters and their description of QCM.

Parameter	Description
M_s	Sprung Mass(kg)
M_u	Unsprung Mass(kg)
K_s	Suspension Stiffness(N/m)
K_t	Tire Spring Stiffness(N/m)
b_s	Suspension Damper Coefficient(Ns/m)
b_t	Tire Damper Coefficient(Ns/m)
Z_s	Sprung Mass Displacement(m)
Z_u	Unsprung Mass Displacement(m)
Z_r	Road Profile(m)

Table 2: Suspension System Parameters values.

Parameter	value
M_s	42.757 kg
M_u	5.6321 kg
K_s	10581.2922 N/m
b_s	96.0739 Ns/m
K_t	98041.2466 N/m

road disturbance of different road classes. Training and testing acceleration response data are generated by Mtalb/simulink and fed to different classification algorithms that are trained and tested to distinguish between the different damping degradation values. Classification is utilized, rather than regression, because classification fits more discrete problem while regression deals with continuous data.

2 MATHEMATICAL MODEL

This section details the mathematical approach, implemented using quarter-car model (QCM), in order to have a health monitoring of vehicles suspension systems. A dynamical model is presented first which will be simulated by Matlab/Simulink. Input and output data to and from the simulink model will replace the real time displacement and acceleration sensors data which are supposed to be used in training and testing the machine learning model.

2.1 Quarter Car Modeling

Dynamical model for a quarter-car model with two-degrees of freedom, namely sprung mass and unsprung mass displacements, is implemented in order to to simulate the car with different speeds, different masses, different fault factors of the damper coefficient and different road profiles or tracks. Tables I and II list the definition and numerical values of all parameters involved in the following two equations of motion.

$$M_s\ddot{z_s} = -k_s(z_s - z_u) - b_s(\dot{z_s} - \dot{z_u}) \tag{1}$$

$$M_u\ddot{z_u} = k_s(z_s - z_u) - k_u(z_u - z_r) - b_s(\dot{z_s} - \dot{z_u}) \tag{2}$$

2.2 Road Profile

Road profiles differ from each other by the road roughness which can be described by Power Spectral Density (PSD) functions.The road roughness can be seen as a stationary process in the space domain while the car is moving. Therefore, the following differential equation 3, which models the road roughness and velocity of the vehicle, could be very helpful in developing a training and testing data sets which represent a wide range of road-vehicle dynamic interaction (He et al., 2008; Zhang et al., 2007).

$$\dot{z_r}(t) + 2\pi n_o v z_r(t) = \sqrt{S_q(n_o)}vw(t) \tag{3}$$

Equation 3 is a first order differential equation, where v is the velocity in (m/s), z_r is the road profile (m), n_o is reference spatial frequency of value 0.1 (cycles/m), $S_q(n_o)$ is the coefficient of road roughness

Table 3: Coefficient of road roughness.

Road Class	Roughness $(10^-6m^2/(cycle/m))$		
	lower	geometric mean	upper
A(very good)	-	16	32
B(good)	32	64	128
C(average)	128	256	512
D(poor)	512	1024	2048
E(very poor)	2048	4096	-

Table 4: Training Simulation variances for the QCM.

Feature	Variance
velocity(kmph)	10 30 40 60 100 120
body mass factor	1 1.03 1.04 1.05
damping fault factor	1.0 0.75 0.5 0.25 0.1
road roughness class	A B C D E

$m^2/(cycle/m)$, $w(t)$ is a white noise signal having a PSD equal to 1. For simplicity $S_q(n_o)$ is named N and $2\pi n_o$ is named n.

According to ISO 8608(ISO/TC et al., 1995), roads are classified according to their roughness into 5 categories A, B, C, D and E as shown in table 3. A and B considered to be the highest quality representing motorways and expressways with more than 60 km/h velocity range, while class C is the average road type with an average velocity between 30 and 60 km/h. Class D and E therefore are categorized to be the worst with less than 30 km/h.

2.3 Machine Learning

Classification algorithms in machine learning are trained and tested with different datasets. One important characteristic that an algorithm should possess is the ability to generalize, i.e. to be able to perform well on testing datasets that differ from the training dataset. For this reason different datasets with different operational conditions should be incorporated in both the training and testing phase to evaluate how well the algorithm can handle varying operational conditions that it will most certainly be exposed to in a real-world application of vehicle's suspension system health monitoring.

It was decided to simulate the QCM on all five different road profile classes by changing their road roughness coefficient. These changes in the road profiles are accompanied by changes in car body masses and speed and damping coefficient. Damping coefficients varies with 4 fault factors 0.75 0.5 0.25 0.1 as well as the reference case (fault factor 1.0). Six different speed profiles are also simulated 10 20 30 40 60 100 120 kmph as well as 4 different car body masses with factors of 1 1.03 1.04 1.05 to represent changes in the number of passengers as table 4.

2.4 Methodology

As explained when making a machine learning algorithm data sets must be provided so that training and testing is applicable. The common structure of this data set and will be used in this work is through a design matrix.

Table 5: Design matrix.

ID	Damping fault	Feature 1	...	Feature n
1	1.0	xx	...	xx
2	0.75	xx	...	xx
3	0.5	xx	...	xx
4	0.25	xx	...	xx
⋮	xx	xx	...	xx
600	xx	xx	...	xx

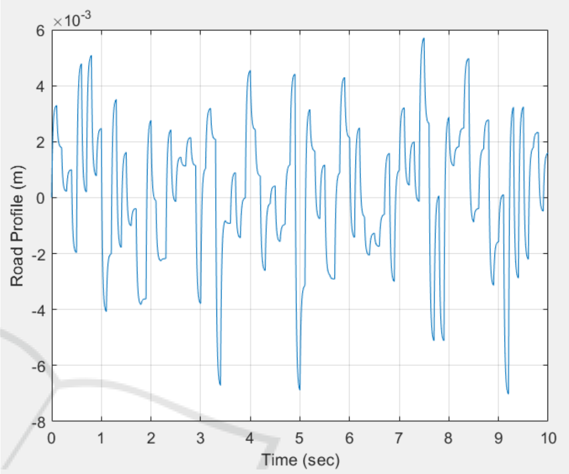

Figure 3: Road surface (class C, velocity 80 kmph).

Each row contains a data point, in table 5 is an example of the used design matrix. Each row contains an ID that identifies that specific data point, as shown in the first column. The second column contains the damping value that will be the target in the classification algorithm. The rest of the columns contains the features which will help the algorithm identify to classify the target. There are total four features like velocity of the vehicle, the peak of the PSD curve, the sprung mass of the vehicle and finally the roughness of the road the vehicle traveling on.

3 RESULTS AND DISCUSSION

The road profile for a vehicle traveling 80 kmph on a road class C with a coefficient of road roughness 512 x 10^{-6} $m^2/(cycle/m)$ is shown in fig3.

The reason of using PSD in health monitoring is that it proved a relation between the peak of this PSD and the damping coefficient. They are inversely proportional so as the damping coefficient increases the peak of the vertical acceleration PSD extracted from the accelrometer decreases. This is proved by three simulations their results shown in fig 4 where all of the other parameters of the QCM is constant and the

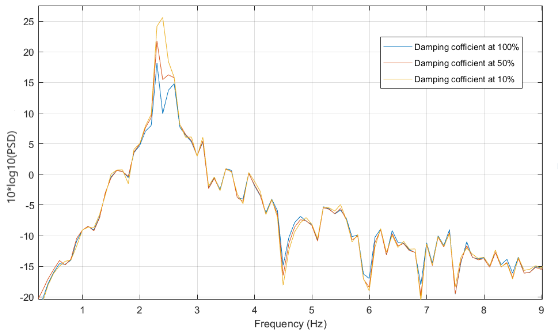

Figure 4: Power spectral densities for sprung mass acceleration of different damping coefficients.

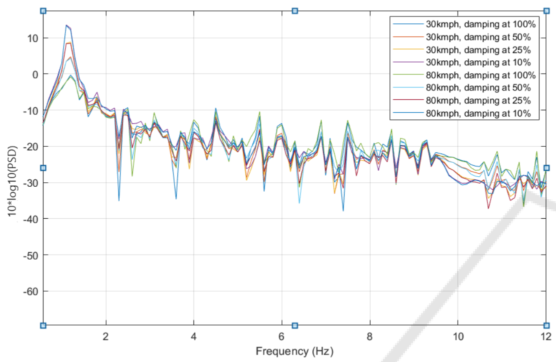

Figure 5: Power spectral densities for sprung mass acceleration of different damping coefficients with different velocities.

only change is in the damping coefficient in order to get reliable results to prove this relation.

In Figure 5 the track class (road profile) is kept constant but the velocity is varied between 30 kmph and 80 kmph. The variation of velocity with damping coefficient shown in figure 5 shows how the velocity affects the peak of the PSD.

The results will be in terms of the two performance measures for different classification algorithms are presented along with dimensional reduction of feature extraction (transformation) which is called PCA. The first performance measure that will be displayed in this section will be the accuracy of the classification algorithm and also with 5-fold cross validation. Validation is made to protect the classification algorithms from overfittng. The second performance measure will be the confusion matrix of each classification algorithm also and it will be explained later in this chapter.

There are total 24 classification algorithm trained with and without PCA made on a dataset containing 6 different velocities, 4 different mass factors, 5 different damping fault factors and 5 different road roughness classes as in table 4. This result of 600 simulation to create this training dataset and there

Table 6: Testing Simulation variances for QCM.

Feature	Variance
velocity(kmph)	20 50 70 80 90 110
body mass factor	1 1.01 1.02 1.06
damping fault factor	1.0 0.75 0.5 0.25 0.1
road roughness class	A B C D E

will be another 600 simulations to create another datasets for more testing as in table 6. This section will show results for the performance measures on both the training dataset and according to this result, the testing data sets will be tested on the algorithms showed the best performance measures in the training datasets.

3.1 Results of Training Datasets

The first performance measure is the correct classification rate (accuracy), defined as the number of correct classifications divided by the total number of classifications, which is the same as adding the true positives and true negatives and dividing by the total number of predictions:

Table 7 shows the output accuracy of each of 24 classification algorithm with PCA on and off with 5-fold cross validation used and it showed a significant drawback of using PCA with our dataset and classification algorithms. Both cubic support vector machine and quadratic support vector machine showed the best results of the first performance measure without PCA. Also table 8 shows the output accuracy of each of 24 classification algorithm with PCA on and off with 10-fold cross validation and it resulted nearly the same result when using 5-fold cross validation.

In many applications it is of the best to investigate what the actual classifications are. This is often done by using the confusion matrix. the rows show the true class, and the columns show the predicted class as in fig 6. When using holdout, then the confusion matrix is calculated using the predictions on the held-out observations. The diagonal cells show where the true class and predicted class match. If these cells are green, the classifier has performed well and classified observations of this true class correctly.

The reason for choosing the confusion matrix as a performance measure is that it shows the true positive rates and false negative rates which are extremely important measure to specify the actual performance of the classification algorithms. The lowest row shows true class of no fault factor(100% damping coefficient) and the columns shows the predicted classes.In fig 6 in the lowest row 99% of the simulations with no fault factors were correctly classified(predicted)

Table 7: Classification algorithms accuracy with 5-fold cross validation.

Algorithm	Accuracy(%) PCA	
	OFF	ON
Fine Tree	84.7	35.8
Medium Tree	74.5	29.8
Coarse Tree	48.7	21.8
Linear Discriminant	74.0	15.8
Quadratic Discriminant	75.3	14.3
Gaussian Naive Bayes	39.7	14.3
Kernel Naive Bayes	50.8	16.3
Linear SVM	75.0	19.7
Quadratic SVM	96.8	21.2
Cubic SVM	95.5	21.2
Fine Gaussian SVM	72.7	10.5
Medium Gaussian SVM	79.7	14.5
Coarse Gaussian SVM	67.5	15.0
Fine k-nearest neighbors	57.8	33.8
Medium k-nearest neighbors	57.2	47.3
Coarse k-nearest neighbors	44.5	17.0
cosine k-nearest neighbors	53.5	18.5
cubic k-nearest neighbors	57.5	47.3
Weighted k-nearest neighbors	59.0	35.3
Ensemble Boosted Trees	84.0	32.2
Ensemble Bagged Trees	76.5	34.3
Ensemble Subspace D	59.7	15.8
Ensemble Subspace K-N	24.8	33.8
Ensemble RUSBoosted Trees	74.5	28.5

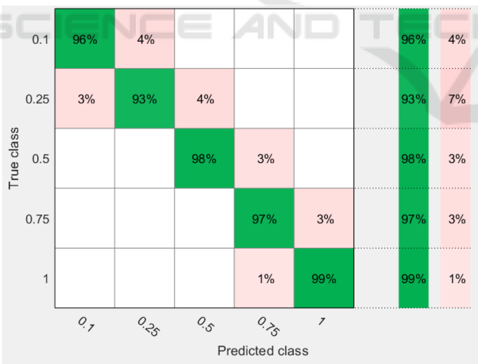

Figure 6: Cubic support vector machine with 5-fold cross validation confusion matrix.

to have 100% damping coefficient while only 1% of the simulations were miss-classified as having 75% damping coefficient, so 99% is the true positive rate for correctly classified points in this class, shown in the green cell in the True Positive Rate column (right side). 1% is the false negative rate for incorrectly classified points in this class, shown in the red cell in the False Negative Rate column(right side). Figures 7, 8 and 9 shows the confusion matrices of the best algorithms in terms of accuracy.

Table 8: Classification algorithms accuracy with 10-fold cross validation.

Algorithm	Accuracy(%) PCA	
	OFF	ON
Fine Tree	86	38.8
Medium Tree	74.7	27.3
Coarse Tree	49.0	22.8
Linear Discriminant	73.5	15.5
Quadratic Discriminant	74.5	12.0
Gaussian Naive Bayes	39.5	12.0
Kernel Naive Bayes	50.3	15.5
Linear SVM	75.8	18.0
Quadratic SVM	96.3	19.8
Cubic SVM	96.3	22.2
Fine Gaussian SVM	75.7	7.7
Medium Gaussian SVM	83.3	11.7
Coarse Gaussian SVM	67.0	14.2
Fine k-nearest neighbors	58.5	35.3
Medium k-nearest neighbors	61.7	47.7
Coarse k-nearest neighbors	46.7	18.3
cosine k-nearest neighbors	56.2	19.7
cubic k-nearest neighbors	60.3	47.7
Weighted k-nearest neighbors	60.7	36.3
Ensemble Boosted Trees	83.2	29.7
Ensemble Bagged Trees	89.0	35.5
Ensemble Subspace D	59.3	15.5
Ensemble Subspace K-N	26.3	35.3
Ensemble RUSBoosted Trees	74.8	27.3

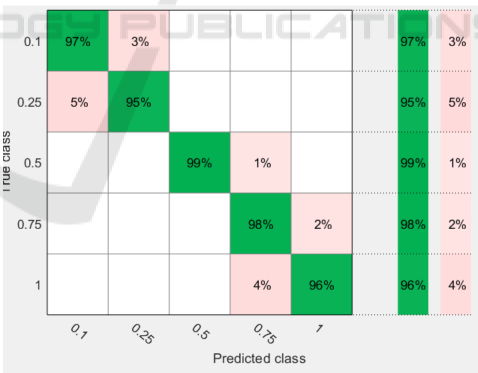

Figure 7: Quadratic support vector machine with 5-fold cross validation confusion matrix.

3.2 Results of Testing Datasets of QCM

Figures 10 and 11 shows how our classification algorithm (Support vector machine with quadratic kernel function representing it) responded to the testing datasets which contains 600 different simulations than the training dataset. It showed extremely promising results in the previous section in accuracy and confusion matrix that's why it was chosen to be further

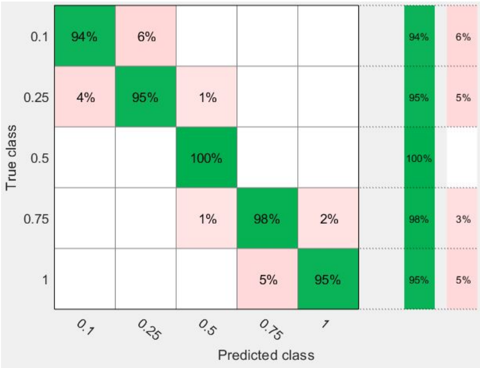

Figure 8: Quadratic support vector machine with 10-fold cross validation confusion matrix.

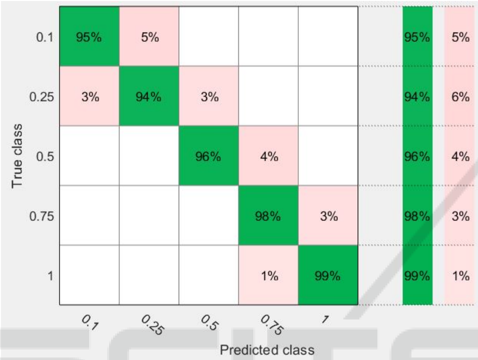

Figure 9: Cubic support vector machine with 10-fold cross validation confusion matrix.

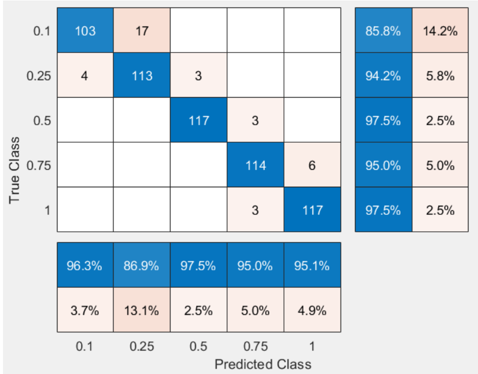

Figure 10: Quadratic support vector machine with 5-fold cross validation confusion matrix of testing dataset.

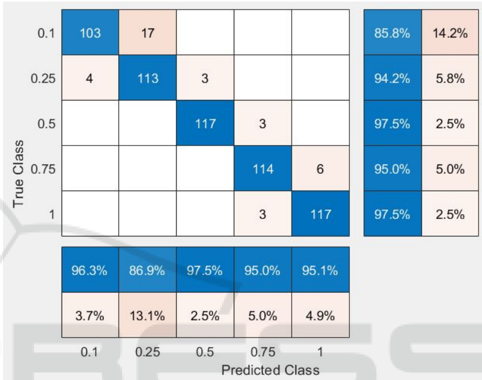

Figure 11: Quadratic support vector machine with 10-fold cross validation confusion matrix of testing datasets.

tested and it showed 94% accuracy for the 5-fold validation and 10-fold validation .

4 CONCLUSIONS

The objective of this paper is to propose a health monitoring technique that can work on real time conditions in the future in order to avoid or decrease the human casualties and the economic loss made because of suspension systems failure. The vehicle safety and reliability have become such important field as the number of road vehicles has increased significantly and still increasing. Health monitoring especially fault detection is now a well known field and with the help of Artificial Intelligence and various simulations like for example car models in Matlab.

The general idea of the approach in this work is to predict the value or the degradation happened in the suspension system in the damping part (damping coefficient) using several features like velocity of the car, the road profile the car traveling on it and the mass of the sprung mass (mass above the suspension part excluding the tires) using these features and arranging them in the design matrix to introduce them to the classification algorithms for further predictions. All of this is based on the relation of the peak of the PSD of the vertical acceleration of the sprung mass and the damping coefficient. The results of Quadratic Support vector Machine in QCM is very promising whether in the training or testing data. Using PCA in both training and testing data resulted a significant decrease in the performance of the models in terms of both accuracy and confusion matrix.

REFERENCES

Cecati, C. (2015). A survey of fault diagnosis and fault-tolerant techniques—part ii: Fault diagnosis with knowledge-based and hybrid/active approaches. *IEEE Transactions on Industrial Electronics*.

Chen, Z., Gryllias, K., and Li, W. (2019). Mechanical fault diagnosis using convolutional neural networks and extreme learning machine. *Mechanical Systems and Signal Processing*, 133:106272.

Dai, X. and Gao, Z. (2013). From model, signal to knowledge: A data-driven perspective of fault detection and diagnosis. *IEEE Transactions on Industrial Informatics*, 9(4):2226–2238.

Gao, Z., Cecati, C., and Ding, S. X. (2015). A survey of fault diagnosis and fault-tolerant techniques—part i: Fault diagnosis with model-based and signal-based approaches. *IEEE Transactions on Industrial Electronics*, 62(6):3757–3767.

He, L., Qin, G., Zhang, Y., and Chen, L. (2008). Non-stationary random vibration analysis of vehicle with fractional damping. In *2008 international conference on intelligent computation technology and automation (ICICTA)*, volume 2, pages 150–157. IEEE.

Hong, N., Li, L., Yao, W., Zhao, Y., Yi, C., Lin, J., and Tsui, K. L. (2019). High-speed rail suspension system health monitoring using multi-location vibration data. *IEEE Transactions on Intelligent Transportation Systems*.

ISO/TC, T. C., Vibration, M., Measurement, S. S. S., of Mechanical Vibration, E., and as Applied to Machines, S. (1995). *Mechanical Vibration–Road Surface Profiles–Reporting of Measured Data*. International Organization for Standardization.

Jayasundara, N., Thambiratnam, D., Chan, T., and Nguyen, A. (2020). Damage detection and quantification in deck type arch bridges using vibration based methods and artificial neural networks. *Engineering Failure Analysis*, 109:104265.

Karlsson, H. (2019). Monitoring vehicle suspension elements using machine learning techniques.

Luo, H., Huang, M., and Zhou, Z. (2018). Integration of multi-gaussian fitting and lstm neural networks for health monitoring of an automotive suspension component. *Journal of Sound and Vibration*, 428:87–103.

Luo, H., Huang, M., and Zhou, Z. (2019). A dual-tree complex wavelet enhanced convolutional lstm neural network for structural health monitoring of automotive suspension. *Measurement*, 137:14–27.

Ngigi, R., Pislaru, C., Ball, A., and Gu, F. (2012). Modern techniques for condition monitoring of railway vehicle dynamics. In *Journal of Physics: Conference Series*, volume 364, page 012016. IOP Publishing.

Peng, Y., Dong, M., and Zuo, M. J. (2010). Current status of machine prognostics in condition-based maintenance: a review. *The International Journal of Advanced Manufacturing Technology*, 50(1-4):297–313.

Zhang, Y., Chen, W., Chen, L., and Shangguan, W. (2007). Non-stationary random vibration analysis of vehicle with fractional damping. In *13th national conference on mechanisms and machines*.