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DIAGNOSTICS OF VIBRATIONS DUE TO LOOSENESS FAULT AND UNBALANCE IN ROTATING MACHINERY WITH NEURAL NETWORK

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Abstract

Current work aims at the development and evaluation of Neural Network (NN) model for diagnosing faults due to unbalanced mass and structural looseness in an induction motor setup. These experiments were conducted with and without structural looseness. This data is processed in MATLAB software and is then used to train NN model to detect the unbalance, and structural looseness faults in the setup. The performance of the model trained is evaluated by model performance metrics, which showed the model predicts the presence of above faults with high accuracy. The, Kruskal Willis algorithm is used in MATLAB software to get the feature importance scores, so that, the number of predictors/features can be reduced. It is found that two mutually perpendicular radial accelerations of the setup have significant importance, and hence, a new NN model is trained with the reduced number of predictors/features. It was found that there is a slight reduction in the model's performance, therefore, to increase the performance, another model is trained with the two mutually perpendicular radial accelerations, and their resultants. This increased the performance of the model considerably, hence making it suitable to deploy for the detection of unbalance, and structural looseness faults.

Keywords: vibration analysis, neural network, unbalance, looseness, MATLAB

1. INTRODUCTION

Rotating machinery are extensively used in various engineering fields viz. oil and gas industry, aviation industry, mining industry, etc. Adverse operating conditions of these machines causes performance deterioration and eventually failure. The sudden failure of the machines can be catastrophic and also leads to machine downtime thereby exerting economic losses. The three main maintenance techniques prevalent in preventing machinery failure are corrective maintenance, preventive maintenance and predictive maintenance. In corrective maintenance, the machine / component is replaced only after its failure, which is suitable only when the failure is not catastrophic whereas in preventive maintenance, the machine/component is replaced after fixed interval of time irrespective of the actual condition of the machine/component, hence there is no utilization of its Remaining Useful Life (RUL)[1]. On the other hand, in predictive maintenance technique, the machine/component is continuously monitored and is replaced only if the model developed predicts an impending failure[2].

For implementing the predictive maintenance framework, it is required to measure the vibrations using suitable accelerometer sensors. These measurements can be divided into high and low frequency categories. High frequency vibrations are related to the natural frequency of the machine, and have a frequency range of 500-16000 Hz. Acceleration measurement of machine is more sensitive to high frequency vibrations and the vibrations are associated with bearing faults and gear faults. Low frequency vibrations are related to the machine speed, and have a frequency range of 10-1000 Hz. Velocity measurement of machine is more sensitive to low frequency vibrations and the vibrations are related to unbalanced mass, misalignment, and structural looseness, which when unchecked, will eventually lead to failure of the machines. Of the total machine failures, electrical faults constitute 36%[3] and mechanical faults, such as unbalanced mass, shaft misalignment, structural looseness, etc. are the reason for the remaining majority of the failures.

Many successful attempts were made in the previous years to analyze the vibration data of rotating machine. Rahman et.al.[4] used analysis of vibrations for condition monitoring, detection of vibration faults, vibration control in rotating systems. Extensive works on the condition monitoring of gears[5], planetary gear boxes[6] and gear surface wear monitoring[7] have been carried

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out. Multiple parameters were found to be useful by modeling the preventive maintenance system. Mey, O. et.al.[8] used combined vibration and acoustic data to develop damage classification model. Chirag Mongia et.al.[9] used vibration, temperature, and acoustic signal for machinery condition monitoring. Horiashchenko et.al.[10] used spectrogram, scalogram, and bispectrum analysis for the evaluation of vibrations of wind turbine.

Virtual instrumentation and vibration severity chart based preventive maintenance model was developed by [11]. Many condition monitoring models have been developed by modifying the raw data from the accelerometer sensors by using techniques such as empirical mode decomposition[12], wavelet packet transform theory[13], spectrum analysis[14], etc. With the availability of economical options to remotely monitor the vibrations, many wireless condition monitoring systems were developed, such as the work of[15]. Micro-electro-mechanical-systems (MEMS) based triaxial accelerometer sensors are extensively used for the measurement of vibration of machines[16]. Zhao, Hongfa et.al.[17] used vibration sensor based triboelectric nanogenerator (VS TENG) for the condition monitoring of machines. W. Wang and Y. Shao[18] used computer vision based condition monitoring using digital optical camera. Vapnik developed the SVM in the year 1960[19]. With the availability of affordable computers with good computing power, several scientists and engineers have developed standalone SVM models, and SVM models in combination with other machine learning and analytical models. Banerjee TP, Das S[20] developed a method which combines data from the sensor with the SVM model. Multiple machine learning models viz. SVM, Multilayer NN, Convolution NN, etc. have been developed for fault diagnosis by [21]. B. Brusamarello, J. C. [22] used SVM and Fiber Brass Grating for fault detection of outer bearing raceways of the induction motor.

Many comparative studies of SVM and Artificial NN have been carried[23]. Studies show that multi-SVM is very good in predicting all mechanical faults in the induction motor by using only feature of vibration signal[24]. Studies to detect minor faults in induction motor by using sound signals with SVM and KNN models showed to have high accuracy[25], similarly, [26] used multiple machine learning models to detect the vibration faults in variable frequency drive-fed induction motors. Multi Layer Perceptron (MLP) based ANN is extensively used to detect faults in induction motor[27]. Work by [28] showed the use of short-time Fourier transform for training the NN model to detect vibration faults. [29] used Morlet function and continuous wavelet transform to obtain the scalogram images from the vibration data, and these images were fed to convolution attention NN to detect different categories of vibration faults. A novel method, developed by [30] combines multiple time-domain and frequency-domain features with multiple classifiers, which are then combined by making use of genetic algorithm for diagnosing vibration faults. Nguyen et.al.[31] used empirical mode decomposition for obtaining characteristic of vibration signals, which form the input to the deep learning network to detect bearing faults. One of the major problems in the diagnostics of rotating machinery, such as an induction motor, is the difficulty in determining the cause of abnormal vibrations. The time and frequency plots in this case usually do not give sufficient information about the faults in the machines.

Though various studies have applied many types of machine learning models to study the vibrations of the rotating machinery, but there is a lack of research in the studies in which the reduction in the number of predictors required to classify the faults in vibrations. To address this literature gap, the current work has been carried out, the purpose of which is to develop an experimental setup to obtain vibration accelerometer and use it to train NN model that can predict the cause of abnormal vibrations and to evaluate model performance. Then a Kruskal Willis algorithm is used in MATLAB to reduce the number of predictors/features and, a new model is trained with these features and the performance of the model is evaluated.

The experiments are conducted by varying magnitudes of unbalanced masses, location of mass from the central axis of motor, and the speed of the motor. All these experiments are conducted with and without structural looseness in the setup.

2. FAULT DIAGNOSTIC SETUP

The fault diagnostic setup/rig used in the current work has a single-phase induction motor with voltage controller to vary/adjust the speed of the motor. This motor is coupled with a rotor system with a feature to attach unbalanced masses at various radial distances from the center of the motor/shaft. Figure 1 shows the fault block diagram of the diagnostic setup, showing the outline of the process. The accelerometer data is acquired from an accelerometer interfaced with NI6009 DAQ and mounted on the motor. This data is used to train the NN model, after which, model performance is evaluated. The fault detection framework consists of the following stages: vibration data acquisition, processing of vibration data, training the NN model to predict the type of fault, and testing the models.

Artificial Intelligence (AI) models often act as black-boxes. Signal processing not only improves diagnostic accuracy and robustness of the model, but also bridges the gap between data-driven and knowledge-driven diagnostics.

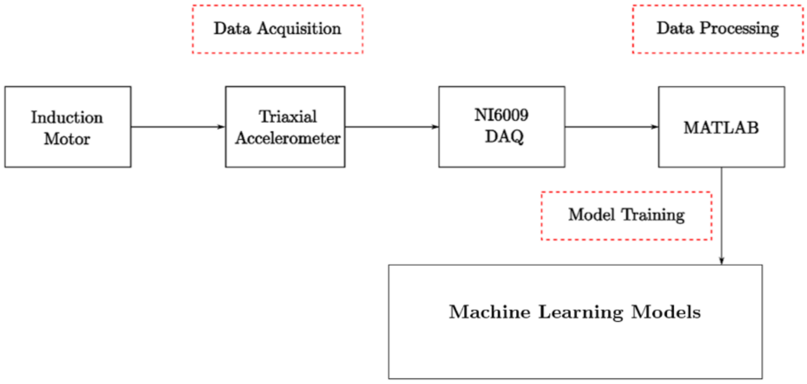

Fig. 1. Block diagram of fault diagnostic setup

The added complexity in using signal processing techniques and artificial intelligence is a deliberate trade-off for better interpretability of the model, which is essential especially in safety-critical systems.

Although methods such as stochastic resonance array (SRA) can use the noise in the signal for the enhancement of weak useful information, but it needs lot of tuning parameters as discussed in [32]. STFT is computationally efficient and easy to implement but SRA requires optimization and increases complexity of the system. Other methods such as Empirical Mode Decomposition (EMD) is less stable under noisy condition and more complex than STFT. Similarly, Variational Mode Decomposition (VMD), which decomposes a signal into various modes, requires high computational cost than STFT. Therefore, as STFT does not require tuning of parameters, and is computationally efficient, it is better suited, especially in real-time scenarios.

2.1. Data acquisition

For acquiring vibration data, a 3-axis accelerometer is attached to the motor-frame and the vibration data is collected for 30 seconds at a sampling frequency of 100 hertz, thereby making the total 30,000 readings collected for each experiment. The data is collected using NI6009 data acquisition (DAQ) system and is sent to MATLAB software for further processing.

2.2. Design of experiments

The varying combinations of the distance of the position of the unbalanced mass from the center of the motor (p), the unbalanced mass (m), and the motor speed (N) is used, and the variation of these parameters is given hereunder:
The position value (p) is varied from an initial value of p1= 95 mm to a final value of p3 = 145 mm with one intermittent value of p2 = 120 mm. The unbalanced mass is varied from an initial value of m1 = 12.65 gram to a final value of m3 = 16.95 gram with one intermittent value of m2 = 14.8 gram. The motor speed is varied from an initial value of N1 = 540 rpm to a final value of N7 = 1380 rpm with five intermittent values viz. N2 = 840 rpm, N3 = 1020 rpm, N4 = 1140 rpm, N5 = 1260 rpm, and N6 = 1320 rpm. There are a total of 70 combinations of experiments conducted by varying aforementioned parameters. The experiments with structural looseness faults are conducted by loosening the bolts of the motor that attach it to the frame.

2.3. Machine Learning Models

Though many AI-based fault diagnostics methods have been developed such as Neural Network (NN), Support Vector Machines (SVM), Decision Trees (DT), k-Nearest Neighbors (kNN), Naïve Bayes (NB), the performance of some models such as DT, kNN, and NB, is poor, mainly while dealing with nonlinearities in the system. SVM is more sensitive to noise than NN. In multi-class classification, such as the current work, the NN performs better, especially when the faults have overlapping features of looseness fault and unbalance. Therefore, NN is selected for developing an AI-based model.

The 3-dimensional accelerometer data recorded by the triaxial accelerometer is processed in MATLAB. The vibration data so recorded is classified as No-Fault, Unbalancing, and Looseness faults. This data is used for training the NN models. Precision, recall, specificity, validation accuracy, and test accuracy were used as performance metrics for evaluating the performance of these models. Of the total data, 10% is used for validation and 5% for testing the models.

3. RESULTS AND DISCUSSION

Figure 2(a)[top plot] shows the time plot when there is no fault in the rotating machinery setup. The frequency spectrum, figure 2(a)[middle plot], has a moderate 1 x frequency peak and weak 2 x frequency peak at about 0.3 & 0.6 normalized frequencies respectively. The scalogram as shown in figure 2(a)[bottom plot] has a single bright horizontal band at 1 x frequency.

The time plot shown in Figure 2(b)[top plot] contains fairly steady oscillations without any notable spikes, which is in contrast with the time plot as given in Figure 2(c)[top plot], wherein multiple spikes can be seen, indicating the that the looseness fault may have been present in the system. Frequency spectrum, that gives an insight on frequencies present in the signal, is shown in Figure 2(b)[middle plot] that has a single dominant peak at 1 x frequency along with smaller peaks at higher harmonics, indicating that the spectral energy is concentrated, which is the case when there is an unbalancing fault. The frequency spectrum given in Figure 2(c)[middle plot] has one dominant peak and strong harmonics showing distribution of energy which is due the presence of structural looseness faults in the system.

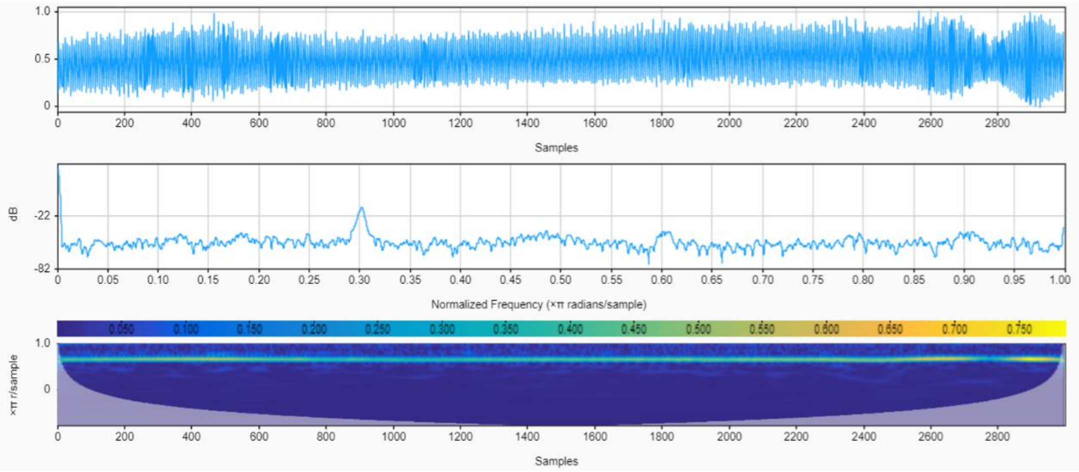

Fig. 2(a). Time series, Frequency Spectrum, and Scalogram of the vibration accelerometer data when there is No Fault

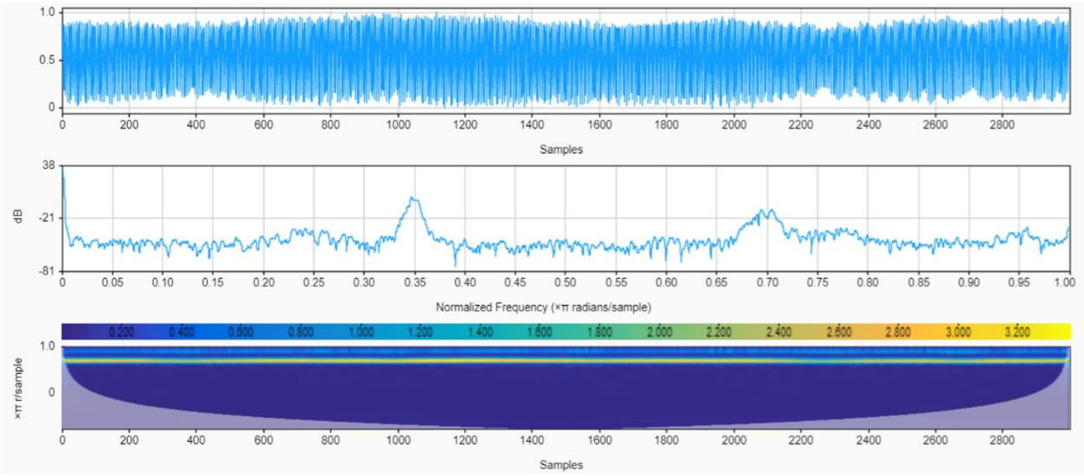

Fig. 2(b). Time series, Frequency Spectrum, and Scalogram of the vibration accelerometer data with only Unbalancing Fault

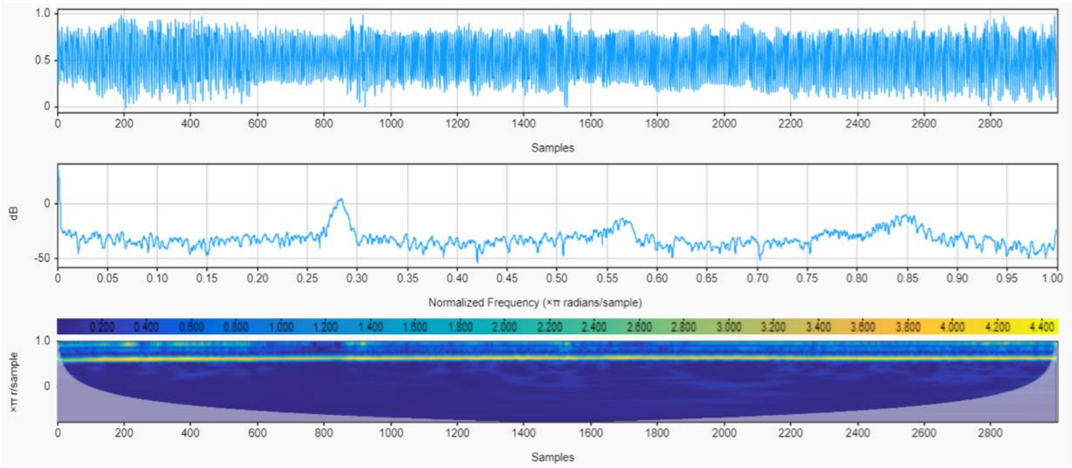

Fig. 2(c). Time series, Frequency Spectrum, and Scalogram of the vibration accelerometer data with Structural Looseness Fault

The spectrogram, as shown in Figure 2(b)[bottom plot], shows a bright band showing dominant 1x frequency with a fainter band at 2 x frequency, whereas the spectrogram given in Figure 2(c)[bottom plot] shows a strong 1x frequency along with intermittent energy bursts, a more scattered high frequency energy, a characteristic of structural looseness fault in the system. The Fast Fourier Transform (FFT) plot of resultant accelerometer data is shown in figure 3(a), when there is no fault in the system, wherein the peak is at about 16Hz which corresponds to the speed of the induction motor, 960 rpm.

There is an enhancement in the amplitude of the signal in FFT plot, as shown in figure 3(b), with a 1 x frequency peak and 2 x frequency minor peak, when there is an unbalance fault in the system. Figure 3(c) shows multiple minor peaks along with peak at 1 x frequency, which is the case when there is a structural looseness in the system. As shown in figure 4(a), the spectrogram shows evenly distributed energy given as a single band, showing no fault in the system. Figure 4(b) shows the spectrogram when there is just unbalance fault in the system, wherein the energy is evenly distributed across a wide range of frequencies. Multiple harmonics are visible around many normalized frequency components which is due to unbalancing fault. Figure 4(c) shows the spectrogram when there is looseness fault in the system. Here, there is a more distinct energy distribution indicating the looseness fault in the system.

The Short-Term Fourier Transform (STFT), shown in figure 5(a) contains one narrow and steady band at 1 x frequency without any higher harmonics, indicating no fault in the system. The STFT when there is an unbalance fault, as shown in figure 5(b), has a strong 1 x frequency along with clear higher harmonics. The STFT of looseness fault as shown in figure 5(c) has multiple scattered bands, with broader spectrum throughout the time-frequency space i.e. the vibrational energy is spread across time and frequency. Though the harmonics are present but they are distorted and less dominant, indicating the presence of structural looseness fault in the system.

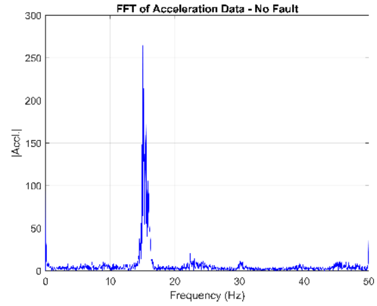

Fig. 3(a). FFT Plot – No Fault

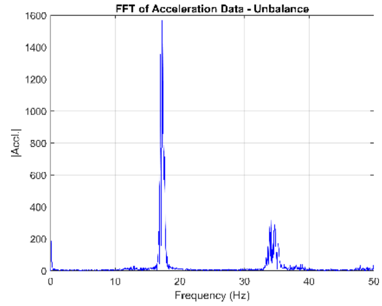

Fig. 3(b). FFT Plot – Unbalance

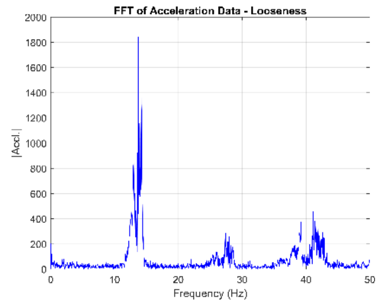

Fig. 3(c). FFT Plot – Looseness

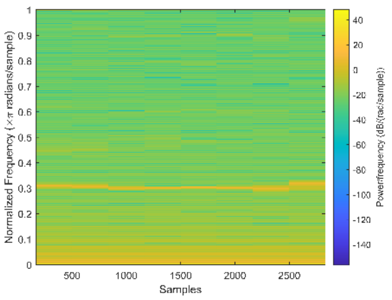

Fig. 4(a). Spectrogram – No Fault

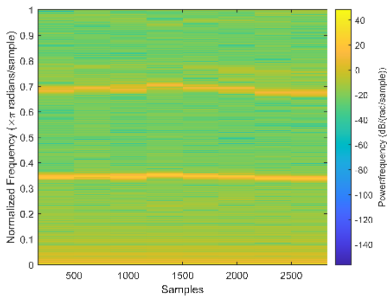

Fig. 4(b). Spectrogram – Unbalance

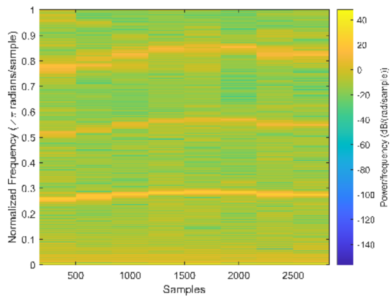

Fig. 4(c). Spectrogram – Looseness

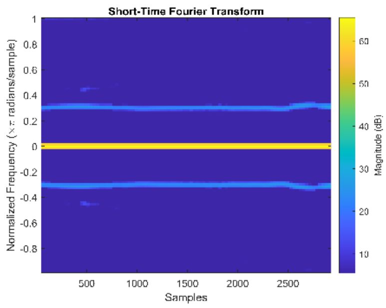

Fig. 5(a). STFT – No Fault

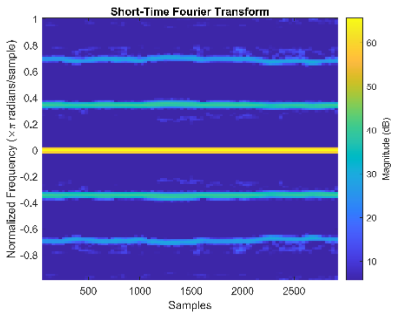

Fig. 5(b). STFT – Unbalance

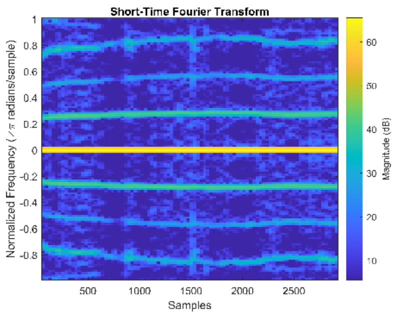

Fig. 5(c). STFT – Looseness

3.1. Machine Learning–Neural Network (NN) Models

The accelerometer data is divided into three classes viz. (i) No Fault, (ii) Unbalance, and (iii) Looseness. This data is used to train the NN Model in MATLAB software. The multi-class confusion matrix for this trained model is given in figure 6.

The performance metrics considered for the evaluation of machine learning models are Precision, Recall, Specificity, F1-score, and Accuracy, which is given in table 1.

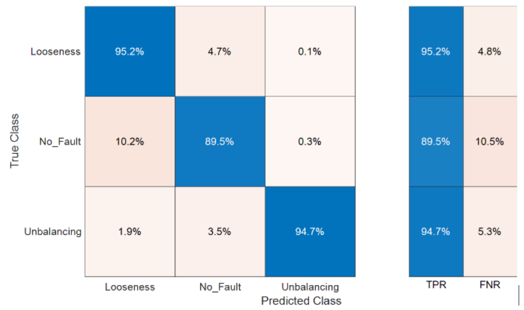

Fig. 6. Multi-class Confusion Matrix of the trained NN (with three features/predictors)

The validation accuracy of the trained model is found to be 93.1%, and test accuracy, 93.5%. The Receiver Operating Characteristic (ROC) curve, as shown in figure 7, has all Area Under Curve (AUC) values closer to 1.0, indicating that the classification is highly effective across all classes. The feature importance scores of the three features/predictors are then determined in order to reduce the number of

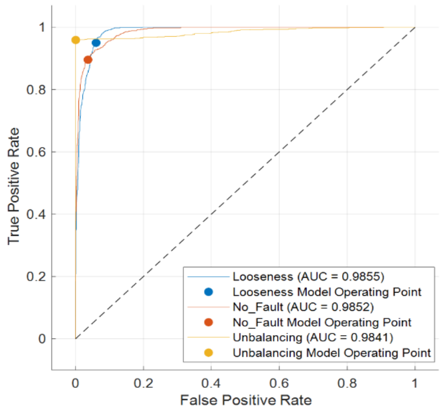

Fig. 7. ROC Curve (three features/predictors)

features/predictors, by using Kruskal Wallis algorithm in MATLAB software as shown in figure 8.

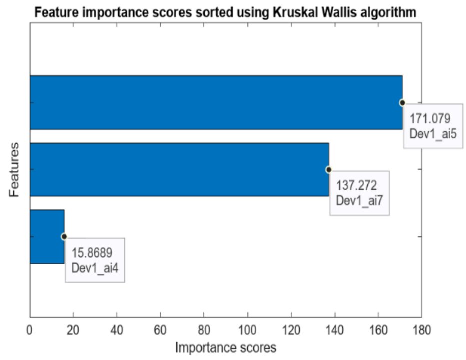

Fig. 8. Feature importance score determined by Kruskal Wallis algorithm

The performance metrics of this model (with two features/predictors) is given in table 2. The validation accuracy of the trained model is found to be 90.4%, and test accuracy, 89.9%. The Receiver Operating Characteristic (ROC) curve, as shown in figure 10, has all Area Under Curve (AUC) values closer to 1.0, indicating that this model's classification is effective across all classes.

But, as the seen from table 2 and figure 9, this model's performance is not as good as the previous model, therefore, another model is trained by considering the two features/predictors, i.e. accelerometer data in x & y direction, along with their resultants. The model is then trained again, the confusion matrix of which is given in figure 11, which clearly shows that this model performance better than the previous one.

Dev1_ai5 and Dev1_ai7 correspond to accelerometer data in local y & x directions respectively, which represent radial vibrations. As seen from the figure, accelerometer data in local x & y directions have significant importance scores, whereas the importance score in local z-direction, i.e. shaft longitudinal direction is low, and is represented by Dev1_4i. Therefore, the NN model is trained again, by using only two features/predictors whose confidence score is high, the confusion matrix of which is given in figure 9.

Table 1. Model Performance Comparison (with three features/predictors)

Sl.No.	Class	Precision	Recall	Specificity	F1-score
1	Looseness	0.8875	0.9522	0.9396	0.9188
2	No_Fault	0.9162	0.8949	0.9591	0.9054
3	Unbalancing	0.9964	0.9467	0.9983	0.9710

Table 2. Model Performance Comparison (with two features/predictors)

Sl.No.	Class	Precision	Recall	Specificity	F1-score
1	Looseness	0.8403	0.9281	0.912	0.882
2	No_Fault	0.8843	0.8415	0.9449	0.8623
3	Unbalancing	0.9973	0.9415	0.9986	0.9686

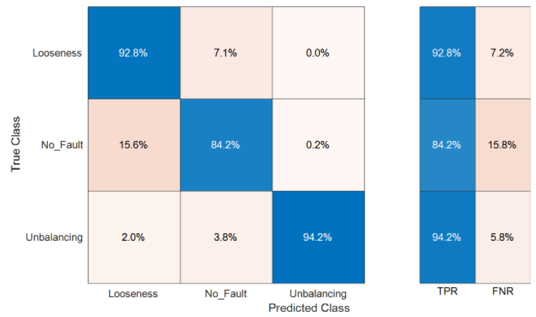

Fig. 9. Multi-class Confusion Matrix of the trained NN (with two features/predictors)

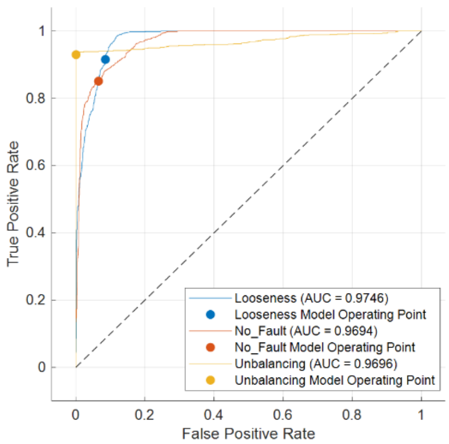

Fig. 10. ROC Curve (two features/predictors)

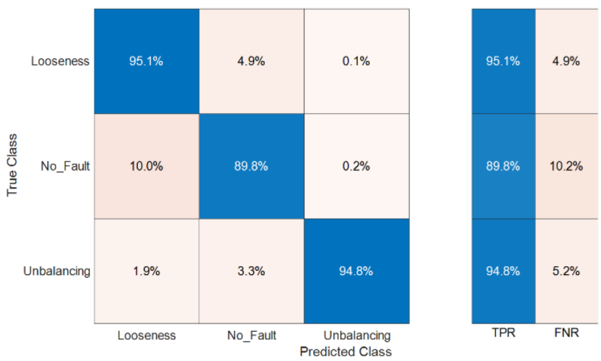

Fig. 11. Multi-class Confusion Matrix of the trained NN (with two features/predictors and their resultants)

The performance metrics of this model is given in table 3, that shows a significant improvement in the model's performance compared to the previous model. The validation accuracy of the trained model is found to be 93.2%, and test accuracy, 92.4%. The Receiver Operating Characteristic (ROC) curve, as shown in figure 12, has all Area Under Curve (AUC) values closer to 1.0, indicating that this model's classification is highly effective across all classes.

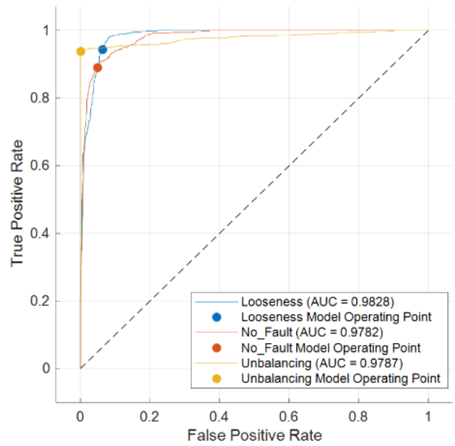

Fig. 12. ROC Curve (with two features/predictors and their resultants)

4. CONCLUSION

An experimental setup was developed to evaluate the vibration in a rotating machinery setup for the diagnostics of unbalance and looseness faults. The unbalance is created by varying three parameters viz. the unbalanced mass, the position of unbalanced mass with respect to the motor center, and the motor speed, whereas the looseness is introduced in the system by loosening the fasteners that attach the motor to the frame. The vibration data, acquired by accelerometer, is visualized by frequency spectrum, scalogram, FFT plots, spectrogram, and STFT plots.

The frequency spectra indicate the presence of unbalance fault with a single dominant peak with weak higher harmonics, and it shows dominant peak with strong harmonics for looseness fault. The unbalance fault spectrogram has a single bright band at 1 x frequency and faint band at 2 x frequency, whereas there are intermittent energy bursts in along with a 1 x frequency peak for looseness fault. The STFT plots also indicate the evenly distributed energy when there is no faults in the system, and energy is spread across a wide range of frequencies with multiple harmonics when there is an unbalance fault. There is even more uneven distribution of energy in case of looseness fault in the system. Similar conclusion can be drawn from STFT plots, wherein there is a narrow, steady band at 1 x frequency when there is no fault in the system. The STFT of unbalance fault is given by a strong 1 x frequency with clear higher harmonics, and multiple scattered bands are present when there is a looseness faults in the system.

Table 3. Model Performance Comparison (with two features/predictors and their resultants)

Sl	Class	Precision	Recall	Specificity	F1-score
1	Looseness	0.8890	0.9506	0.9407	0.9187
2	No_Fault	0.9166	0.8983	0.9592	0.9074
3	Unbalancing	0.9970	0.9480	0.9986	0.9718

After processing, the accelerometer data that contains accelerometer values in three mutually perpendicular cartesian coordinates, is used to train the NN model. The performance metrics were evaluated for this model. The multi-class confusion matrix show that the model can successfully detect the fault in the system, and the performance metrics of Precision, Recall, Specificity, F1-score, Validation Accuracy and Test Accuracy were all higher than 90%. The ROC curve shows that the AUC for all classes is closer to 1.0, indicating that the model predicts well across all the classes.

The feature importance scores of the three features/predictors are then determined in order to reduce the number of features/predictors, by using Kruskal Wallis algorithm in MATLAB software, and then, a new NN model is trained with only two features / predictors that have high importance score. The performance of this model is found to be not as good as the previous model, hence another NN model is trained with two features, i.e. two accelerometer readings along with their resultants. The accuracy of this model is found to be better. Thus, the trained NN model can be used in identifying the fault condition (no-fault/unbalancing/looseness) present in the system, and can be deployed for detecting these faults in the rotating machinery setup.

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Declaration of competing interest: *The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.*

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