Enhancing Gearbox Condition Monitoring using Randomized Singular Value Decomposition and K-Nearest Neighbor

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Abstract

Efficient gear and bearing diagnosis has become a critical requirement across diverse industrial applications precisely due to their complex design and exposure to difficult operating conditions, which predispose them to frequent failure. Early fault identification remains problematic, as defects are commonly obscured by extensive background noise. Moreover, the exponential increases in gearbox data further complicate the defect classification process, confusing even the most sophisticated algorithms and significantly making the procedure time consuming. Singular Value Decomposition (SVD) has proved to be highly efficient in signal denoising, stability preservation, and feature extraction reliably under varying conditions, filtering out non-linear signals to reconstruct relevant features only. However, its considerable computation time necessitates exploring alternatives like Randomized SVD (RSVD) to mitigate processing time while maintaining classification accuracy. In this work, an intelligent algorithm for gear and bearing fault diagnosis is developed, incorporating Maximal Overlap Discrete Wavelet Packet Transform (MODWPT) and Time-Domain Features for feature extraction. RSVD is employed for signal denoising and feature reconstruction, while K-Nearest Neighbor (KNN) for feature classification. The combined techniques ensure enhanced diagnostic accuracy, addressing critical challenges in industrial maintenance and performance optimization.

Keywords: Fault diagnosis, Gearbox, Feature extraction, Rotating machines.

1. Introduction

In rotating machines, particularly gearboxes, gears and bearings are susceptible to vulnerabilities due to their complex design and severe operating conditions which often compromise system reliability, leading to frequent failures requiring unscheduled maintenance and, ultimately, machine breakdowns. Notably in wind turbines, over 50% of gearbox faults come from bearings (de Azevedo et al., 2016), while approximately 80% of transmission machine problems are due to faulty gears (Soualhi et al., 2019). Consequently, the urgent need for machine fault diagnosis arises to ensure the safety and reliability of mechanical transmission systems. Moreover, today's competitive, dynamic and technology-driven industrial environment requires industry to adapt to new technologies, and to continually reduce costs (Benaggoune et al., 2020).

Intelligent fault diagnosis techniques primarily rely on machine monitoring parameters, with vibration analysis being a prevalent method for detecting early defects by identifying any deviations in these parameters. Vibration signals are especially favored due to their non-intrusive nature in machinery operation, making them a widely adopted tool for fault detection and analysis (Afia, Gougam, Rahmoune, et al., 2023). This approach enables continuous monitoring of machine health, allowing for timely interventions to prevent potential failures and to optimize maintenance schedules. Extracting fault-related characteristics from vibration signals poses a significant challenge, particularly in the initial fault development stages (Afia, Gougam, Rahmoune, et al., 2023). Moreover, gears and bearings can incorporate a variety of defects, compounding the fault detection classification complexity. Recognizing these defects requires highlighting relevant information gleaned from measured vibration signals in a mathematically meaningful manner. Features serve as crucial signal characteristics aimed at encapsulating the overall data within a reduced dimensionality, facilitating their utilization in the classification process. Despite the complexities involved, effective feature extraction remains integral to accurately diagnosing faults and ensuring machinery reliability. Many decomposition methods have been developed for feature extraction. For instance, Gilles has proposed the empirical wavelet transform (EWT) (Afia, Gougam, Rahmoune, et al., 2023), in which input data is decomposed into multiple modes using a set of adaptive wavelet filters. The resulting EWT modes are narrow-band functions with fewer mixed modes, beneficial for many applications (Gilles, 2013). Nevertheless, EWT is highly dependent on the mode number selection, with improper selection potentially causing undesirable decomposition results (Adel et al., 2022). Furthermore, the wavelet filtering bandwidth adaptability in EWT is inherently limited, following a linear proportional bandwidth pattern (Adel et al., 2022). Discrete wavelet transform (DWT) is an alternative technique extensively used in fault diagnosis and condition monitoring (Syed & Muralidharan, 2022). DWT decomposes signal data through band pass filters in the time and frequency domains, producing a set of signals with specific frequency bands (Syed & Muralidharan, 2022). Yet, the dyadic step in the subsampling process represents a significant limitation in DWT efficiency (Adel et al., 2022). The Maximal overlap discrete wavelet transform (MODWT) has been developed as an optimized version of DWT to address the issue (Adel et al., 2022). Like DWT, MODWT invariably presents problems associated with poor frequency resolution [6]. As a solution, maximal overlap discrete wavelet packet transform (MODWPT) has appeared as a more suitable choice. MODWPT decomposes complex signals into individual components while maintaining circular shift equivariance, which is crucially important for gear and bearing condition monitoring (Adel et al., 2022). Moreover, MODWPT provides numerous improvements compared to MODWT, including uniform frequency bandwidths, the ability to overcome time-varying transformations, and to reconstruct the original signal without any information loss (Adel et al., 2022). MODWPT can extract relevant features from vibration data without compromising accuracy, thereby enhancing fault diagnosis processes.

Time-energy indicators such as kurtosis, entropy, root-mean square (RMS), etc., represent useful indicators in advanced signal processing algorithms for classifying different fault types (Soualhi et al., 2019; Gougam, Afia, Aitchikh, et al., 2024; Soualhi et al., 2020; Tahi et al., 2020). However, detecting bearing and gear signatures in early stages is extremely difficult as defects features are inherently weak. In such case, acquired vibration signals are often overwhelmed by a substantial amount of low-frequency noise, which makes significant impact on the analysis results' accuracy. For instance, in the event of local failure within the bearing, vibration signals exhibit a distinctly non-stationary behaviour, complicating the diagnostic process even more (Afia, Gougam, Touzout, et al., 2023). Consequently, achieving efficient fault identification continues to be an important issue in rotating equipment fault diagnosis. Addressing this issue is critical for enhancing the efficiency and accuracy of fault classification algorithms, necessitating strategies for noise reduction and optimization in feature selection processes. Singular value decomposition (SVD) is among the most commonly used methods, as highlighted in (Gougam et al., 2018; Touzout et al., 2020) due to its remarkable signal noise reduction and feature extraction capabilities, particularly in complex noise conditions. SVD is able to effectively reflect the matrix features since the singular values represent the intrinsic matrix features (Gougam et al., 2018; Touzout et al., 2020). Furthermore, SVD can maintain stability and improve the robustness of feature extraction under varying conditions. Since it is invariant, stable, and efficient for denoising, SVD has been used in practical applications, such as gear and bearing fault identification, to filter the nonlinear signal and ensure that only useful features are reconstructed. Despite its numerous advantages, the primary limitation of SVD lies in its high computational complexity. Addressing this challenge, Halko et al. proposed randomized SVD (RSVD) as an enhanced version of SVD (Halko et al., 2011). RSVD operates by generating an approximate basis for a range of input matrices through a process of "random sampling," wherein samples of the input matrix are multiplied by a random matrix (Song et al., 2017). This approach effectively captures the fundamental characteristics of the input matrix, including its singular values and most relevant vectors, reminiscent of data compression techniques. By enabling standard factorizations such as QR decomposition and SVD to be computed on a substantially smaller matrix than the original, RSVD significantly diminishes the computational cost (Song et al., 2017).

After feature extraction and noise reduction, K-Nearest Neighbor (KNN) has been widely adopted for gear and bearing fault detection and classification (Afia et al., 2024). The primary objective of this research is to investigate the effectiveness of a machine learning classifier in accurately classifying features extracted from vibration signals using MODWPT alongside temporal statistical indicators and RSVD. This paper presents a gear and bearing fault diagnosis method using vibration analysis, aiming to discern and categorize five distinct gear and bearing conditions. During the feature extraction phase, experimental vibration signals are decomposed by MODWPT, yielding several wavelet coefficients (WCs). Subsequently, 38 statistical features are applied to each decomposed mode to construct a feature matrix corresponding to each gear and bearing condition. RSVD is then employed to reduce noise and to reconstruct feature matrix, ensuring the retention of pertinent features. Finally, KNN is utilized for feature classification, enabling the detection, classification, and identification of the five gear and bearing health states with precision and accuracy. This methodology represents a comprehensive approach towards enhancing gear and bearing fault diagnosis through advanced signal processing techniques and machine learning algorithm.

2. PROPOSED METHODOLOGY

In this section, the different steps of the proposed methodology are discussed. First, a total of 16 raw experimental vibration signals representing either a gear or a bearing state are decomposed using maximal overlap discrete wavelet packet transform (MODWPT) by 6 levels into 26 wavelet coefficients (WC) with different frequency levels. For one state, 16 matrices of (64×1048560) are produced, wherein 1048560 is the signal points number. Then, 38 combined time features are applied to each WC to construct the feature matrix corresponding to each condition. For one condition and one time feature, each matrix of (64×1048560) would be converted to a vector of 64 rows. Therefore, for one condition (16 measurements), a feature matrix (16×64) is provided to represent each gear or bearing condition. Combining 38 time features gives a feature matrix (608×64). After that, RSVD is used to reduce noise by calculating the right eigenvector, the singular value, and the left eigenvector in which Each feature matrix is reconstructed retaining the useful information only. The reconstructed feature matrices are used as inputs for KNN to detect, identify and classify the different states. To avoid over-fitting during the training and testing phases, 10-fold cross-validation is used, in which the dataset is randomly divided into 10 complementary subsets. Each subset is retained in turn, and the training model is trained on the remaining nine-tenths. Figure 1 provides an overview of the proposed technique.

3. Maximal Overlap Discret Wavelet Packet Transform

MODWPT uses raw data $X = [X_0, X_1, ..., X_{N-1}]^T$ as input for filtering and data decomposition. As with Mallat's algorithm (Gougam, Afia, Soualhi, et al., 2024; Too, Abdullah, Mohd Saad, & Tee, 2019), MODWPT is based on quadrature mirror filters. $\widetilde{g}_l$ and $\widetilde{h}_l q$ respectively represent a low-pass and a high-pass filters, each of length L (assumed to be even).Thus, the developed filters are given in Equation 1.

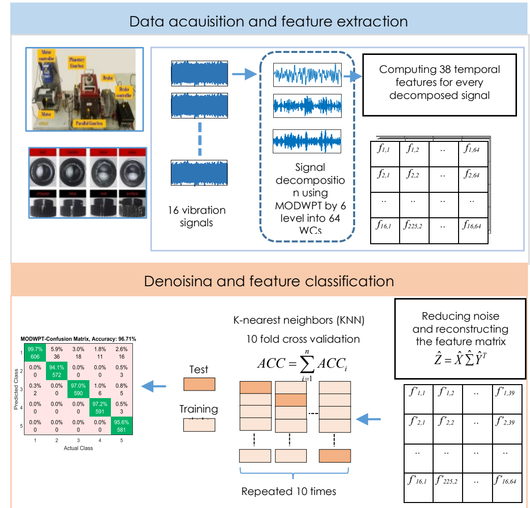

Figure 1. Diagram of the proposed method.

$$\left\{ \begin{array}{l} \sum_{l=0}^{L-1} \tilde{h}_l^2 = \frac{1}{2} \\ \sum_{l=0}^{L-1-2k} \tilde{h}_l \tilde{h}_{l+2k} = 0, \quad k = 1, 2, ..., \frac{1}{2}(L-2) \\ \tilde{g}_l = (-1)^{l+1} \tilde{h}_{L-l-1}, \quad l = 0, 1, ..., L-1 \end{array} \right\} \tag{1}$$

MODWPT differs from Mallat's approach by using interpolation instead of a 2-base decimation operation. Specifically, at each MODWPT level, $2^{(j-1)} - 1$ zeros are inserted between two consecutive adjacent coefficients of $\widetilde{g}_l \, and \, \widetilde{h}_l$. Thereby ensuring that the wavelet coefficients produced (WT) for each wavelet sub-band maintain the same length as the input signal (Afia et al., 2024; Gougam, Afia, Soualhi, et al., 2024). For a discrete-time sequence $x(t), t = 0, 1, ..., N-1$, where N is the sequence length, the wavelet coefficients$W_{j,n,t}$ of the nth sub-band at level j are calculated according to the following equations in which $n = 0, 1..., 2^j - 1, W_{0,0,t} = x(t)$ (Afia et al., 2024; Gougam, Afia, Soualhi, et al., 2024):

$$\tilde{f}_{n,l} = \begin{cases} \tilde{g}_l, & \text{if } n \bmod 4 = 0 \text{ or } 3 \\ \tilde{h}_l, & \text{if } n \bmod 4 = 1 \text{ or } 2 \end{cases} \tag{2}$$

4. Temporal features

The aim of this step of the methodology is to detect pattern changes in a given signal, in which statistical parameters are useful for extracting features related to the different machine states, since a failure will produce a change in the overall signal energy. For this purpose, 38 temporal features are used for feature extraction. The used time features are discussed in (Too, Abdullah, Mohd Saad, & Tee, 2019; Too, Abdullah,

& Saad, 2019).

5. Randomized Singular Value Decomposition

Standard approaches use the extracted features from the previous step and directly train machine learning models for classification. However, achieving efficient fault classification accuracy seems to be a major issue in rotating equipment fault diagnosis, requiring noise reduction and optimization feature selection algorithms. In this situation, RSVD is used to reflect matrix features since singular values represent intrinsic matrix features, thus maintaining stability and improving the feature extraction reliability under varying conditions in practical applications, such as gear and bearing fault identification, by filtering the nonlinear signal and ensuring that only useful features are reconstructed with low computational complexity. For a matrix with m×n as dimension and k as rank, SVD gives this formula of$Z = XSY^*$, in which X is an orthonormal matrix $(m \times k)$, Y is an orthonormal matrix $(n \times k)$, while S is a non-negative diagonal matrix $(k \times k)$ which is defined in (Chakraborty et al., 2017):

$$W_{j,n,t} = \sum_{l=0}^{L-1} \tilde{f}_{n,l} \; W_{j-1,[n/2](t-2^{j-1}l) \bmod N} \tag{3}$$

$$S = \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \vdots \\ \sigma_k \end{bmatrix} \tag{4}$$

σ_j is the non-negative diagonal matrix S are the singular values of Z arranged as follows: $\sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \sigma_4 \geq \sigma_k \geq 0$. The$XandY$ columns are the left and right singular vectors, respectively, while the singular values are related to the matrix approximation. At each level j, the number$\sigma_j + 1$ is equal to the spectral norm deviation between Z and an optimal rank-j approximation, in which (Too, Abdullah, & Saad, 2019):

$$\sigma_j + 1 = \min \{kZ - Bk \,:\, B\, has\, rank\, j\} \tag{5}$$

And the SVD of a matrix $Z \in \ R^{m \times n}$ is described as below (Chakraborty et al., 2017):

$$Z = X \sum Y^T \tag{6}$$

With X and Y being orthonormal, while $\sum$ is a rectangular diagonal matrix with diagonal entries being the singular values signified by σ_i. The column vectors of $XandY$representing the left and right singular vectors respectively, are indicated by$x_i andy_i$. In terms of $x_i andy_i$, the truncated SVD (TSVD) approximation of Z as a matrix Z_k is defined by (Chakraborty et al., 2017):

$$Z_k = \sum_{i=1}^{k} \sigma_i x_i {y_i}^T \tag{7}$$

And the randomized SVD (RSVD) is given as follow [23]:

$$\hat{Z} = \hat{X} \hat{\sum} \hat{Y}^T \tag{8}$$

In which and are each orthonormal while is diagonal that has as diagonal entries. The column vectors of and are referred as , and correspondingly. Elucidate the residual matrix of a TSVD approximation and the residual matrix of RSVD approximation are given below (Chakraborty et al., 2017):

$$R_k = Z - Z_k,\, and\, \hat{R}_k = Z - \hat{Z}_k \tag{9}$$

While the random projection of a matrix is elucidated as in (Too, Abdullah, Mohd Saad, & Tee, 2019):

$$Y = \Omega^T Z \;\; or \;\; Y = Z\Omega \tag{10}$$

In which Ω is a random matrix with independent and identically distributed entries. RSVD is an algorithm that examines approximate matrix factorization by employing random projections to divide the entire process into two steps. First, a random sampling is performed to obtain a reduced matrix with a range close to $Z's$ range. Thereafter, the reduced matrix is factorized using the first step on the matrix Z to find the orthonormal column matrix Q for $\xi > 0$ as defined in (Chakraborty et al., 2017):

$$\left\| Z - QQ^T Z \right\|_F^2 \; \leq \xi \tag{11}$$

In the second step, the SVD of the reduced matrix $Q^T Z \in \mathbb{R}^{l \times m}$ is calculated, where $l \ll n$. Based on $\hat{X}\hat{\Sigma}\hat{Y}^T$ to denote the SVD of $Q^T Z$, Z is given in the following expression (Chakraborty et al., 2017):

$$Z \approx (Q\tilde{X}) \hat{\sum} \hat{Y}^T = \hat{X} \hat{\sum} \hat{Y}^T \tag{12}$$

Where $\hat{X} = Q\tilde{X}$ and $\widehat{Y}$ are orthogonal matrices.

6. K-nearest neighbors

The reconstructed feature matrices are used as inputs for KNN to detect, identify and classify the different states. KNN is a simple and effective supervised classification approach, particularly in the field of pattern recognition, since it operates without the need for specific learning steps (Too, Abdullah, & Saad, 2019). When classifying a new input sample, KNN identifies the nearest neighbors of the training dataset and assigns the most common class to the new sam-

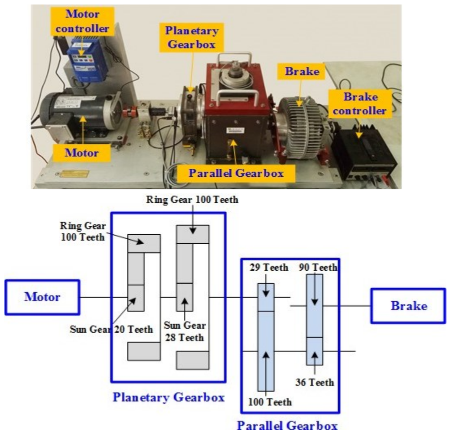

Figure 2. Gearbox setup schematic.

ple on the basis of a similarity measure. This process is conducted via unsupervised algorithmic methods, in which results are ranked on the basis of the majority of KNN categories (Anggoro & Kurnia, 2020). The algorithm works as follows:

1. **D**etermining the parameter k, representing the number of nearest neighbors.
2. **C**alculating the distance between the evaluated and the training data.
3. **S**orting the distances from high to low values.
4. **S**electing the nearest distances up to the order of k.
5. **A**ssigning the appropriate class based on the majority vote among the nearest neighbors.

7. Application and Results

The described methodology is applied to experimental data, which includes various fault states as well as a healthy state. The experimental setup is designed for multi- faults classification. With the proposed methodology, our objective is to evaluate the effectiveness of the extracted features in separating the different health states .

7.1. Case Study

components: motor, brake, planetary gearbox and parallel gearbox (see Figure 2) (Afia, Gougam, Rahmoune, et al., 2023). Defects (Table 1) were investigated in two distinct operating modes, with rotational speeds and loads ($20Hz - 0V$ and $30Hz - 2V$).

Eight 608A11 vibration sensors were placed on the test bench surface, with a 0.5 Hz-10 kHz frequency range, a $\pm 50g$ measurement range and 100 mV/g accuracy. Vibrations in the planetary gearbox directions were measured using three sensors, another three sensors to measure vibrations in the three

Figure 3. Gear and bearing defects.

Table 1. Types of bearing and gear components

Component	Types	Description
Gear	Chipped	Crack in the feet
	Miss	Missing
	Surface	Wear
.	Root	Crack
Bearing	Ball	Crack
	Comb	Crack in inner and outer ring
	Inner	Crack
	Outer	Crack

directions of the parallel gearbox, and the remaining sensors monitored the drive motor. Load measurement was provided by an FT293 torque transducer with a measuring range of $\pm 5V$ and an accuracy of 4 Nm/V, placed between the motor and the planetary gearbox. Signal acquisition was achieved using a Spectra PAD compact data acquisition instrument able to process up to 20 channels, with a 1024 Hz sampling rate and a 512 second sampling window (Afia, Gougam, Rahmoune, et al., 2023).

7.2. Result and discussion

Raw vibration signals measured by the eight accelerometers corresponding to all five bearing and gear states for two operating modes (see TABLE I) are decomposed into 64 WCs using MODWPT. 38 time-based features are applied to each WC to create the feature matrices describing each gear or bearing's health state. Afterwards, RSVD computes right eigenvector, singular value and left eigenvector, and then each gear or bearing's feature matrix is reconstructed. The reconstructed matrices are taken as KNN inputs.

Model stability is an extremely important factor in determining potential model reliability in terms of overfitting, data variability or model sensitivity. By considering accuracy over repeated training iterations, a more complete model reliability assessment is provided. To evaluate the machine learning model's accuracy, TABLE II provides overall accuracy over ten training iterations using the proposed approach with and without RSVD. Figure 4 compares the model accuracy over ten training iterations, while Figs.5 and 6 provide a better illustration of the classifier's overall performance in terms of confusion matrices.

Compared with MODWPT and MODWPT-SVD, MODWPT-

Table 2. Classification accuracy of faults.

Method	***Classification accuracy (%)***									
	Gear									
MODWPT	*96.45*	96.51	96.68	96.38	96.55	96.58	96.22	**96.71**	96.48	96.28
MODWPT-SVD	96.81	96.74	96.78	96.97	96.84	96.88	96.97	96.71	**97.01**	96.68
MODWPT-RSVD	97.60	97.66	97.93	97.63	97.53	97.80	97.57	**97.99**	97.74	97.96
	Bearing									
MODWPT	95.23	95.46	95.26	95.53	95.43	94.93	95.56	**95.82**	95.16	94.77
MODWPT-SVD	95.89	**96.12**	95.72	95.49	95.76	95.43	95.79	95.53	95.20	95.30
MODWPT-SVD	**97.27**	97.01	96.97	96.74	97.20	96.78	97.11	96.74	96.84	97.07

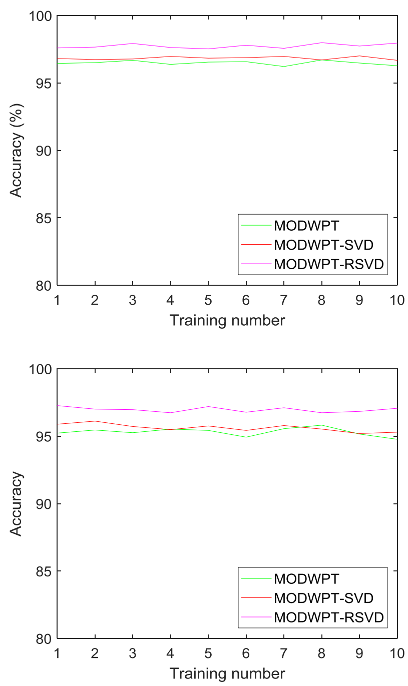

Figure 4. Model accuracy gear (a) bearing (b).

RSVD has achieved the best accuracy rates, mainly 97.99% for gears and 97.27% for bearings. This highlights our proposed method as a superior feature extraction technique, making it the optimal choice among the evaluated methods. Figure 4further confirms the proposed model's stability, providing highly satisfactory results in terms of fault classification. Thus, for accurate early defect detection and classification, MODWPT, with RSVD, provides the optimal approach.

8. Conclusion

The paper presents an enhanced fault diagnosis technique for gearboxes. Feature extraction, classification and experimental processes have been described in detail. The proposed algorithm, applied to real-time gearbox vibration signals in different health states, successfully identified all gear and bear-

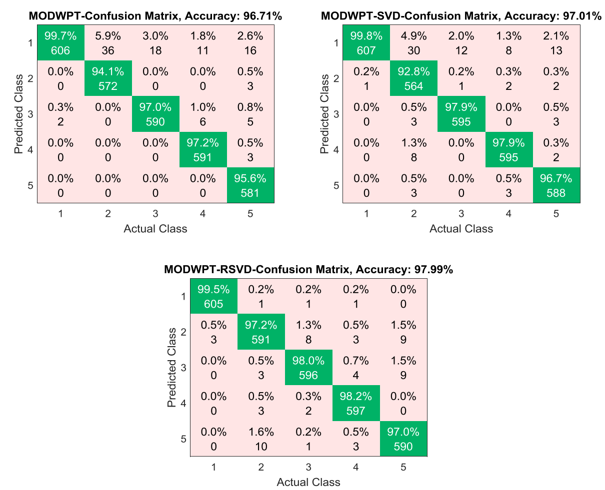

Figure 5. Confusion matrices for all gear states.

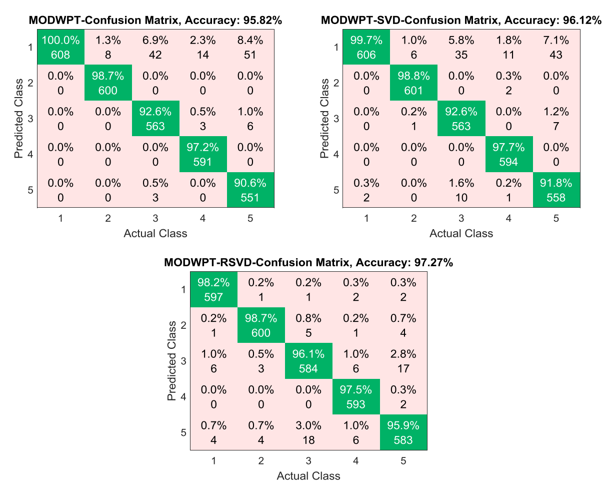

Figure 6. Confusion matrices for all bearing states.

ing states accurately and efficiently.

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