International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I12P204

Volume 70 Issue 12, 26-34, December 2022


*Original Article*

# Machinery Faults Diagnosis using Support Vector Machine (SVM) and Naïve Bayes classifiers

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Received: 10 August 2022 Revised: 21 November 2022 Accepted: 04 December 2022 Published: 24 December 2022

***Abstract*** *- This work aims to investigate some machinery conditions viz. (healthy, imbalance, misalignment, gear fault, inner bearing fault, outer bearing fault, and ball bearing fault). The machinery conditions are simulated based on real-time vibration data acquired from a Machinery Fault Simulator (MFS). There are three main stages for the diagnosis process, which are the data acquisition, pre-processing (feature extraction), and the classification of the condition based on Artificial Intelligence (AI) classifiers, where the Continuous Wavelet Transform (CWT) method is applied to pre-process the obtained datasets (signals), and extract the features based on five statistical parameters namely: RMS, Kurtosis, Peak, Impulse Factor and Shape Factor. Two classifiers based on Artificial Intelligence (AI) are applied and compared to classify the machinery conditions; namely, Support Vector Machine (SVM) using three different kernels, namely; Radial Basis Function (RBC), Linear and Polynomial, and Naïve Bayes classifiers, and the best number of feature inputs and the best value of some kernel parameters are investigated and identified. The classification accuracy and rate in SVM are evaluated through different evaluation metrics, and the results are compared with the classification rates from Naïve Bayes, where SVM has shown better performance in terms of classification. This work emphasized the novelty by integrating feature extraction methods like CWT with the two different AI classifiers and using different performance evaluation parameters.*

***Keywords*** *- Machinery Fault Simulator (MFS), Continuous Wavelet Transform (CWT), Support Vector Machine (SVM), Naïve Bayes and Feature Extraction*.

## 1. Introduction

Rotating machinery is one of the most important mechanical equipment. Rolling bearings and gears are the main components used in rotating machines. Rolling bearings are used to reduce the friction between moving parts of the machines and play a crucial role in determining their performance. Bearings are vulnerable to defects such as cracking, pitting, and wear and faults such as inner race and outer race faults due to the long working periods [1]. Bearings are one of the most important components of rotating machines. One of the foremost reasons for the failure of rotating machines are bearing faults (40% of overall fault rate) and transmission gear defects [2] which may lead to hazardous working environments and affect the fidelity, safety and performance of the rotating machines. Thus, it is essential to detect the faults in bearings and monitor the health condition of the machines to prevent failures and shutdowns, which lead to money losses [3].

Condition monitoring (CM), fault diagnosis and detection play a crucial role in the rotating machine's protection from downtime [4]. Vibration signals are widely used in condition monitoring of rotating machineries. The condition of the machines affects the stability of vibration signals obtained from them. Sometimes, serious faults produce vibrations and noise that conceal fault-related signals, making fault detection more complex. Decomposing the signal into a set of components provides useful information for fault diagnosis [5]. Detecting the faults that occur concurrently is highly challenging in rotating machines.

Vibration analysis using Machinery Fault Simulator (MFS) is widely used in health monitoring and detecting fault conditions like imbalance misalignment to identify faults in the shaft, bearing gearbox, motors, etc. [6]. Azeem, N et al., 2019 [7] detected the misalignment and cracks in shafts using vibration analysis with MFS using order analysis. Bastami, A R and Vahid, S., 2021 [8] analyzed the relationship between defect size and vibration patterns generated by defective rolling bearings. Defects on the outer bearing, inner bearing and rolling element have been considered individually. Vibration signals have been acquired numerically from the developed model, and their statistical features, such as RMS, kurtosis is calculated for different defect sizes.

The four main phases involved in automatic fault detection of rotating machinery are data acquisition, pre-processing, feature extraction and selection, and fault diagnosis [8]. Time-based, frequency-based and time-frequency-based techniques are used in health indicator analysis. Non-automatic fault detection in the time domain aids in studying the statistical parameters of vibration signals such as root mean square (RMS), kurtosis, and standard deviation (SD) [10]. Frequency domain-based techniques are Fast Fourier transform (FFT) and time-frequency-based techniques such as wavelet transform like Continuous Wavelet Transform (CWT). Wavelet Packet Transform (WPT), Discrete Wavelet Transform (DWT), and Kalman filtering are popular denoising techniques widely used to extract useful features from sound and noise signals [11]. Among them, CWT, DWT and WPT are widely used for feature extraction and in AI-based classification [12], [13], [14].

The vibration signals obtained from rotating machines contain useful data and noise. Thus, pre-processing the obtained data using any of the abovementioned techniques and extracting useful information is essential [11]. In recent years, Machine Learning (ML) and Deep Learning (DL) approaches have been extensively used in feature extraction, fault diagnosis and detection [15]. Several techniques, such as wavelet analysis, wavelet transformation techniques, stochastic resonance, multi-segment cascaded stochastic resonance (MS-CSR) and Fourier spectral analysis, are applied to process the raw information and to extract useful information from vibration, sound, and temperature signals.

The researchers developed and used vibration and acoustics signal processing algorithms to classify the faults in gears and bearings. Altaf. M et al., 2019 [37] diagnosed bearing ball faults, inner faults and outer faults by capturing the sound signal produced by rotating machinery and extracted the spectral and statistical features using average FFT (AFFT), PSD, average PSD, RMS values of PSD, and STFT. Further, classified using machine learning ML techniques K-nearest neighbor (KNN), support vector machine (SVM), kernel liner discriminant analysis (KLDA), sparse discriminant analysis (SDA) and evidenced that AFFT and KLDA outperformed other feature extraction, classifier techniques [37].

Chen Z et al., 2019 [17] carried out gearbox fault diagnosis by denoising the obtained raw signals using CWT, extracted the features using a specially built Convolutional Neural Network (CNN) with square-pooling and classified the gearbox faults using SVM. The combination of CWT, CNN and SVM have provided accurate results with low computational cost [17].

In recent years, the advancements in the Internet of Things (IoT), intelligent sensors and diverse data collection techniques have led to the automation of rotating machines [18]. Multilayer Perceptron Neural Network (MLP-NN) and Deep Learning Library (DLL) methods are highly useful for the stator, bearings and gear fault detection in feature extraction and selection [19]. Several methods, such as Fourier spectral analysis, stochastic resonance, wavelet analysis, wavelet transformation techniques, and multi-segment cascaded stochastic resonance (MS-CSR), are used to process and extract useful information from raw vibration, sound, and temperature signals [20].

Regression-based models, Naïve Bayes, Statistical, hypothesis, SVM, ANN, Multi-Layer Perceptron (MLP), Hidden Markov Models, Radial Basis Function (RBF), Probabilistic Neural Network (PNN), Deep Neural Networks (DNNs), CNN, KNN, Hybrid classifier based on SVM and ANN are the widely used classification methods in gears, motors, bearings, wind turbines fault detection [21], [22].

(Al Tobi et al, 2019) [12] carried out fault diagnosis to identify five mechanical faults of centrifugal pumps. SVM and MLP are used to classify the fault conditions. The features are extracted using CWT with three kernels, namely, linear, polynomial and radial basis function (RBF) separately, where better performance is scored using the polynomial. Examined the classification performance of two AI techniques: MLP-NN with backpropagation (MLP-BP) algorithm and MLP-BP with genetic algorithm (MLP-GABP). Proved MLP-BP shows better performance than MLP-GABP and SVM.

SVM is a commonly used classification method in identifying mechanical faults and is more effective in classifying small samples and nonlinear signals Deng W,2019 [9]. The classification accuracy of SVM is limited by kernel parameters, weights between different kernel functions, and penalty factors [8]. Fan Y et al., 2020 [24] detected and classified rolling bearings faults using high-performance SVM based on automated particle swarm optimization. Fan Y et al., 2020 [24] and Sun et al., 2020 [25] proposed a novel fault diagnosis algorithm, namely; moth-flame optimization based on the Levy mode (LMFO) algorithm, to detect rolling bearing faults with high accuracy, efficiency and low time cost. It used ensemble empirical mode decomposition (EEMD) for data pre-processing and the Naïve Bayes method for feature extraction.

Zhang et al., 2018 [26] applied the Naïve Bayes classifier to diagnose bearing fault, where the extracted statistical features are first pre-processed using the Decision Tree algorithm in which the best features only are selected. Also, the Selective Support Vector Machine (SSVM) is applied to abandon the redundant vectors. The proposed pre-processing methods could enhance data independence and improve bearing fault classification using the Naïve Bayes classifier.

Throughout the obtained literature review, it has been shown that the application of AI methods-based classification like SVM and Naïve Bayes needs further investigation with more and different machinery conditions. There are some gaps obtained from the literature review. The pre-processing phase needs other efforts in terms of the features extraction methods. The classifiers like SVM have to be tested with different kernels and using different evaluation metrics to illustrate its classification performance. As a result, this work is proposed to investigate the application of CWT in feature extraction and compares the classification performance rates of SVM with different kernel functions and also the Naïve Bayes classifier, which also, along with SVM, to be investigated with varying metrics of evaluation for the classification performance. (Figure 1) illustrates the main stages and processes which are proposed in this work.

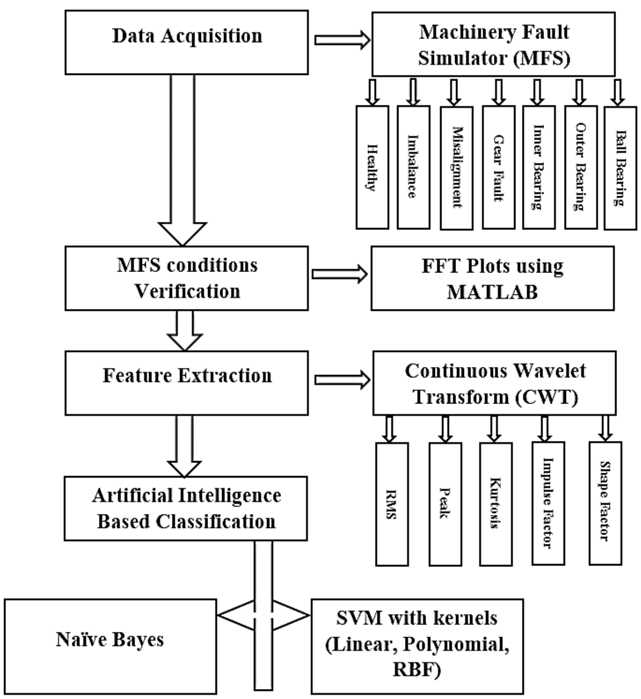



**Fig. 1 Flow diagram of the overall process starts by the data acquisition, then conditions and signals verification, feature extraction, and ending with the conditions classification using SVM and Naïve Bayes**

## 2. Continues Wavelet Transform

### *2.1. Theoretical Principles*

As opposed to sine and cosine, CWT uses wavelets composed of wavelet families with two parameters (scale and translation); therefore, a signal can be represented as a two-dimensional time-scale plane rather than a one-dimensional plane, which is more accurate than the Fourier Transform. [27], [12] and CWT is given by:

$$\boldsymbol{Wx(a+b;\psi) = a^{\frac{-2}{2}}\int x(t)\psi*\left(\frac{t-b}{a}\right)dt} \quad (1)$$

From Equation 1, *Wx* is indicated to the wavelet transform, denoted by the two parameters; a, which is the scale parameter; b is the translation parameter, $\psi$ is the wavelet function, and *x(t)* is the original signal.

### *2.2. Support Vector Machine*

In 1995, Cortes and Vapnik introduced the Support Vector Machine (SVM), which was used as a new approach for pattern recognition based on nonlinear projections of input features to a larger dimensional pattern space [28].

SVM provides a globally optimal solution because it is a curve square optimization problem. It could also handle many practical problems with acceptable solutions for small sample sets, high dimensionality, and non-linearity [29]. SVM can be used with three main kernel functions: linear, polynomial, and RBF. RBF was selected by [30] due to its nonlinear mapping efficiency and ability to map features onto a high-dimensional space.

The SVM is based on a mechanism separating or classifying two classes, class A and class B, as shown in (Figure 2). The optimal hyper-plane (separator) works to separate the two classes with a maximum width (margin) as the larger margin (width) between the two classes, the more generalization and ultimately improved linear classification. The support vectors specify the margins and place them beside the classes' boundaries, where they have all the vital information of the classification. The linear classifier (hyper-plane) is expressed as [12]:

$$W^TX+b = 0 \quad (2)$$

When class A is indicated as the hyper-plane, then it is > 0 and indicated as +1, which is given by:

$$W^TX+b = +1 \quad (3)$$

And class B is < 0 as -1 and given by:

$$W^TX+b = -1 \quad (4)$$

Where *W* is the weight vector, *X* is the input, and *b* is the bias.

A decision function is used to separate two different classes (i.e. A and B) and given by [31]:

$$f(x) = sign((W.X)+b) \quad (5)$$

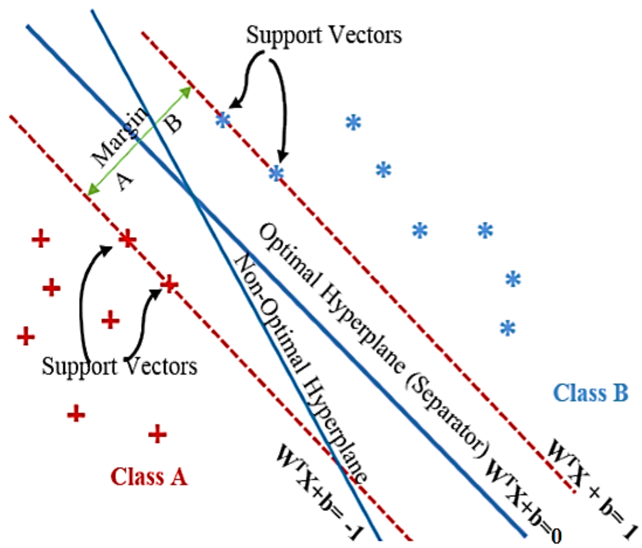



**Fig. 2 Working principle of SVM. The optimal hyper-plane can separate the two classes (A and B) with a wider margin compared to the non-optimal hyper-plane**

Using Equation 2 and Equation 5, the decision function can be expressed by:

$$f(x) = sign(\sum_{i=1} vi(X.Xi) + b) \tag{6}$$

Where L is the number of training data and $v_i$is applied as a weighting factor to recognize the appropriate support vectors from the given inputs.

Nevertheless, a linear boundary is not always guaranteed that able to classify the two different classes. Consequently, to organise the two classes with better margin, SVM can map the nonlinear training data into a higher dimensional level which is known as the feature space s using a transformation Φ (X) and s is given by [32]:

$$s = \Phi (X) \tag{7}$$

Where $X \in R^N$and $s \in R^Q$. Then by substituting Equation 8 in Equation 7, the decision function can be given by [32]:

$$f(x) = sign(\sum_{i=1} vi(\varphi(X).\varphi(Xi)) + b) \tag{8}$$

Moreover, to provide such transformation into nonlinear classification, a kernel function is used K(X.Y), which is defined as [31]:

$$k(X.Y) = \varphi(X).\varphi(Y) \tag{9}$$

Where k points out the kernel.

By substituting Equation 9 in Equation 10, the decision function for the nonlinear classification can be given by [31]:

$$(x) = sign(\sum_{i=1}^{L} vi\, k(X.Xi) + b) \tag{10}$$

There are different kernel functions which can be used with SVM for the purpose of nonlinear classification, such as the Polynomial kernel function and given by [31]:

$$k(X.Y) = k(X.Y)^a \tag{11}$$

Where d indicates the dimension. RBF and given by [31]:

$$k(X.Y) = exp(-\frac{\|X-Y\|^2}{2\sigma^2}) \tag{12}$$

Where $\sigma$ is the width parameter of RBF kernel function. Sigmoid and given by [31]:

$$k(X.Y) = tanh(\,k(X.Y) + \Theta) \tag{13}$$

Where $\kappa$ is known as the gain parameter and $\Theta$is the offset parameter of the sigmoid kernel function

### *2.3. Naïve Bayes*

Naïve Bayes is known as one of the probabilistic classifiers like SVM, and it is derived from Bayes' theorem, which Reverend Thomas Bayes initially introduced in the 1760's. The Bayes is integrated with Naïve in which the classifier offers independence to the input features, where each single input feature is assumed independent from the other input features. Bayes rule is based on the probability calculation and indicated by [33]:

$$P(H|E) = (P(E|H) * P(H))/P(E) \tag{14}$$

Where H is a hypothesis, and E is the evidence

And applying the Bayes rule with Naïve, as a number of independent input features are introduced (Xi1, Xi2,……, Xin), then output Y can be predicted accordingly by:

$$P(Y = y_i|Xi1\ldots.Xin) = (P(Xi1|Y = y_i) * P(Xi2|Y = y_i) * P(Xin|Y = y_i) * P(y_i)/P(Xi1) * P(Xi2) * P(Xin) \tag{15}$$

## 3. Experimental Work

The experimental work is implemented using A Spectra Quest's Machinery Fault Simulator (MFS), where various mechanical conditions can be simulated and studied based on the vibration signals acquired from the MFS. An AC motor of 3 phases and 1 HP is used to run the MFS. The MFS consists of many parts used for the fault simulation, as illustrated in (Figure 3). The signals (vibration data) are acquired by an accelerometer and also processed using a data acquisition system (DAQ), which are both from National Instruments (NI). The DAQ system comprises of NI-9234 model comprises 4 input channels and is linked to the NI cDAQ-9174. The accelerometer model IMI 621B40 has a sensitivity of 10 mV/g and a frequency range from 3.4 to 18 kHz for (±10%) and 1.6 to 30 kHz for (±3 dB).

A DAQ is used to acquire the vibration signals from the MSF, as the signals are amplified and noise filtered out before digitization and filtering are used with a bandwidth of 2.5 kHz; then transmitted to a computer equipped with A LABVIEW software to capture and display the signals. Data are acquired for a period of 2.4 s at a sampling rate of 25 kHz, resulting in the acquisition of 25.6 samples. Averaging over periods of 10 samples is applied.

The seven different machinery conditions (healthy, imbalance as shown in (Figure 4), misalignment, gear fault as shown in (Figure 5), inner bearing fault, outer bearing fault, and ball bearing fault) are classified using Orange simulator-based Python as shown in (Figure 6). All data on the machinery conditions are acquired at a motor speed of 20 Hz (1200 RPM).

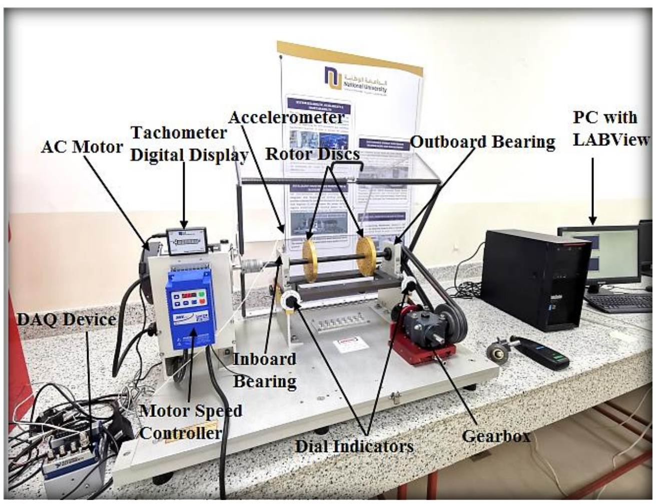



**Fig. 3 The Machinery Fault Simulator Setup**

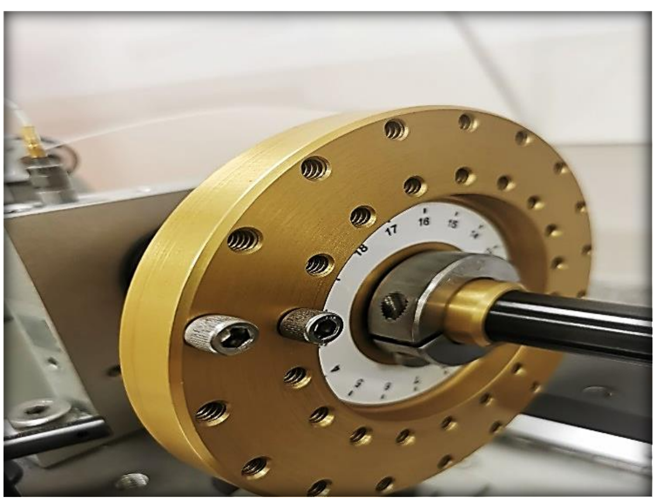


**Fig. 4 The imbalance condition is simulated by installing two pieces of ¼-20 socket head cap screws**

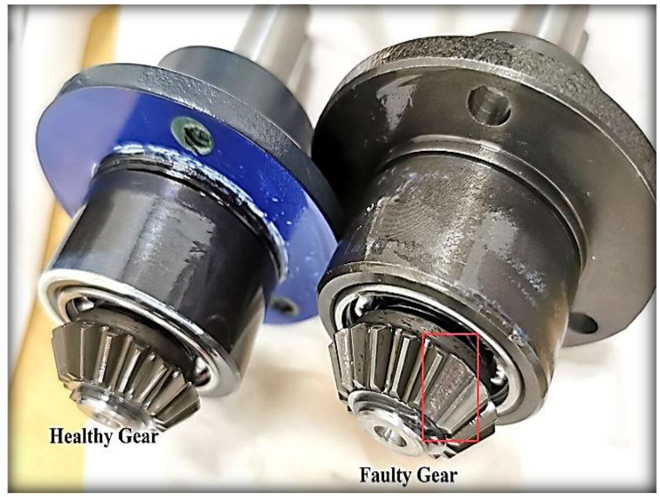



**Fig. 5 A defective straight teeth bevel gear with one of its teeth damaged is installed in the gearbox.**

## 4. Results

### *4.1. CWT-Based Feature Extraction*

Continuous Wavelet Transform (CWT) has been utilized for this work, where Morlet is selected as a mother wavelet function in CWT. In this work, due to the good adaption of the shape of Morlet with the rotating machine fault signals [12] [34], [35]. Seven conditions are acquired from the machinery fault simulator representing the vibration signals. In each condition, a signal of a length of 25,600 samples is recorded. These signals are each divided into 10 segments of a length of 2560 samples [36].

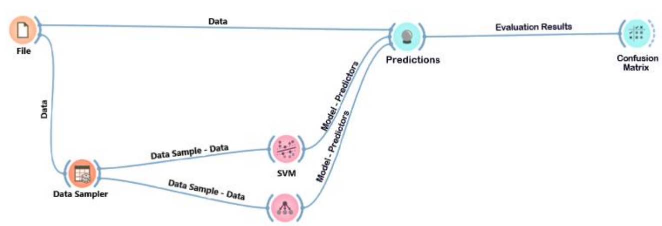
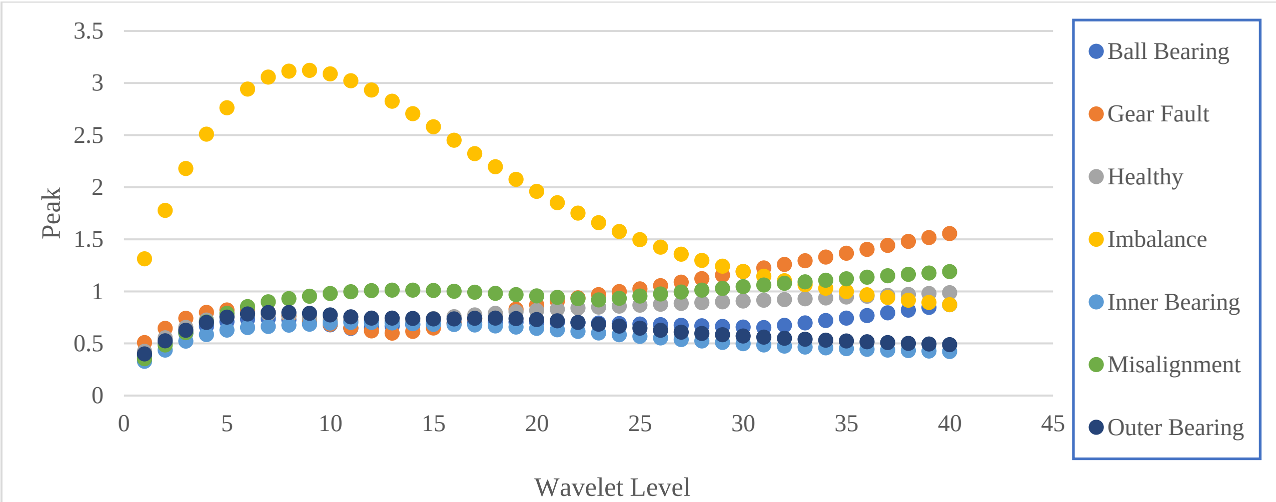
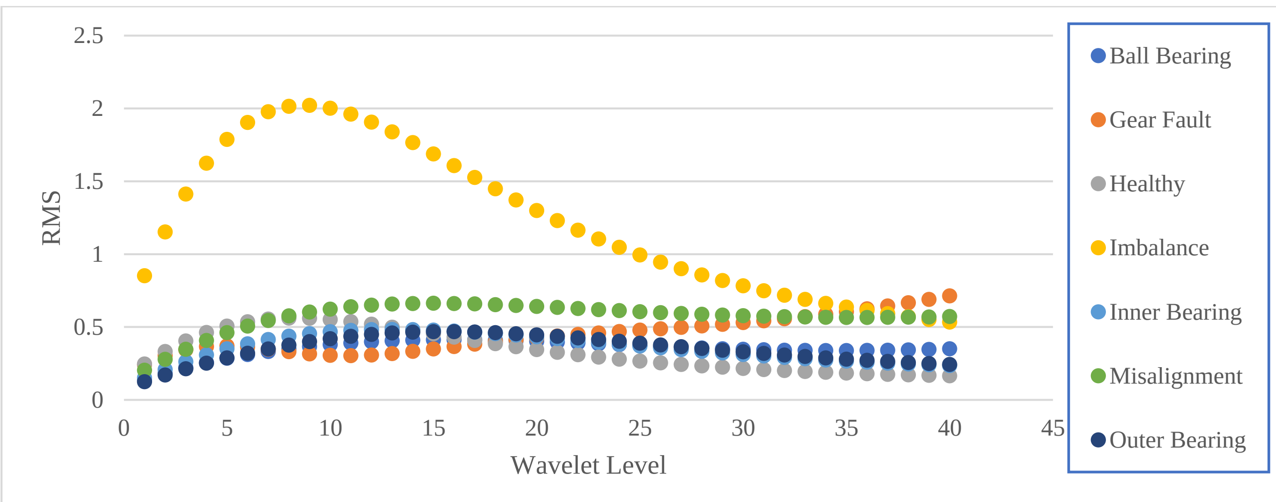



**Fig. 6 SVM and Naïve Bayes Classifiers using Orange Simulator.**

From each of the 10 segments, the wavelet transforms produced 40 features (the wavelet scale). From these 400 features, 5 parameters (Kurtosis, RMS, Peak, Shape Factor and Impulse Factor) are computed for the signal from each condition. For the classification using SVM and Naïve Bayes, 200 features are selected from each parameters Peak and RMS due to their good effectiveness [12], where Peak and RMS have almost similar effects against the machinery conditions, and they illustrate better distribution compared to the other parameters. The effectiveness (sensitivity) of the peak and RMS parameters against all conditions are plotted in (Figure. 7) by selecting the first 40 features from each parameter. Normally, when healthy is the lowest, it indicates good effectiveness of the parameter [36].




**(a)**




**(b)**

**Fig. 7 The effectiveness (sensitivity) of the (a) peak and (b) RMS parameters against all conditions.**

### *4.2. SVM and Naïve Bayes Classifiers*

In SVM, three different kernels are applied; namely, linear, polynomial, and radial basis function (RBF), and five different evaluation metrics for the classification rates are used, which are Area Under Curve (AUC), Classification Accuracy (AC), F1 score, Precision, and Recall. All obtained performance rates represent the overall performance rates of training and testing, where 85% of the dataset is considered for the training and the remaining 15% for the test.

**Table 1. Overall classification performance rates using SVM (Polynomial kernel) with a different number of features.**

| Number of features | Performance (%) |
|---|---|
| **40** | 13 |
| **100** | 41 |
| **200** | 81 |
| **240** | 98 |

Different input features are investigated with SVM to identify the best number of features, as shown in Table 1. It is remarked that with more number of features, then better performance. Therefore, selecting 400 features as inputs to both SVM and Naïve Bayes is considered.

The different parameters used in SVM kernels are considered and investigated to identify the best values for the best classification performance. Gamma parameter (G) is used to determine the nonlinear hyperplanes, and it's commonly used in RBF kernel. The selected values to investigate the best gamma variable value are 1, 2, and 2.5. C value, also known as the penalty parameter, is useful in guiding the trade-off between smooth decision boundaries and provides the proper training classification.

**Table 2. The overall performance rates of all tested parameters.**

| Evaluation Metrics | Polynomial | | | | RBF | | |
|---|---|---|---|---|---|---|---|
| | G= 1.00 C=0.5 Poly-degree= 1 | G= 1.50 C=1.00 Poly-degree= 2 | G= 2.00 C=1.50 Poly-degree= 2.5 | G= 2.5 C=2.0 Poly-degree= 3.00 | G= 1.00 | G= 2.00 | G= 2.5 |
| **AUC** | 90.2% | 90.10% | 86.67% | 93.36% | 97.5% | 98.6% | 99.3% |
| **CA** | 77.7% | 90.15% | 87.77% | 76.2% | 93.5% | 95.55% | 96.3% |
| **F1-Score** | 76.66% | 91.15% | 87.77% | 75.8% | 93.5% | 95.55 | 96.2% |
| **Precision** | 84.6% | 92.3% | 88.6% | 78.2% | 93.7% | 95.8% | 96.5% |
| **Recall** | 77.77% | 91.5% | 87.77% | 76.2% | 93.5% | 95.5% | 96.3% |

**Table 3. Overall classification performance rates using SVM and Naïve Bayes.**

| Evaluation Metrics / Kernel | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| **SVM Linear** | 95.76 | 93.67 | 93.63 | 93.97 | 93.68 |
| **SVM Polynomial** | 96.80 | 95.56 | 96.53 | 96.16 | 95.49 |
| **SVM RBF** | 96.36 | 95.09 | 94.99 | 95.63 | 95.05 |
| **Naïve Bayes** | 95.32 | 90.66 | 90.62 | 90.72 | 90.66 |

The values 0.5, 1, 1.5 and 2 are selected to investigate the best value for the C variable. Then the polynomial degree parameter (Poly-degree) is only applied in the polynomial kernel, and its selected values for the investigation are 1, 2, 2.5, and 3.

It is significantly remarked that the polynomial degree value is proper to be 2, where below than 2 causes less classification performance, and above 2 can also lead to less performance due to over-fitting. The Gamma variable shows better classification performance with higher values (i.e., 2.5 compared to 1 and 2), and the penalty parameter can be with value (1) for proper classification performance. Table 2 illustrates the overall performance rates of all tested parameters investigated with a dataset of 400 features representing healthy and misalignment conditions.

The performance rates show that SVM slightly outperformed the Naïve Bayes, and comparing the three different SVM kernel functions, the polynomial kernel scored the highest rates with 96.8%, as shown in Table 3.

## 5. Conclusion

This work emphasized the experimental work by acquiring a number of mechanical conditions from a machinery fault simulator, and the application of the frequency domain in revealing and detecting the corresponding frequencies (signatures) of each condition has been conducted successfully in which, remarking the vital role of frequency domain for the faults detection.

Moreover, it is observed that using CWT in extracting the features has been done successfully, where five parameters have been considered for the feature extraction, and two parameters are selected for the classifiers, namely, peak and RMS. 200 features from each of the two parameters are selected as inputs to the classifiers, in which a total of 400 features are chosen. The number of features has been tested with various numbers to identify the best number of features, and it found that more features have better performance.

The obtained results of the SVM and Naïve Bayes performance classification rates illustrate significant outperformance of the SVM with Polynomial kernel compared to the other SVM kernel functions and Naïve Bayes classifier in which the best performance rates are scored at 96.8%. Further future investigations with more advanced methods like optimization and feature selection methods are planned for this work to enhance and approach the best machinery diagnosis procedures.

The novelty of this work is reflected by introducing CWT in the pre-processing stage, where the features are extracted using the time-frequency domain with CWT, which showed a significant impact of CWT and promoted the good ability of CWT in extracting the relevant features. Moreover, testing SVM with different kernels and different evaluation metrics has illustrated the performance of SVM throughout different parameters. Comparing the classification performance of SVM with the Naïve Bayes is considered a good contribution in terms of novelty, as a few previous published research works approached such comparison of the two classifiers with the machinery fault diagnosis.

## Funding Statement

This work was supported and funded by the Ministry of Education, Research & Innovation- Sultanate of Oman under Grant BFP/RGP/EI/19/274.

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