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Identification of Loosening in a Bolted Flanged Pipe Connection under Random Forces Using Convolutional Neural Networks

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Abstract

This study investigates condition monitoring for detecting bolt loosening in flanged pipe connections critical components widely used in fluid-transfer industries. Since corrosion, cracks, and especially bolt loosening can lead to leakage and system failure, early detection is essential. In the experimental setup, a flanged pipe is subjected to random excitation using white-noise signals. Dynamic responses of the pipe are recorded under healthy conditions as well as faulty conditions involving half-loosened and fully loosened bolts. The collected signals are then processed using a Haar filter bank at a selected decomposition level, employing both low-pass and high-pass filter coefficients. After filtering, the Smoothed Pseudo Wigner–Ville distribution is applied to obtain detailed time–frequency representations of the responses. These time–frequency images serve as input features for training convolutional neural networks (CNNs). The CNNs are trained, validated, and tested using the generated datasets to classify the condition of the flange connection. The proposed method demonstrates a classification accuracy exceeding 95%, highlighting its effectiveness. Finally, the performance of this approach is compared with other feature-extraction techniques to confirm its superiority.

Keywords: Looseness detection; Smoothed Pseudo Wigner-Ville Distribution; Haar filter bank; Convolution neural networks.

1. Introduction

Mechanical systems and structures are constantly subjected to environmental and operational forces, leading over time to wear, deformation, and potential failure. Maintenance and repair are essential to ensure the safety and integrity of these systems, particularly for critical components such as bolted connections. Bolt loosening and fracture are among the most common failure modes, and their occurrence in applications such as flange connections in pipelines can result in significant human and financial losses [1–4, 17–19]. Condition monitoring is therefore essential to prevent failures and support timely maintenance decisions.

Bolted connections, especially flanged pipe joints, have been extensively studied for their static and dynamic behaviour. Analytical models and finite element analyses have examined non-linear deformation, vibrational characteristics, and the effects of preload and partial loosening [1–4, 17–19]. Experimental studies complement these analyses, providing insight into the response of bolted and flange connections under tensile, torsional, and bending loads, as well as evaluating gasket sealing performance and joint stiffness [18, 19]. Understanding these behaviours is critical for pipeline integrity, particularly in oil and gas applications.

Condition monitoring techniques for bolted and flanged connections include non-destructive testing, electrical conductivity measurements, vibration analysis, and the use of piezoelectric sensors and acoustic emission methods [5–16]. These approaches enable detection of bolt loosening, partial fractures, and other structural defects. Recent studies have also focused on probabilistic modelling and maintenance optimization for pipeline networks, addressing system reliability and the combined effects of environmental and operational stresses [12, 16].

Signal decomposition and feature extraction are critical in fault diagnosis. Wavelet-based methods, including Haar wavelets, Empirical Mode Decomposition (EMD), and Smoothed Pseudo Wigner-Ville distributions, have been applied to vibration and ultrasonic signals to extract fault-sensitive features and generate time-frequency representations [20–25]. These features are then used as inputs for convolutional neural networks (CNNs), which have demonstrated high accuracy in classifying bolt conditions such as fully tight, semi-tight, and fully loose [20–25]. CNN-based approaches allow automatic detection, localization, and quantification of bolt loosening, offering a robust framework for structural health monitoring in real-time applications.

In this study, an experimental flanged pipe model was subjected to dynamic excitation using white noise signals. Responses were recorded for fully tight, semi-tight, and fully loose conditions. Signals were decomposed using a Haar filter bank, and the Smoothed Pseudo Wigner-Ville distribution was applied to generate time-frequency images for CNN training. The proposed method successfully classified the bolt conditions, demonstrating the effectiveness of integrating advanced signal processing with deep learning for reliable fault detection in bolted flange connections [20–25]. This approach provides practical insights for early fault detection and maintenance decision-making, enhancing the safety and reliability of mechanical and structural systems.

Overall, integrating analytical modeling, experimental testing, signal processing, and deep learning offers a comprehensive framework for monitoring bolted flange connections. The use of CNN-based classification on time-frequency images enhances sensitivity to contact-type defects and supports proactive maintenance strategies, reducing the risk of structural failures in industrial applications [1–25].

This study proposes using Convolutional Neural Networks (CNNs) for fault diagnosis in bolted flange pipe connections. An experimental flanged pipe is excited with white noise, and dynamic responses for fully tight, semi-tight, and fully loose states are analysed using the Haar Filter Bank and Smoothed Pseudo-Wigner Ville distribution. The resulting images are then classified by the CNN, and the proposed method's performance is compared with other approaches.

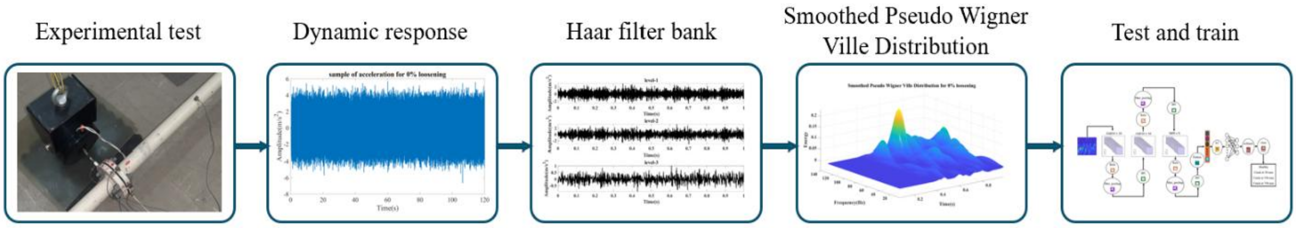


Figure 1. Flowchart related to the fault detection of the flange pipe

2. Experimental Test

The dynamic responses of a flanged pipe were experimentally recorded for fully tightened, semi-tight, and fully loosened bolt states. The pipe was excited using white noise via a shaker (B&K Type 4809) connected through a force transducer (PCB Type 27263), amplified with a B&K amplifier (Type 2706), and responses were captured by four accelerometers (B&K Type 4507) with a data acquisition system (B&K SV Type 22827), processed using B&K Pulse software (Figs. 2 and 3). Each state was tested in two 2-minute repetitions, and the resulting time-series signals were stored for analysis.

Figure 2. Experimental setup for bolt loosening test

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

Figure 3. Equipment for conducting the experiment: a) Accelerometer b) Pulse Data Acquisition c) Shaker d) Force transducer e) Amplifier f) Torque Wrench

3. Haar Filter Bank

This section explains that for fault diagnosis, the raw structural signal containing several dominant frequencies must be decomposed using a Haar filter bank. The Haar filter separates the signal into low-pass and high-pass components according to the following Eqs. (1-2):

$$LPF = \frac{X[n] + X[n-1]}{2} \tag{1}$$

$$HPF = \frac{X[n] - X[n-1]}{2} \tag{2}$$

Here, $X[n]$ and $X[n-1]$ represent the input signal and its one-sample-shifted version, respectively. The low-pass output is repeatedly decomposed so that useful information can be extracted from the high-pass components. After decomposition, the Smoothed Pseudo-Wigner Ville distribution is applied to the signal. For two minutes of experimental data, 1-second segments with 30% overlap are used, and each signal is decomposed five times to obtain features for training and testing the network. The structure of the Haar filter bank is shown on Fig. 4.

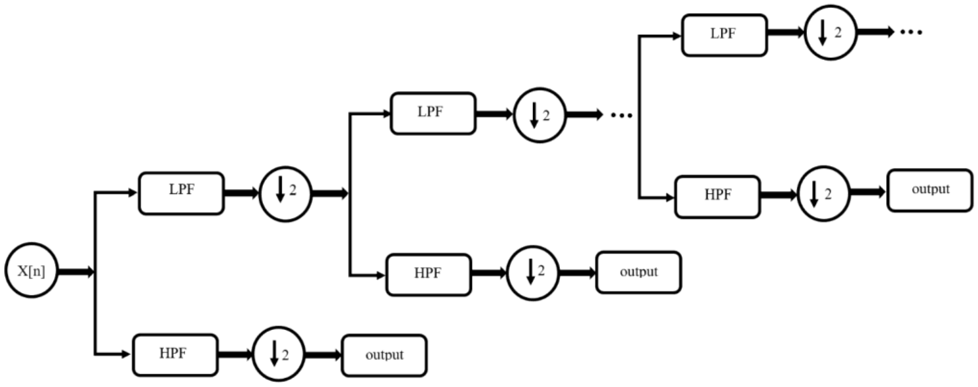


Figure 4. Structure of the Haar filter bank

4. Smoothed Pseudo Wigner-Ville Distribution

The Wigner-Ville distribution transforms a signal into the time-frequency domain with high resolution of instantaneous power, outperforming the Short-Time Fourier Transform (STFT) in representing energy variations. It is a bilinear analysis method, defined as the Fourier transform of the signal's autocorrelation function with respect to the time lag, as shown in Eq. (3).

$$WVD(t,f)=\int_{-\infty}^{\infty} x\left(t+\frac{\tau}{2}\right)x^*\left(t-\frac{\tau}{2}\right)e^{-j2\pi f\tau}\,d\tau \tag{3}$$

In the above equation, $x(t)^*$ is the conjugate signal. If the signal $x(t)$ is considered an analytic signal, it follows Eq. (4).

$$x(t)_a = x(t) + jx(t)_h \tag{4}$$

In the above equation, $x(t)_h$ is the Hilbert transform of $x(t)$, and it follows Eq. (5).

$$H\big(x(t)\big) = x(t)_h = \frac{1}{\pi}\int_{-\infty}^{\infty} x(\tau)\frac{1}{t-\tau}\,d\tau \tag{5}$$

Considering a window $h(\tau)$ for time shift, the Pseudo Wigner-Ville distribution results in the following relation, as shown in Eq. (6).

$$PWVD(t,f)=\int_{-\infty}^{\infty} x\left(t+\frac{\tau}{2}\right)x^*\left(t-\frac{\tau}{2}\right)h(\tau)e^{-j2\pi f\tau}\,d\tau \tag{6}$$

Next, considering the smoothing function $g(u-\tau)$ for the Pseudo Wigner-Ville distribution and obtaining the Smoothed Pseudo Wigner-Ville distribution, Eq. (7) is derived.

$$SPWVD(t,f)=\int_{-\infty}^{\infty} h(\tau)\int_{-\infty}^{\infty} g(u-\tau)x\left(t+\frac{\tau}{2}\right)x^*\left(t-\frac{\tau}{2}\right)h(\tau)e^{-j2\pi f\tau}\,d\tau \tag{7}$$

5. Proposed Convolutional Neural Networks

This section describes the use of Convolutional Neural Networks (CNNs) to classify the image-based outputs obtained from the Smoothed Pseudo-Wigner Ville distribution of the filter bank signals. The goal is to design a simple yet accurate network with few hidden layers for faster learning. The CNN includes convolution layers with Leaky ReLU activation, max pooling, batch normalization, flattening, and fully connected layers, ending with a SoftMax classifier. A total of 171 images represent the healthy state, and 342 images represent faulty states, used for training and validation, while another 342 images from the second test are used for testing. The network architecture is shown in Fig. 5. Table 1 provides detailed information about the neural networks.

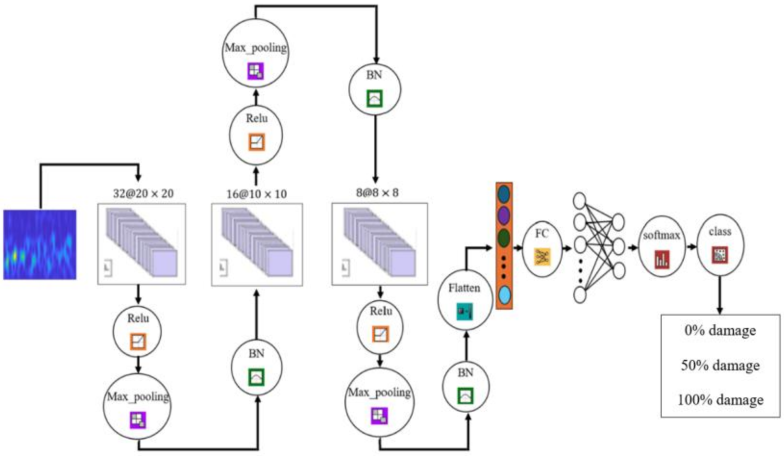


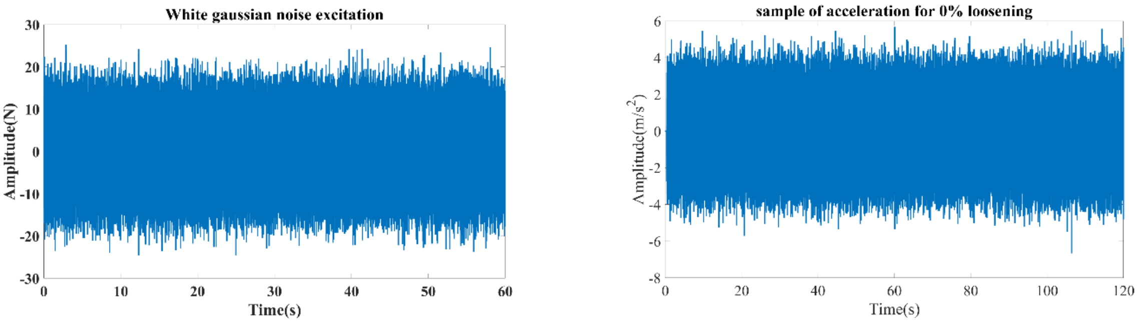
Figure 5. Proposed Convolutional Neural Network Architecture

Table 1. Complete Details of the Proposed Network

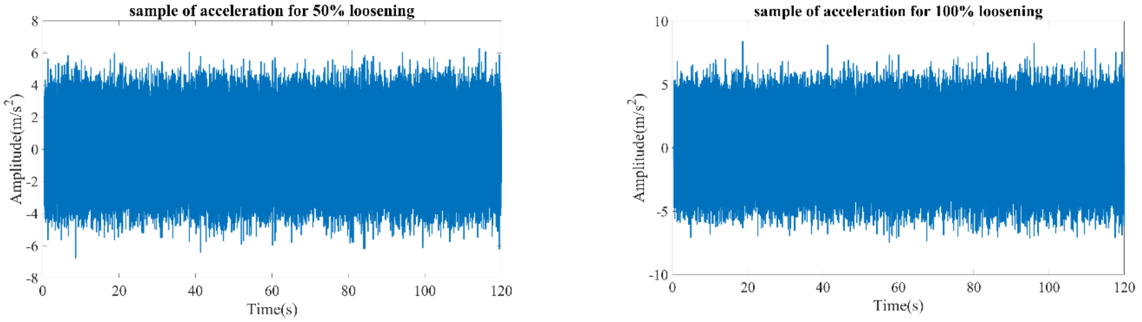
Type of layer	Number of convolution kernels	Size of kernel	Activation function	Stride
Convolution 2-D	32	20×20	Relu	10
Max_Pooling 2-D	32	2×2	-	2
Convolution 2-D	16	10×10	Relu	5
Max_Pooling 2-D	16	2×2	-	2
Convolution 2-D	8	8×8	Relu	4
Max_Pooling 2-D	8	2×2	-	2
Flatten	-	-	-	-
Fully connected	-	-	Softmax	-
Classify	-	-	-	-

6. Results and Discussion

An experimental test was carried out to obtain the dynamic responses of a flange pipe using a shaker with white Gaussian noise excitation to cover all frequencies. Measurements were taken for both fully tightened and defective bolt conditions. The force and accelerometer signals for these cases are shown in Fig. 6.



(a) (b)



(c) (d)

Figure 6. Sample signals for defective conditions: a) For force transducer b) For 0% loosening c) For 50% loosening d) For 100% loosening

After recording the signals for each of the states mentioned, the signals are separated one second at a time, and for each state, the Haar filter bank is applied, and the signal is decomposed up to 6 levels. Fig. 7 shows the decom-posed signal of one second for the fully tight state.

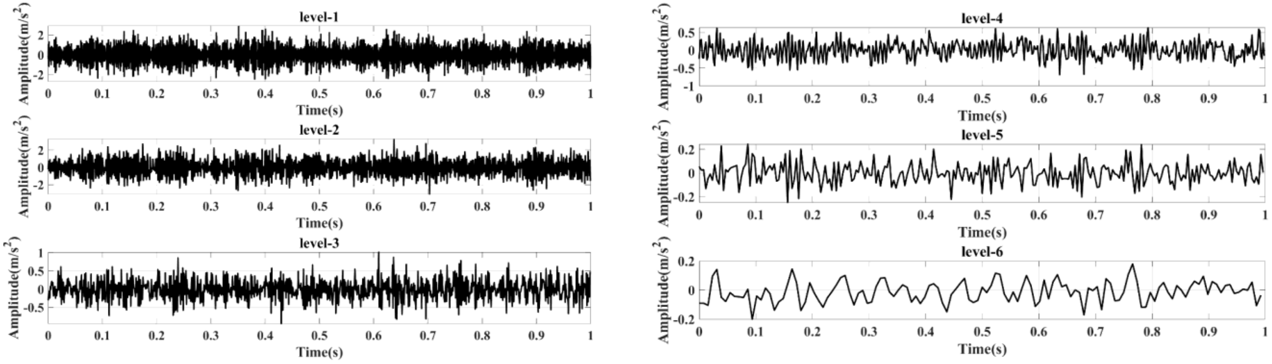


Figure 7. Decomposed signal of one second for the fully tight state

The fifth level of the Haar filter bank decomposition provides the best clarity for detecting defect-sensitive features, where the Smoothed Pseudo-Wigner Ville distribution is applied to emphasize defects across different states. Figure 8 shows the energy comparison for each state, Figure 9 illustrates the training and validation process, and presents the confusion matrix and t-SNE results for the proposed neural network with wavelet transform.

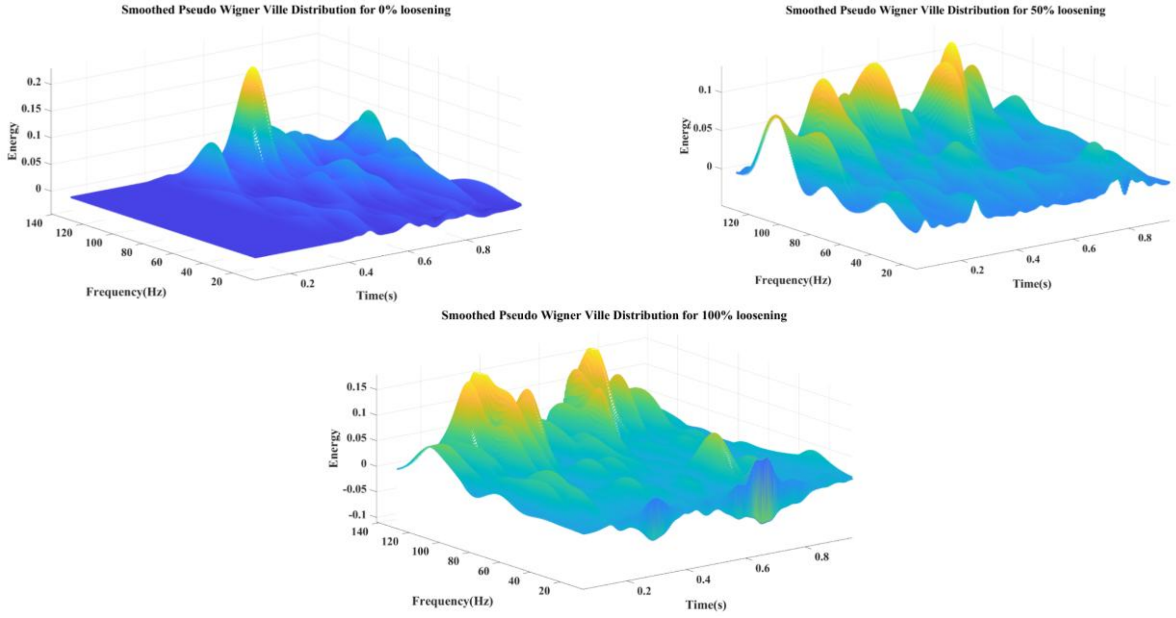


Figure 8. Smoothed Pseudo Wigner-Ville Distribution

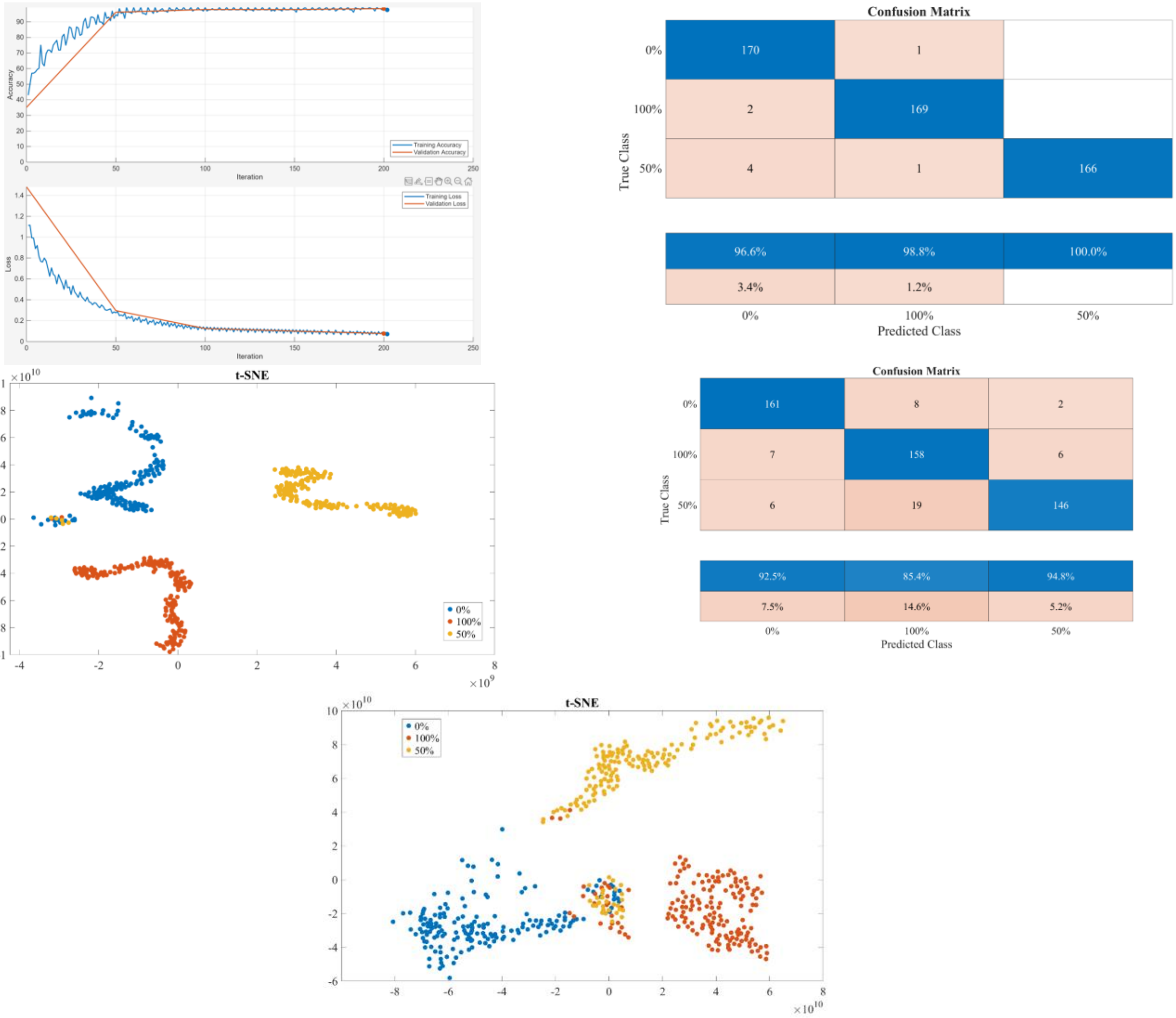


Figure 9. Training and validation process, confusion matrix, and t-SNE visualization of the proposed CNN using wavelet-transformed signals.

7. Conclusion

This study presented a reliable method for detecting bolt loosening in flanged pipe connections using vibration analysis and deep learning. White-noise excitation produced broadband responses that reflected the mechanical differences between fully tight, semi-loose, and fully loose states. The Haar filter bank effectively decomposed the signals and isolated fault-sensitive components, while the Smoothed Pseudo Wigner–Ville distribution generated clear time–frequency images for feature extraction. These images were used to train a CNN that achieved over 95% classification accuracy, demonstrating strong capability in recognizing looseness levels. The results confirm that combining advanced signal processing with CNN-based classification provides a robust framework for structural health monitoring. This approach can be applied to similar bolted structures to support early fault detection and improve maintenance decision-making.

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