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Intelligent Diagnostic Methods Based on Machine Learning for Enhanced Fault Identification in Permanent Magnet Synchronous Motors Used in Electric Vehicles

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Abstract

The Permanent Magnet Synchronous Motor (PMSM) has emerged as the predominant engine in electric vehicles due to its numerous advantages. However, the occurrence of faults in PMSMs can compromise the vehicle's power, stability, and safety, posing potential risks to both the vehicle and its occupants. Therefore, the accurate detection and diagnosis of these faults play a crucial role. In recent years, intelligent diagnostic methods leveraging machine learning techniques have garnered significant attention as they offer enhanced precision and differentiation in fault identification, enabling effective monitoring of PMSM health. This work presents a comprehensive review of intelligent diagnostic methods based on machine learning, including wide margin separators, expert systems, neural networks, fuzzy logic, and deep learning approaches. These methods have shown promising results in accurately identifying and classifying faults in PMSMs, contributing to the maintenance and optimal performance of electric vehicles.

Keywords: Permanent magnet synchronous motor (PMSM), Electric vehicles, Deep learning theory, Wide margin separators, Neural network, Intelligent diagnosis, Machine learning.

1. Introduction

The Permanent Magnet Synchronous Motor (PMSM) has emerged as the preferred choice for electric vehicles due to its inherent advantages. However, the occurrence of faults in PMSMs can adversely impact the vehicle's power, stability, and safety, posing significant risks to both the vehicle and its occupants [1, 2]. Thus, the detection and diagnosis of faults in PMSMs are of utmost importance. In recent years, intelligent diagnostic methods based on machine learning have gained considerable attention owing to their ability to provide precise and differentiated fault identification, facilitating effective health monitoring of PMSMs. This paper aims to provide an overview of intelligent diagnostic methods employed by researchers for fault identification in PMSMs used in electric vehicles. Various machine learning-based approaches, such as wide margin separators, expert systems, neural networks, fuzzy logic, and deep learning techniques, will be discussed in detail, highlighting their potential for accurate fault detection and diagnosis.

Intelligent diagnostic methods based on machine learning have become increasingly prominent in the field of fault detection and diagnosis in Permanent Magnet Synchronous Motors (PMSMs) used in electric vehicles. These methods offer enhanced precision and differentiation in fault identification, enabling effective monitoring of the health state of PMSMs. Wide margin separators, expert systems, neural networks, fuzzy logic, and deep learning approaches have demonstrated their effectiveness in accurately identifying and classifying faults, contributing to the maintenance and optimal performance of electric vehicles. As technology continues to advance, researchers are actively exploring novel [14] machine learning techniques to further enhance fault diagnosis accuracy and real-time monitoring capabilities for PMSMs in electric vehicles.

1.1. *Electric Vehicle (EV)*

The “all-electric” vehicle is an automobile towed by an electric motor and powered by an accumulator battery. The latter stores electricity, and it is rechargeable by using a charger and a cable from an external source. The revcovery of energy during the braking phases is also possible by means of the motor switching to generator mode and a voltage rectifier ensuring the AC/DC conversion. The inverter allows the DC/AC conversion of the batteries necessary for the operation of the traction motor. These days, the EV is much more intended for the urban perimeter because it does not cause air or noise pollution. This is what makes it ideal to meet the requirements of urban traffic [3].

1.2. *Permanent Magnet Synchronous Machine (PMSM)*

Permanent Magnet Synchronous Machine (PMSM) is an electromechanical system that is based on the principle of rotation of the magnetic field at the stator in synchronism with the rotor. The rotating field from the armature to the stator is created by the quasi-sinusoidal currents flowing through its windings and generated by the voltage or current supply source. The rotor inductor is the moving part of the machine, linked to its axis of rotation and on which the permanent magnets generating its permanent excitation are arranged. The interaction between these two fields gives rise to the electromagnetic torque which allows the rotation of the rotor. However, if the rotation of the stator field takes place independently of the instantaneous position of the rotor, as is the case with the conventional synchronous machine, there will be a risk of the rotor stalling in the case of a variable speed drive. To avoid this risk and to stabilize the behavior of the machine, the switching of the inverters must be carried out in synchronism with the position of the rotor, by means of a position sensor [4].

1.3. *Types of Faults in PMSM*

1.3.1. *Stator faults*

The stator of the machine consists of a ferromagnetic yoke and the windings located in its slots. Faults can occur in the stator at the yoke or windings. As for stator cylinder head defects, they are relatively rare for small and large machines and are neglected in studies [5]. In this regard, we mention the most important defects of the fixed part. • Stator winding faults;

• Short circuit faults.

1.3.2. *Rotor faults*

Rotor defects depend on the type of machine considered, among which we can cite the most important [5].

- Demagnetization fault for permanent magnet synchronous machines;
- Faults in rotor windings for conventional synchronous machines;

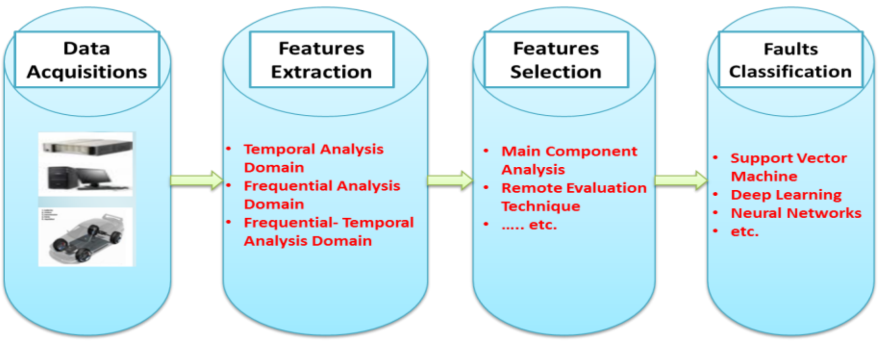

Figure 1: Smart Fault Diagnosis Flowchart

- Mechanical bearing faults;
- Rotor eccentricity.

2. Fault Diagnosis Methods Based on Artificial Intelligence

Data-driven intelligent diagnostic systems are beginning to emerge as prospective strategies for fault diagnosis in a wide range of applications [6]. Intelligent fault diagnostics is an urgent technology combining signal analysis, modeling, and knowledge processing. It can replace specialists in order to quickly and efficiently process collected signals and provide accurate diagnostic results [7]. Without the need of a diagnostic specialist to review data and diagnose problems, intelligent fault diagnosis can be a potential tool to manage massive data of machine fault diagnosis in the era of big data [8]. In the framework of intelligent fault diagnosis, four main steps are represented in Figure 1: data acquisition, feature extraction, feature selection, and fault classification [9, 10].

2.1. *Artificial Neural Network*

An artificial neural network (ANN) is an information processing paradigm inspired by the way the human brain processes information [11]. It can play an important role in identifying and diagnosing machine faults. This intelligent fault diagnosis can provide self-diagnosis procedures. In the field of intelligent monitoring condition analysis, ANN can be employed for a variety of applications, such as function approximation, classification, pattern recognition, clustering, and prediction.

Artificial neural network methods were used to analyze power supply imbalance and phase loss of permanent magnet synchronous motor. An artificial neural network was proposed to combine the three-phase stator, current, and voltage of PMSM. The voltage imbalance ratio under different loads was diagnosed by detecting the ratio of the third harmonic DC in the fundamentals of current and voltage [12].

Some researchers have proposed improved methods of artificial neural networks, such as Back-Propagation (BP) and Self-Organized Map (SOM) neural networks as detailed in [13]. According to [14], the neural network simulates the human nervous system for information processing and has strong learning ability and adaptability. However, the disadvantage is that a large amount of sample training is required. Add to this the fact that the diagnostic capacity and generalization performance in the context of high-dimensional big data are insufficient.

2.2. *Support Vector Machine (SVM)*

Support Vector Machines (also called Wide-Margin Separators) are recent methods of supervised classification; they were introduced by Vapnik in 1995 [15]. Support Vector Machines are used when the data has exactly two classes. The SVM algorithm classifies data by finding the best hyperplane that separates all data points of one class from those of the other class. The best hyperplane for an SVM is the one with the largest margin between the two classes[16]. The SVM algorithm can also be used with more than two classes; in this vein, the model will create a set of binary classification subsets. The aim is to find the best hyperplane for separating data into two classes as shown in Figure 2 and Figure 3. The SVM algorithm is called linear classifier; this means that in the ideal case, the data must be linearly separable. It becomes possible to find the best separator (line, plane, or hyperplane) between the two classes. There are some advantages to using the SVM algorithm. First, it is extremely accurate and does not tend to overfit the data. Second, linear support vector machines are relatively easy to interpret. Third, because SVM models are very fast, once your model has been trained you can delete the training data if you have limited available memory capacity. It also tends to handle complex and non-linear classifications very well using a technique called the ”kernel trick”. However, SVM algorithms need to be trained and tuned in advance, so you need to invest time in the

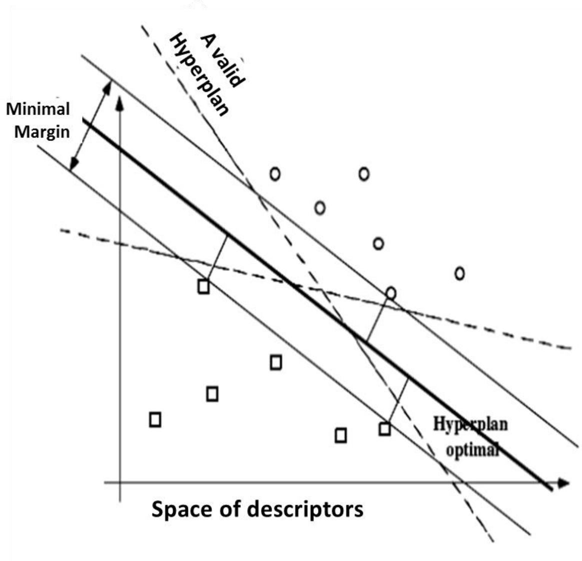

Figure 2: Wide Margin Separators

model before you can start using it. Also, its speed is heavily affected if you use the model with more than two classes.

Nonetheless, the choice of the kernel requires a significant amount of time. Add to this the fact that the number of classes (directly) affects the recognition rate.

2.3. *Multi-Class SVM*

The previously discussed SVM deals with binary classification; its labels take only two values, i.e. one and – one. In the diagnosis of rotating machinery faults, however, the classification problem traditionally has more than two classes. Therefore, the multi-class classification strategy of SVM should be investigated [17].

One- Against - ALL (OAA):. The method commonly used for the multi-class classification of SVM is the *OAA* method. It builds k SVM models and k is the number of classes. The i_{SVM}, (i = 1,2,3...K) is formed with all the samples of the i class with positive labels and other samples with negative labels. So, given M training samples $(X_1,Y_1)...,(X_M,Y_M)$ where ,

$Xj \in R^n$ with $J = (1,2,.....,M)$ is $Y(i) \in [1,..,K]$ the labels of X_j, the i_{SVM} solves the problem as follows:

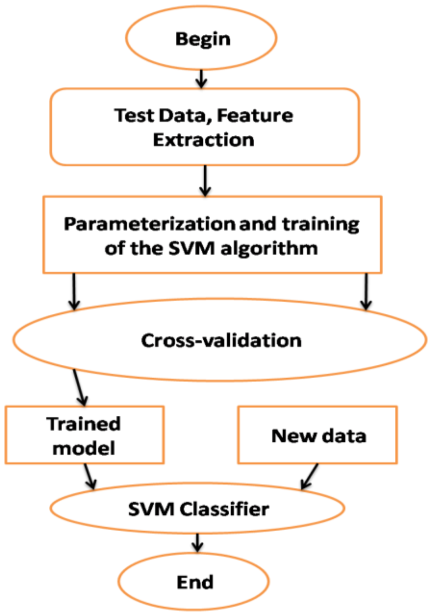

Figure 3: Flowchart of the SVM algorithm

(1)

where *c* is the penalty parameter

One- Against-One (OAO): . This method constructs $\frac{k(k-1)}{2}$ SVMs, each of which is formed by samples of two classes. For training samples of classes *i* and *j*, we solve the following classification problem:

(2)

The decision of training samples using the OAO method is made by the following strategy: if sign $[(W^{ij})^T\theta(X)+b^{ij}]$ indicates a single *x* in the *i* class, then the votes of *x* for the *i* class increase by one. Otherwise, the *th* is added by one. Then the label of *x* is predicted using the largest vote in the class. It has great value for the application of SVM in the field of fault diagnosis: SVM can achieve similar performance to neural networks with a training set of 50% or less in classification tasks [18]. Specifically, inspired by [19], a sparsely represented SVM classifier is proposed to detect different sensor faults in PMSM drive system on electric vehicles. Using Motor Current Spectrum Analysis (MCSA) in combination with SVM, [20] introduced a method that successfully extracted fault characteristics from stator currents and improved fault diagnosis and classification accuracy. In [21], researchers have used a sparse representation and SVM to detect short-circuit faults between turns. The sparse representation is used to extract signal features, and SVM is used to classify normal conditions or faulty conditions. In [22], researchers combined principal component analysis (PCA) and SVM to study the fault characteristics of bearings. The fault feature dimension was effectively reduced, and the fault diagnosis accuracy after dimension reduction was still as high as 97%. Compared to back-propagation (BP) neural networks, SVM classifiers, according to [23], have proposed two SVM-based asynchronous motor diagnostic schemes: (1) simple diagnostics to detect if the motor has failed; (2) complex system diagnostics to detect the location of the fault using one-class and two-class SVMs, respectively. Both solutions provide reliable diagnostic information for asynchronous motor faults. SVMs do not require precise mathematical models; they have good nonlinear mapping and good learning ability.

2.3.1. *Deep Learning*

The Deep Belief Network (DBN) serves as a probabilistic generative model with the capacity to produce training data by optimizing inter-neuron weights to match maximum probabilities. An integral component of this network architecture is the Restricted Boltzmann Machine (RBM). Training is undertaken through an unsupervised, layer-wise, and greedy approach, involving pre-training and subsequent fine-tuning stages. The DBN structure, illustrated in Figure 4 [24], incorporates multiple RBM networks to extract and classify object characteristics.

There are many proposed Deep Learning Models, such as Deep Belief Network (DBN), Convolutional Neural Network (CNN), Stacked Autoencoder (SAE), Recurrent Neural Network (RNN), and Generative Adversarial Network (GAN), to mention but a few.

The refinement of DNNs involved an automatic adjustment and updating of network weights based on the inherent characteristics of input data. This process facilitated the enhancement of feature extraction capabilities and the acquisition of novel knowledge, as outlined in reference [25]. Consequently, the theoretical groundwork was laid for the attainment of comprehensive solutions to targeted problems through learning, coupled with the inherent ability to detect faults. Within the realm of deep learning, a plethora of models have been proposed, each designed to cater to specific data processing requirements. Notable among these are the Deep Belief Network (DBN), Convolutional Neural Network (CNN), Stacked Autoencoder (SAE), Recurrent Neural Network (RNN), and Generative Adversarial Network (GAN), among others. These models collectively embody the diversity and versatility of deep learning techniques in addressing multifaceted challenges.

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DBN structure, illustrated in Figure 4 [26], incorporates multiple RBM networks to extract and classify object characteristics. A

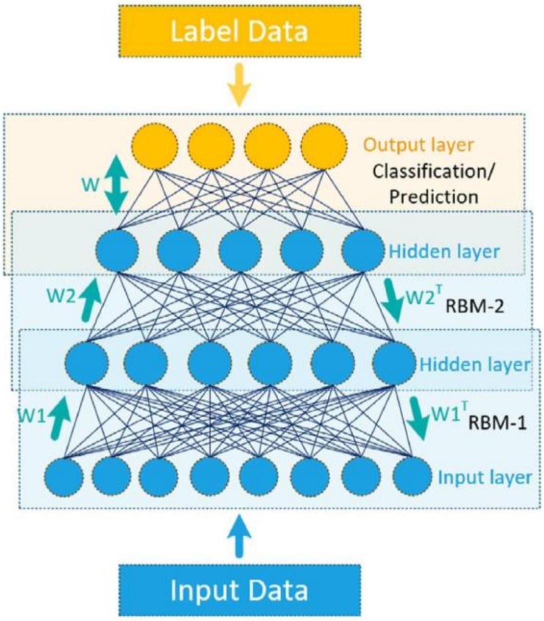

Figure 4: DBN structures

notable strength of DBN lies in its capacity to automatically refine data characteristics without necessitating manual intervention. This automated refinement surpasses the efficacy of manual extraction methods. In [27], an approach to enhancing the Deep Belief Network for ball bearing fault diagnosis is presented. The optimal DBN structure is engineered through the stochastic gradient descent method. Similarly, [28] introduces a regression-based Deep Belief Network for detecting valve leakage defects, contrasting its performance against BP neural networks, linear support vector regression, polynomial regression, and radial basis functions. The results underscore the superior fault prediction accuracy of the DBN model compared to conventional prediction methodologies.

- **Convolutional Neural Network (CNN)** On a different front, the Convolutional Neural Network (CNN) specializes in extracting local features from input data and progressively combining them to generate hierarchical high-level features. This stratagem is well-suited for fault diagnosis and the discernment of extensive datasets [29]. In [29], a convolutional neural network is harnessed to implement fault detection and recognition algorithms devoid of expert input. The application effectively addresses fault diagnosis intricacies posed by outer ring raceway failure and lubrication performance degradation in rotating machinery. Furthermore, [30] presents a fault diagnosis approach grounded in empirical mode decomposition and deep CNN to contend with challenges posed by non-stationary vibrations and substantial noise interference. The amalgamation of Deep Belief Networks and Convolutional Neural Networks, as delineated in the studies referenced, underscores the potency of deep learning techniques in diverse fault diagnosis scenarios, offering automated and accurate solutions that surpass conventional approaches.

- **Generative Adversarial Network (GAN)** In the realm of scientific testing and experimentation, the Generative Adversarial Network (GAN) has found application in the training of image datasets, augmenting the training set, and generating complete sample data. The utilization of deep learning techniques involves the deployment of Deep Neural Networks (DNN) as classifiers. The process of training classification is depicted in Figure 6. A specific study referenced as [31] introduces a novel approach to create images of samples contrasting against potent samples, emphasizing robust structural effects. The process of enriching the training dataset entails the extension of positive instances through the inclusion of challenging classifications for sample images. This augmentation serves to enhance the accuracy of individual training instances against samples, thereby addressing anomalies generated during machine operations. A complementary study denoted as [32] proposes the application of an auxiliary classifier to generate an adversarial network known as Auxiliary

Classifier GAN (ACGAN). This method leverages categorical labels as auxiliary tools to facilitate the training and generation of labeled data, thereby yielding improved data quality. This approach is demonstrated in the context of capturing vibration signals from induction motors. Empirical outcomes affirm the superiority of the GAN-based oversampling technique in addressing the challenge of imbalanced fault data vis-a`-vis normal data. A profusion of reliable data is generated using the ACGAN methodology, as elucidated in Figure 7. Analogously, [33] introduces the concept of Enhanced Generation-based Adversarial Network (EGAN), aimed at

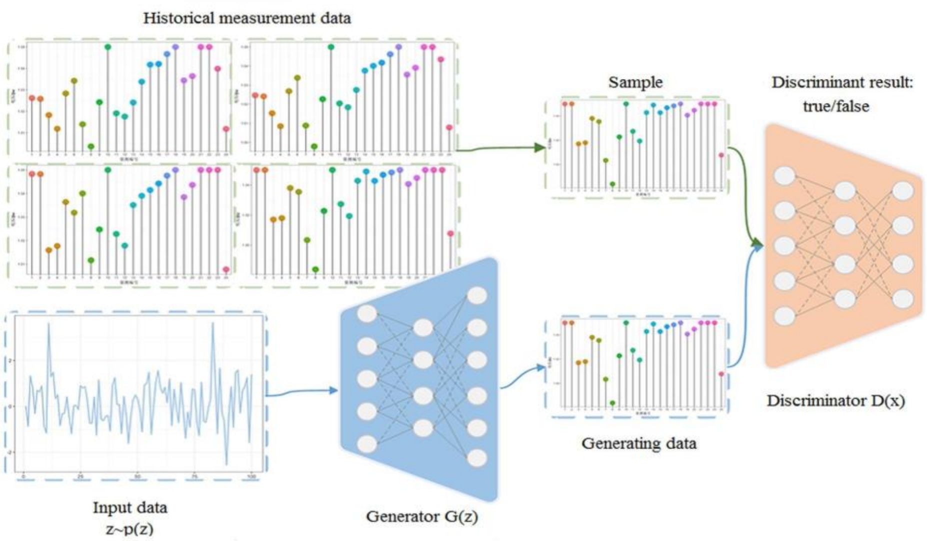

Figure 5: The basic structure of the GAN

automating the enhancement of modest sample sizes to establish equilibrium between defective and normal data. The proposal encompasses an adaptive training strategy tailored to expedite convergence rates and ensure network stability. Model accuracy is substantiated through evaluation against two distinct datasets. Notably, [34] delves into a comparative exploration of two data sampling techniques for typical induction motor faults: the conventional oversampling technique and the GAN-based oversampling method.

In [34], the researchers have proposed a way to generate images of samples against strong samples with strong structural effects. The training dataset has been expanded by extending the positive example of the additional difficult classification of the sample image. The accuracy of individual training against samples has been further improved in order to solve the fault data generated in the operation of the machine. According to [35], the researchers have proposed the method of using the auxiliary classifier to generate the anti-network (ACGAN), using the category label as an auxiliary tool to train and generate data with the label to obtain data improvement effect. The vi-

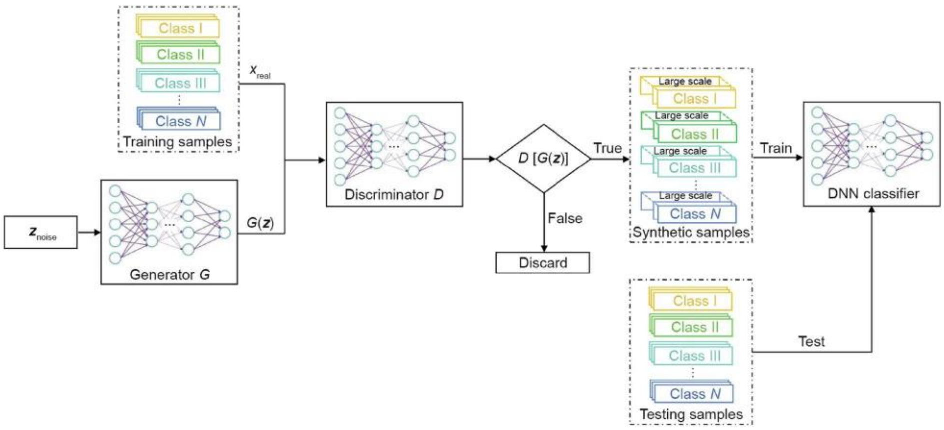

Figure 6: Training classification process.

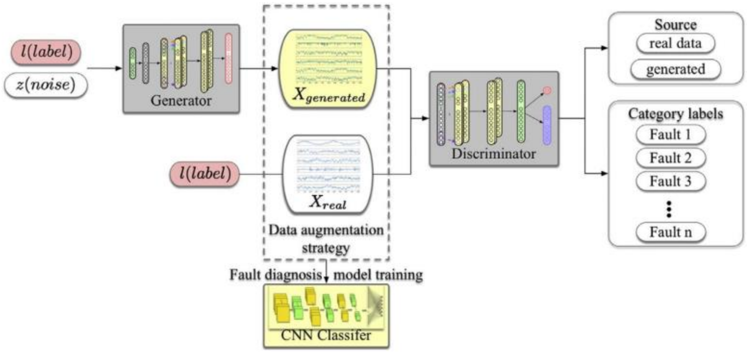

Figure 7: ACGAN Data Enhancement Specific Flow.

bration signal of the induction motor was taken. The experimental results showed that the GAN-based oversampling method is better for the problem of unbalanced fault data and normal data. The results showed that ACGAN could generate a large amount of reliable data. Figure 7 shows the specific flow of ACGAN data enhancement. Similarly, the work presented in [36] proposed an enhanced generation based confrontation network (EGAN) and generated models to automatically improve small samples to balance defects with normal data. An adaptive training strategy has been proposed to optimize convergence speed and network stability. The accuracy of the model was verified using two data sets. According to [15], two data sampling methods have been investigated for common induction motor faults: the standard oversampling method and the GAN-based oversampling method.

3. Conclusion

In this paper, a theoretical study on the intelligent approaches of machine learning and the tools for diagnosing PMSM engine faults in electric vehicles have been presented. Machine learning methods have given good results, especially in the detection of simple defects. On the other hand, the detection of concurrent and random defects remains limited and requires improvements in the following:

• The application of a separation algorithm (or isolation) between the target signal and the noise signals in order to have good samples. • The proposal of a method for optimizing the selection of characteristics in order to have a good compromise between the number of characteristics (preferably as few as possible) and a good recognition rate.

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