# Intelligent Fault Classification of a Misaligned Geared-Rotor Machine Equipped with Active Magnetic Bearings

Pantha Pradip Das(✉), Rajiv Tiwari, and Dhruba Jyoti Bordoloi

Indian Institute of Technology Guwahati, Assam, India
{p.pantha,rtiwari,djb}@iitg.ac.in

**Abstract.** Gear can be considered as one of the most vital components in any rotating machine. Like any mechanical system, geared-rotor systems can experience various types of faults or failures. One of the most commonly experience faults is shaft misalignment, which can cause due to improper installation or wear. In recent years, machine learning and deep learning techniques have sparked great interest in accurately diagnosing geared-rotor faults. Therefore, in this paper a fault detection intelligent method is implemented to predict the type of fault class provided with a labeled set of input vibration and current data. A multi-class classification artificial neural network (ANN) model is developed with statistical features extracted from time-domain vibration. The vibration dataset is built by conducting an experiment on a geared-rotor test rig where angular misalignment is deliberately introduced with four fault conditions: no misalignment and three severity levels of misalignment. Transverse vibration data are recorded with proximity probes. The set-up is also equipped with two active magnetic bearings (AMBs) mounted on the input and output rotors, which are used for vibration suppression. The control current signal running through the AMB coils and time-domain vibration signal at three different speeds are used for misalignment diagnosis. Features like mean, root mean square and entropy have been found to perform the best. The optimum tuning of the hyper parameters of the ANN model is done to achieve about 98.33% prediction accuracy.

**Keywords:** Fault Diagnosis · Geared-Rotor System · Misalignment · Active Magnetic Bearings · Artificial Neural Network (ANN)

## 1 Introduction

Gears are widely used in various applications like automobiles, wind turbines, power industries, etc. A rotor system with gearbox is susceptible to transverse vibration vastly caused by faults in the machine. One serious fault is shaft misalignment which is responsible for generating additional dynamic forces on the gear teeth and thereby leading to excessive vibration during gear engagement [1]. Therefore, intelligent condition monitoring of such geared-rotor systems where artificial intelligent (AI) techniques are


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used to accurately and automatically predict the machine health condition [2]. Traditional machine faults identification includes advanced signal processing techniques on the recorded data which requires specialized engineers. However, around the past two decades, accurate diagnosis of machine faults using machine learning and deep learning techniques, have generated utmost curiosity [3].

Samanta [4] implemented an ANN and a support vector machine (SVM) based classifiers to predict two classes of a faulty gearbox. The author selected the features based on genetic algorithm (GA) from vibration signals, and studied the efficiency of the proposed model at different loads and sampling rates. Both the algorithms were compared and with use of GA, the testing was highly accurate. Zang et. al. [5] also used GA for feature selection on an ANN classifier from 9 fault conditions of the gear test setup. The fault classes comprised combination of various faults like structural faults like unbalance, looseness, and misalignment, and gear failure like broken tooth, tooth crack, etc. Classification accuracy using GA combined with back propagation (BP) was found to be improved when compared with BP alone. Bansal et.al. [6] proposed a novel interpolation/extrapolation method for SVM classifiers, where in the absence of input data for training at all operating speeds, the required training data is estimated at speeds near the speed of the test data. A healthy gear and three faulty gear conditions were used as four classes and the time domain and frequency domain signals were used for prediction. The experiment was performed on a bevel gear rotor system and signals were recorded using tri-axial accelerometers at various speeds. Bordoloi et. al. [7] implemented SVM techniques with algorithms like grid-search, GA and artificial bee colony (ABC) to estimate the optimum parameters. The test rig was same as mentioned in [6]. They also used interpolation and extrapolation for performing training and testing at speeds other than measured ones.

Other than ANN based and SVM based algorithms, different classifiers like K-nearest neighbors (KNN), convolution neural network (CNN), etc. are also used for gear fault problems. Wang [8] examined three experiments on gear setup to establish that the developed methodology delivers superior fault detection accuracies compared to KNN based approaches in identifying various levels of gear crack under varying motor operating frequencies and loads. Principal component analysis (PCA) was employed to decrease the dimension of the insignificant statistical characteristics and produce the valuable ones. Khan et. al. [9] performed axial, radial and angular misalignment fault experiments and predicted the types and severity of the fault using regression models with proportional change in the RMS condition indicator. The dataset was constructed by using vibration signals and sound signals measured using accelerometer and microphone respectively. Li et. al. [10] implemented one dimensional CNN using vibration signal and combined with a gated recurrent unit (GRU) which was trained by acoustic emission signals. Seven gear pitting fault conditions were used to test the proposed model. The performance of single CNN and GRU model was also compared. Zuber et. al. [11] used gear fault dataset including faults like tooth crack, wear, missing, and chipped tooth at various frequencies and loads to test the performance of ANN classifier. They also showed how dimension reduction by using PCA with eigenvalues, there was a large increase in prediction accuracy. Habbouche et. al. [13] made a relative analysis of two machine learning (ML) models with signal processing techniques. The one proposed model used long short-term memory (LSTM) for classification, and other used CNN and LSTM for feature extraction and classification respectively. The dataset was constructed by using multiple sensors on a test rig with four heath conditions. Le et. al. [12] used shaft misalignment in a rotating system to capture vibration time-domain data. The time-domain data was converted to frequency domain for feature extraction using PCA method for reducing the dimension. For defect classification SVM was used. Lee et. al. [14] used novelty class detection method to predicts better with lesser frequency of fault data which is generally seen in any rotating machine industry. For feature selection GA and for extraction PCA was implemented. The dataset was recorded from a gearbox system with various faults like misalignment, backlash, tooth breakage, and SVM was used for fault classification.

It is seen from the literature that shaft misalignment fault on gear rotor system is rarely used to build a dataset for intelligent fault prediction. Therefore, in this paper vibration data are recorded along with control current signal from AMB coils which is proposed to be used as an integral component of the geared-rotor test rig, to benefit vibration suppression and precise prediction of various alignment conditions. Artificial neural network (ANN) was used for learning from the selected features and for classification. Angular misalignment is introduced in the setup and measurements were taken at three different speed which are below the fundamental natural frequency of the machine. The raw time-domain vibration and current signals are used to extract features from and feed them to the different classifiers for predicting the fault classes.

## 2 Experimental Test Rig

The experimental geared-rotor AMB system (Fig. 2) was developed in the advanced dynamics and vibration lab, IIT Guwahati. The schematic of the physical system is depicted in Fig. 1, which exhibits the spur gear pair with the pinion on the input shaft

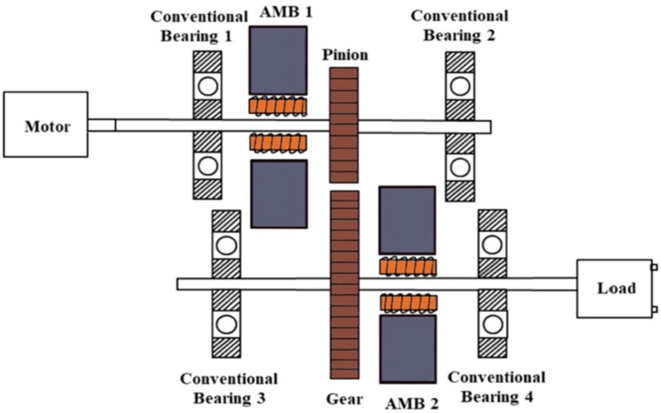


**Fig. 1.** A schematic diagram of the experimental test rig with the spur gear pair, four conventional rolling element bearings, two AMBs (each mounted on the input and output shaft), electric motor and load.

and gear wheel mounted on the output shaft. Conventional rolling element bearings are used to support both the shafts.

(a)

(b)

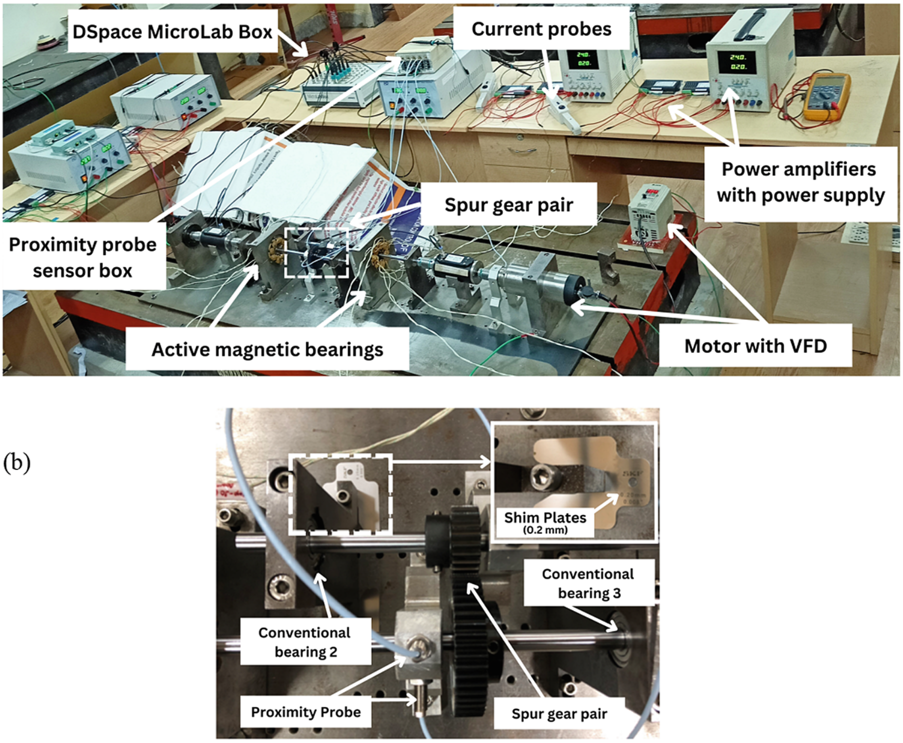


**Fig. 2.** (a) Spur geared-rotor experimental test rig (b) Zoomed view of the gear pair with shim plates installed under conventional bearing 2 for inducing the angular misalignment fault in the geared-rotor experimental test rig.

Two magnetic bearings are positioned in between the conventional bearings which actively suppress the transverse vibration of the shafts. Active magnetic bearings (AMBs) are electromechanical devices that use magnetic fields to diminish the transverse disturbances of the core attached to a rotating shaft, allowing it to spin without any contact with the stator core [15].

Figure 2(a) demonstrates the physical test rig developed to study the dynamic behaviour of a spur gear pair rotor machine equipped with active magnetic bearings. The centre distance between the input and the output shaft is 56.25 mm. A pinion of 25 teeth is mounted on the input shaft and the gear wheel with 50 teeth is mounted on the output shaft. As shown in the figure (Fig. 2), the physical deviation of the shaft centreline with respect to the bearing centreline is captured by the proximity probes in terms of voltage. These Bently Nevada manufactured probes are non-contact sensors that are sensible to any change in the gap between the sensor head and the conductive surface of the shaft. In order to obtain a linearized output, this gap should be maintained at $-5.75 \pm 0.5VDC$ and the probe has a sensitivity of 1.27 V/mm. A total of four eddy current probes are used, two for each shaft that measures horizontal and vertical transverse displacement response. The recorded signal run through the sensor box as it amplifies and then it gets fed to the dSpace MicroLab Box data acquisition system. The designed PID (proportional, integral and derivative) controller is executed in real-time in the DSpace-SIMULINK interface and the response is displayed in the DSpace software (DS2102).

## 2.1 Principal of Operation of Active Magnetic Bearings

The operational concept of an active magnetic bearing depends on the closed-loop arrangement of the AMB components. In Fig. 3(a) the schematic design of the closed-loop system is represented where a slight shift of the rotor core is recorded by the sensor and sent to the controller which then generate the control current. The required control current is amplified by the power amplifiers and then it passes through the AMB actuator coils to produce the magnetic flux for minimizing the vibration. This control current is measured by current probes as shown in Fig. 2(a). The implemented control law PID, is designed and implemented through MATLAB Simulink. The parameters of the PID (proportional gain, derivative gain and integral gain) are adjusted with trial and error method in order to obtain a stable operation of rotor. The tuning of the PID parameters are done until a desired vibration suppression is achieved. Depending on the control parameters, the required coil current is produced in accordance to which magnetic force is generated in the actuator. Since, control current time domain data is also used for training the model, therefore the model performance will in turn depend on the control law. The probe used in our research is KEYSIGHT TECHNOLOGIES (1146B) made, that measures both AC and DC signals (100 mA to 100 A RMS) using hall-effect sensing

(a) (b)

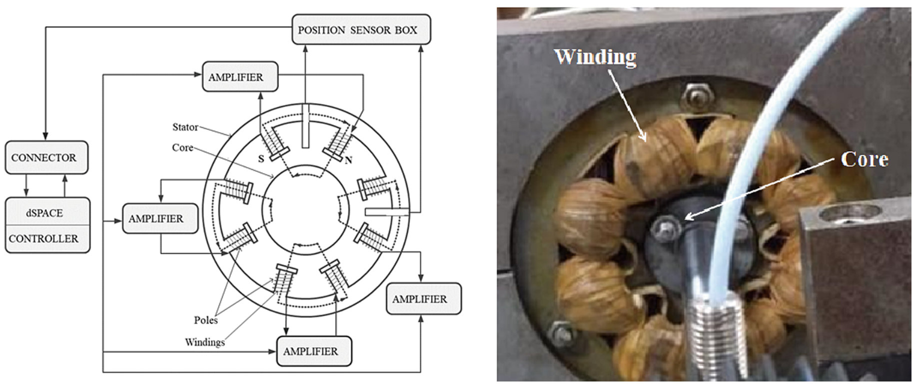


**Fig. 3.** (a) A schematic of the working principal of an 8-pole active magnetic bearing depicting the stator and the rotor core, and the direction of the flow of control current (b) The actual AMB showing the windings of the 8-pole actuator, and the rotating core.

technology. The probes are attached with the wire through it that is directly connected to the poles of the AMB actuators.

As such, the control current flowing through the electromagnet windings to minimize the vibration gets captured by the current probe. The probes directly connect to DSpace controller input channel through insulated BNC and the current signal is displaced in the monitor in real time. The system parameters of the experimental test rig and the PID parameters are mentioned in Table 1.

## 2.2 Introduction of Angular Misalignment Fault in the Test Rig

In this paper, we have developed a machine learning model to classify the four levels of angular misalignment defects purposefully induced in the geared-rotor test rig. To mimic angular misalignment in a practical scenario, we have use precision shim plates of three thickness value; 0.1 mm, 0.2 mm, and 0.4 mm under the conventional bearing 2 (refer Fig. 1 & 2(b)). This will create four defect conditions; no misalignment, 0.1 mm misalignment, 0.2 mm misalignment, and 0.4 mm misalignment in the input shaft.

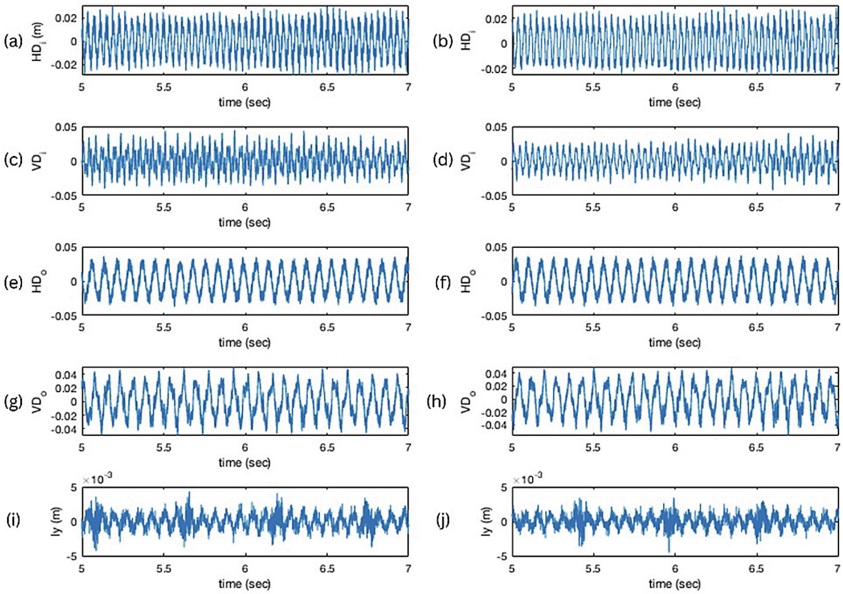


**Fig. 4.** Transverse displacement and control current signals for no misalignment (M0) fault condition (left column) and for 0.4 mm misalignment (M3) fault condition (right column), where (a, b) depicts the input shaft horizontal displacement (c, d) input shaft vertical displacement (e, f) output shaft horizontal displacement (g, h) output shaft vertical displacement (i, j) control current through the coil of poles in vertical direction.

Moreover, the data is recorded at three different speed values; 15 Hz, 23 Hz, and 30 Hz. Figure 4 shows the raw vibration and control current signals obtained from the experiment. From these raw signals, statistical features were extracted to be fed to the classification algorithm. The fault conditions and operating parameters are mentioned in Table 2.

**Table 1.** Parameters of the Experimental Test Rig

| Parameters | Values |
|---|---|
| Number of teeth (Pinion & Gear) | 25 & 50 |
| Module (mm) | 1.5 |
| Tooth width (mm) | 15 |
| Shaft diameter (mm) | 12 |
| Shaft Length (mm) | 600 |
| Gear Pair Material & Type | Stainless Steel & KHK |
| $K_P$ (Proportional Gain for Pinion & Gear) | 2750 |
| $K_D$ (Derivative Gain for Pinion & Gear) | 1.5 |
| $K_I$ (Integral Gain for Pinion & Gear) | 500 |

**Table 2.** Experimental parameters and fault conditions.

| Parameters | Values |
|---|---|
| **Fault Classes** (Misalignment Severities) | **M0** (No Misalignment), **M1** (0.1 mm Misalignment), **M2** (0.2 mm Misalignment), **M3** (0.4 mm Misalignment) |
| Operating Frequencies | 15 Hz, 23 Hz, 30 Hz |
| Total quantity of defect conditions | **4 × 3 = 12** |
| Sampling rate | 10,000 samples/sec |

## 3 Intelligent Fault Classification Framework

The general structure of machine learning fault class prediction of a given problem comprises of: dataset building, pre-processing of the data for transforming the data into a suitable format for analysis, feature engineering, dataset splitting, classification model selection and training, model testing [16]. For building the dataset, the test rig is run for 50 s with a sampling rate of 10,000 samples/sec for each fault condition.

### 3.1 Construction of Suitable Features

Feature extraction strategies aid in lowering the dimensionality of the data through the selection of a more condensed set of valuable features and thereby eliminating any redundancy in the dataset. These are health indicators which are used as input attributes to boost the learning algorithms' efficacy and efficiency [17]. Features are domain specific so in this paper features that are suitable for time-domain signals are utilised. Widely used such features [3, 18] are: mean, standard deviation, root mean square which are dimensional ones and dimensionless features that can be used are skewness, kurtosis, entropy. These six features are used in our research. Table 3 gives a brief explanation of all the selected features, where $X_i$ denotes individual data points ($i^{th}$ number data point), $N$ denotes the total number of data points in the dataset. $\overline{X}$ X' denotes mean of all the data points.

**Table 3.** Feature definition and formula

| Features | Definition | Formula |
|---|---|---|
| Mean | In statistics, mean represent the central average of samples of a dataset [6] | $\overline{X} = \frac{1}{N}\sum_{i=1}^{N} X_i$ |
| Standard Deviation | Standard deviation is a statistical measure of value variance. It measures the deviation from the mean [6] | $X_{SD} = \sqrt{\frac{1}{N}\left(\sum_{i=1}^{N}(X_i - \overline{X})^2\right)}$ |
| Root mean square | RMS values can describe signal amplitude and energy. It is not sensitive to the sign of the samples [9] | $X_{RMS} = \sqrt{\frac{1}{N}\left(\sum_{i=1}^{N} X_i^2\right)}$ |
| Kurtosis | Kurtosis measures distribution shape statistically. It compares a distribution's peak prominence or flatness to a normal distribution [9] | $X_k = \frac{N\sum_{i=1}^{N}(X_i - \overline{X})^4}{\left(\sum_{i=1}^{N}(X_i - \overline{X})^2\right)^2}$ |
| Skewness | Skewness is an indicator of statistics that characterises the lack of symmetry of a probability distribution [9] | $X_{skw} = \frac{N\sum_{i=1}^{N}(X_i - \overline{X})^3}{\left[\sqrt{\frac{\left(\sum_{i=1}^{N}(X_i - \overline{X})^2\right)}{N-1}}\right]^3}$ |
| Shannon Entropy | The Shannon entropy, which is also referred to as simple entropy, is a statistical metric that quantifies the level of uncertainty or randomness present in a given dataset [19] | $H = -\sum_{i=1}^{N} X_i^2 \log(X_i^2)$ |

### 3.2 Performance of Various Features

Among various supervised learning techniques for fault classification of gear systems, SVM, decision tree, random forests are widely popular [3]. In this paper, after extracting suitable attributes from the raw data, the above three and Naïve Bayes (NB) classification was implemented to find the best performing feature. NB classifier is used since it is quite simple to implement and performs well in large datasets [21].

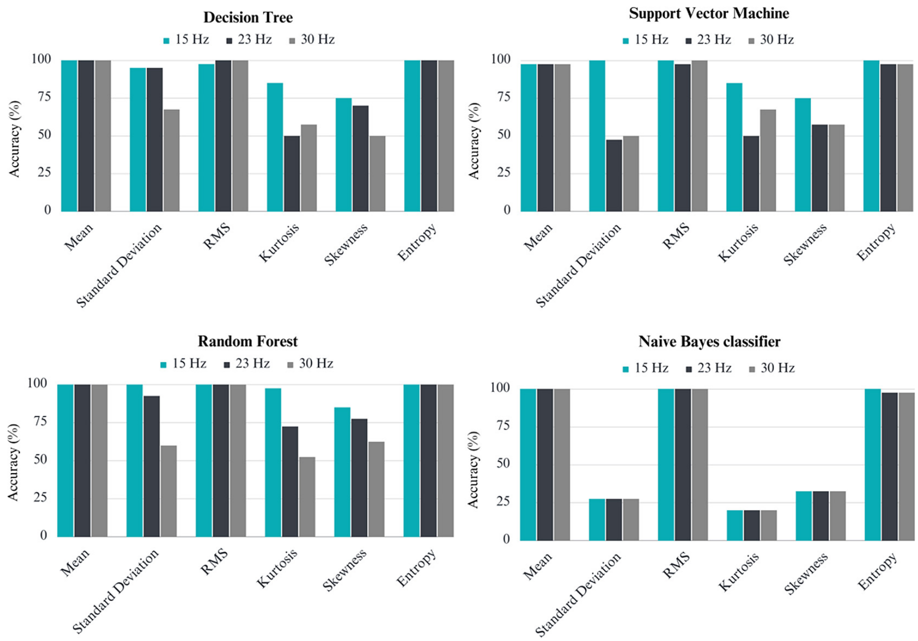


**Fig. 5.** Bar chart depicting prediction accuracy score of the four different classifiers fed by the extracted attribute at three different operating frequencies with all the fault classes combine using 80:20 training testing ratio.

As seen in the Fig. 5, mean, RMS, and entropy proved to perform excellent (all close to 100%) for all the classification algorithms. The bar chart in the figure shows the performance of these three condition indicators to be the best in all the speeds using all the sensor data (vibration and current data). However, these algorithms have some demerits which motivated us to implement deep learning algorithm like ANN for the best performance in various given situations. For instance, when we have large datasets, it can pose challenges while fitting for Support Vector Machines (SVMs), which can demand on higher computation time and power [3].

### 3.3 Implementing ANN Based Multilayer Perceptron

ANN allows us to implement a multilayer perceptron [3] with input layer, one or more hidden layers and output layer which are fully connected, i.e. every neuron in one layer is linked to every neuron in the layer next to it [20]. This gives high flexibility and also allows handling large datasets. The number of neurons in the output layer depend on the fault class used in the study, in our research it is four. In this study, an ANN model was developed using Keras library in Tensorflow Python.

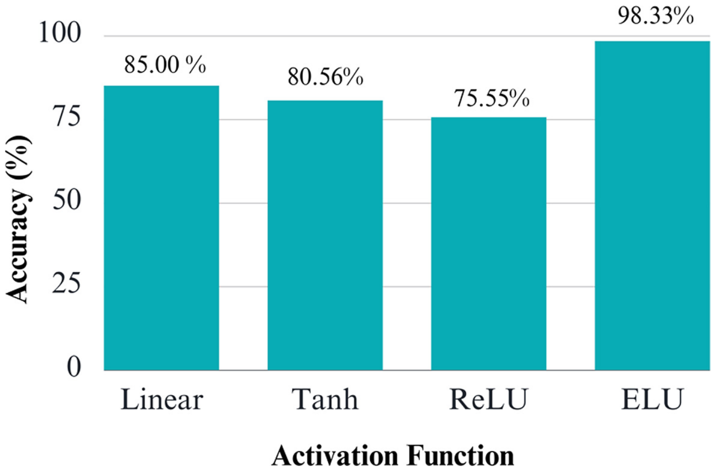


**Fig. 6.** Bar diagram depicting classification accuracy of the developed artificial neural network model, using four different activation functions, namely linear, tanh, ReLU and exponential linear unit (ELU) with 7 hidden layers and 80:20 training testing dataset, showing maximum prediction accuracy of 98.33%.

The features that were found to perform the best in the Sect. 3.2 were used for training and testing the ANN model. Since our prediction involved 4 fault classes with misalignment defect, so the dataset comprised of four misalignment classes each with a single feature, hence 4 files for a single feature. Since the output column has 4 defect conditions as such one hot encoder is used as a data pre-processing technique to create 4 binary columns, so that each row with the four columns represents a fault category. Now, the training and testing data was split as 80:20. For improving the convergence of the algorithm, feature scaling is done by performing standardization. The transformed training and testing data is now fed to the ANN model input layer. The model has 7 hidden layers with 65 perceptions in each hidden layer.

For weight initialization *kernel-initializer* is used and 4 activation functions for each hidden layer ere used and with 200 mini batch size and 100 number of epoch, the overall prediction accuracy was found to be 98.33% (comparison shown in Fig. 6). In the output layer, there are 4 neurons representing 4 defect classes and the activation function used was softmax. Softmax activation function was used since it gives probabilistic output, which is common in multi-class classification problem. The optimizer variable has been configured to utilise the Adam optimisation algorithm, with a specified learning rate of 0.001.

As mentioned in the introduction section, many researchers have used ANN or combined ANN with genetic algorithm or principal component analysis (PCA) for gearbox fault classifications. In [4], the prediction accuracy with ANN was found to be in the range 48.61% to 100% and ANN with genetic algorithm (GA), in range 97.22–100%. Similarly, in [5] overall accuracy with ANN with the application of GA was found to be 95%. And in [11] an overall accuracy of about 98.67% was found by using PCA dimensional reduction with ANN. Whereas in our study, an overall prediction accuracy of 98.33% was achieved by using ANN and three statistical features (mean, entropy and RMS) as the input (Fig. 6).

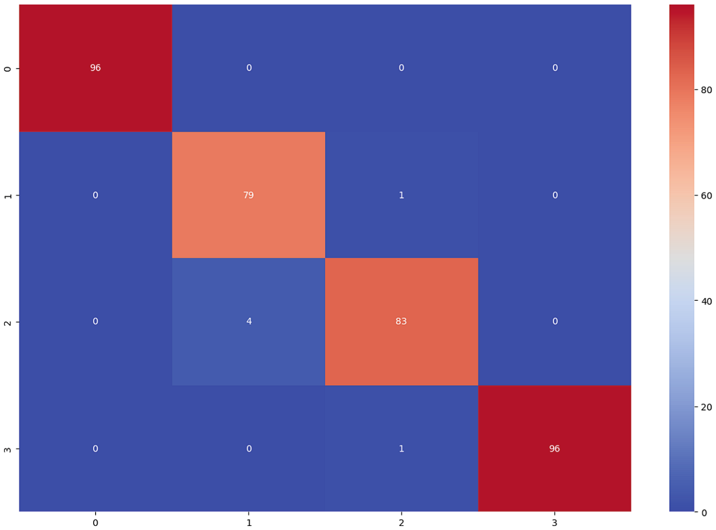


**Fig. 7.** Confusion matrix to check the performance of the classification algorithm for batch size of 200 and epoch 100, with activation function exponential linear unit (ELU).

## 4 Conclusion

In this paper, we have highlighted the potential faults that can occur in a gear rotor machine, with a specific focus on shaft misalignment. The paper emphasizes the use of machine learning and deep learning techniques for accurately diagnosing faults classes. The data was recorded from an experimental test rig with AMB as an integral component. An ANN model was developed that takes input vibration and current data and predicts the type of fault class. The raw time-domain vibration data and AMB control current data was pre-processed for significant feature extraction, where 6 statistical condition indicators were selected and their performance were tested by popular machine learning based classifiers like SVM, Decision Tree, Random Forest, and Naïve Bayes. Among the six features, mean, RMS, and Shannon entropy performed the best with accuracy very close to 100%. These three features were then used for classification in the ANN model. The hyper-parameters namely activation function, mini batch size, epoch, etc. of the ANN model were optimized to achieve a high accuracy rate of approximately 98.33%.

In future, a different deep learning model like 1-dimensional convolution neural network can be incorporated, and a dataset with larger number of faults and operating frequencies may be used.

## References


1. Saxena, A., Parey, A., Chouksey, M.: Effect of shaft misalignment and friction force on time varying mesh stiffness of spur gear pair. Eng. Fail. Anal. **49**, 79–91 (2015)
2. Stetco, A., et al.: Machine learning methods for wind turbine condition monitoring: a review. Renew. Energy **133**, 620–635 (2019)
3. Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., Nandi, A.K.: Applications of machine learning to machine fault diagnosis: a review and roadmap. Mech. Syst. Signal Process. **138**, 106587 (2020)
4. Samanta, B.: Gear fault detection using artificial neural networks and support vector machines with genetic algorithms. Mech. Syst. Signal Process. **18**(3), 625–644 (2004)
5. Yang, Z., Hoi, W.I., Zhong, J.: Gearbox fault diagnosis based on artificial neural network and genetic algorithms. In: Proceedings 2011 International Conference on System Science and Engineering, pp. 37–42. IEEE (2011)
6. Bansal, S., Sahoo, S., Tiwari, R., Bordoloi, D.J.: Multiclass fault diagnosis in gears using support vector machine algorithms based on frequency domain data. Measurement **46**(9), 3469–3481 (2013)
7. Bordoloi, D.J., Tiwari, R.: Optimization of support vector machine based multi-fault classification with evolutionary algorithms from time domain vibration data of gears. Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci. **227**(11), 2428–2439 (2013)
8. Wang, D.: K-nearest neighbours based methods for identification of different gear crack levels under different motor speeds and loads: revisited. Mech. Syst. Signal Process. **70**, 201–208 (2016)
9. Khan, M.A., et al.: Gear misalignment diagnosis using statistical features of vibration and airborne sound spectrums. Measurement **145**, 419–435 (2019)
10. Li, X., Li, J., Qu, Y., He, D.: Gear pitting fault diagnosis using integrated CNN and GRU network with both vibration and acoustic emission signals. Appl. Sci. **9**(4), 768 (2019)
11. Zuber, N., Bajrić, R.: Gearbox faults feature selection and severity classification using machine learning. Eksploatacja i Niezawodność **22**(4), 748–756 (2020)
12. Lee, Y.E., Kim, B.K., Bae, J.H., Kim, K.C.: Misalignment detection of a rotating machine shaft using a support vector machine learning algorithm. Int. J. Precis. Eng. Manuf. **22**, 409–416 (2021)
13. Habbouche, H., Benkedjouh, T., Amirat, Y., Benbouzid, M.: Gearbox failure diagnosis using a multisensor data-fusion machine-learning-based approach. Entropy **23**(6), 697 (2021)
14. Yu, H.T., Park, D.H., Lee, J.J., Kim, H.S., Choi, B.K.: Novelty class detection in machine learning-based condition diagnosis. J. Mech. Sci. Technol. **37**(3), 1145–1154 (2023)
15. Tiwari, R.: Rotor Systems: Analysis and Identification. CRC Press, Boca Raton (2017)
16. Koukoura, S., Carroll, J., McDonald, A.: A diagnostic framework for wind turbine gearboxes using machine learning. In: Annual Conference of the PHM Society, vol. 11, no. 1 (2019)
17. Guyon, I., Elisseeff, A.: An introduction to feature extraction feature extraction: foundations and applications, 1–25 (2006)
18. Sánchez, R.V., Lucero, P., Vásquez, R.E., Cerrada, M., Cabrera, D.: A comparative feature analysis for gear pitting level classification by using acoustic emission, vibration and current signals. IFAC-PapersOnLine **51**(24), 346–352 (2018)

19. Karaca, Y., Baleanu, D., Zhang, Y. D., Gervasi, O., Moonis, M. (Eds.).: Multi-Chaos, Fractal and Multi-Fractional Artificial Intelligence of Different Complex Systems. Academic Press (2022)
20. Liu, R., Yang, B., Zio, E., Chen, X.: Artificial intelligence for fault diagnosis of rotating machinery: a review. Mech. Syst. Signal Process. **108**, 33–47 (2018)
21. Yuan, Y., Li, S., Zhang, X., Sun, J.: A comparative analysis of svm, naive bayes and gbdt for data faults detection in wsns. In: 2018 IEEE International Conference on Software Quality, Reliability and Security Companion (QRS-C), pp. 394–399. IEEE (2018)