A Comprehensive Approach for Gearbox Fault Detection and Diagnosis Using Sequential Neural Networks

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***Abstract*—Gearbox faults can lead to significant damage and downtime in industrial machinery, resulting in substantial losses for manufacturers. Detection of faults in gears in the incipient state is essential to ensure safe and reliable operation of industrial machineries. In recent years, there has been an increasing interest in using machine learning algorithms to automate gearbox fault detection. This paper proposes a machine learning approach for identifying different categories of faults in a gearbox based on vibration signals. The proposed method was evaluated on a dataset of vibration signals collected from a two-stage gearbox under different operational conditions. The research is focused on developing a sequential neural network-based method for detecting multiple gear faults simultaneously. The results showed that the developed method achieved high training and validation accuracies and relatively low training and validation losses, indicating the model's ability to accurately detect and classify faults in gearboxes. The testing accuracies were also high, demonstrating the model's ability to generalize well to new data. The practical implications of the research are significant for improving the reliability and maintenance of gearboxes in various industrial applications. The developed method has the potential to reduce downtime, maintenance costs, and improve safety and efficiency.**

Keywords—gearbox fault detection, vibration analysis, sequential neural network, maintenance

I. Introduction

The problem of gearbox fault detection is a critical issue in industrial machinery maintenance. Gearboxes are essential components in many machines, and faults in gearboxes can lead to significant damage, downtime, and financial losses for manufacturers [1]. Identifying gearbox faults is crucial to prevent catastrophic failures, minimize downtime, and reduce maintenance costs. However, gearboxes are subjected to a range of wear and tear [2]. If left undetected, faults in gearboxes can escalate rapidly, leading to complete machine breakdown, loss of productivity, and increased maintenance costs. Early detection and repair of gearbox faults can prevent these issues and ensure optimal machine performance [3].

Existing methods for gearbox fault detection include visual inspection, acoustic analysis [4], and vibration analysis [3]. Visual inspection involves physically inspecting the gearbox for signs of wear, damage, or other faults. This method requires significant expertise and can only detect faults that are visible to the naked eye and reduces the operation capacity in order to perform such inspection. However, recent studies have proposed combining visual inspection with machine learning techniques to improve the accuracy and efficiency of fault detection [5].

Acoustic analysis involves measuring and analysing the sound generated by the gearbox to detect potential faults. This method is limited in its ability to distinguish between different types of faults and is susceptible to environmental noise. Nevertheless, studies have shown that acoustic analysis can be effective in detecting certain types of gearbox faults [6].

Vibration analysis is currently the most widely used method for gearbox fault detection. Vibration monitoring is a technique used to detect faults in gears by analysing the vibrations they produce. Healthy and faulty gears generate different vibration signals, which can indicate the presence of faults such as gear tooth wear, gear tooth cracks, and pitting. Various techniques such as time domain, frequency domain, and time-frequency domain techniques are used to analyse these vibration signals. The frequency domain technique involves using the Fast Fourier Transform (FFT) of the time domain signal to evaluate the condition based on the signal's frequency content. However, vibration signals from gears are considered non-stationary and non-periodic, making it challenging to detect multiple gear faults using conventional FFT analysis [7]. To overcome this limitation, sophisticated signal processing method, such as wavelet analysis, can be used for feature extraction from the noisy gear signal. Vibration analysis requires advanced signal processing, feature extraction and machine learning techniques for accurate and reliable predictions of multiple faults simultaneously [8].

The objective of this paper is to develop a method for analysing vibration signals to monitor the health of industrial gear box systems and enable multiple fault detection simultaneously. The proposed methodology involves data collection, feature extraction, and training a machine learning model to predict the state of the gear condition. The effectiveness of the proposed approach is evaluated on a dataset of vibration signals collected from a two-stage gearbox under different operational conditions. The paper presents the results of the study, demonstrating the accuracy and reliability of the proposed approach in identifying different fault categories, including normal working condition, surface wear, chipped, cracked, and tooth missing. This paper provides a useful framework for gearbox fault detection that can improve the reliability and safety of industrial machinery.

The paper is structured as follows, in Section II, the framework developed for this study is described. Section III discusses the case study and the application of the framework to the case. In Section IV, the modelling results and discussion are presented. Finally, Section V concludes of the paper.

II. Method

Gearbox fault detection using machine learning involves the use of algorithms to automatically identify the presence of faults in gearbox systems from vibration signals. The general framework for gearbox fault detection using machine learning involves the two key steps which are briefed explained in this section.

A. Data Collection and Feature Extraction:

This step involves collecting the vibration signals from the gearbox system using sensors and processing the collected data for analysis. The following are the actions involved in this step:

1) Data collection and preprocessing: data collection involves the collection of the vibration signals from the gearbox system using sensors and are most commonly mounted on the gearbox housing or on the shaft. Preprocessing involves cleaning and preparation of the collected data for analysis. The data may be filtered, normalized, and segmented to remove noise and artifacts.

2) Feature extraction: involves the extraction of relevant features from the vibration signals. The extracted features should capture the underlying fault patterns in the data. There are several types of features that can be extracted from vibration signals for gearbox fault detection such as, time domain features [9] describing the behavior of the vibration signal over time, mean, standard deviation, kurtosis, and skewness are examples; frequency domain features [10] describing the behavior of the vibration signal in the frequency domain, spectral density, power spectrum, and Fourier coefficients are examples; time-frequency domain features [11] describing the behavior of the vibration signal in both the time and frequency domains wavelet transform, short-time Fourier transform, and Gabor transform are examples and finally statistical features [12] describing the statistical properties of the vibration signal include entropy, correlation, and covariance are examples.

3) Feature ranking and feature selection: involves the identification and selection of the most relevant features for the fault detection model. Feature ranking involves the computation of a ranking score for each feature, based on its ability to distinguish between the different fault categories. A higher ranking score indicates that the feature is more important in distinguishing between fault categories. Different feature ranking methods such as ANOVA, ReliefF, Extra Trees Classifier, and Correlation-based feature selection etc., can be used to rank the features. Feature selection, on the other hand, involves the selection of the top-ranked features from the feature ranking step. The selected features should have high discriminatory power and low redundancy. The goal of feature selection is to reduce the dimensionality of the feature space, thereby improving the performance and interpretability of the fault detection model.

B. Machine Learning Model Development

This step involves developing a machine learning model to detect faults based on the extracted features. The following are the actions involved in this step:

1) Model selection: involves selecting the appropriate machine learning algorithm for the problem at hand. There are several types of machine learning models that can be used for gearbox fault detection, including, supervised learning models - which learn from labeled data and can be used to classify the data into different fault categories, Decision Trees, Random Forests, Support Vector Machines (SVMs) [13]–[15], and Neural Networks [16] are examples; unsupervised learning models - these models learn from unlabeled data and can be used to identify patterns and anomalies in the data, K-Means Clustering, DBSCAN clustering [17]–[19], Principal Component Analysis (PCA) [20], and Autoencoders [21] are examples; semi-supervised learning models - these models learn from a combination of labeled and unlabeled data and can be used when only a small amount of labeled data is available, self-training [22] and co-training models [23] are examples; transfer learning models - these models learn from a pre-trained model on a related task and can be used when there is a limited amount of labeled data available for the specific application, fine-tuning [24] and domain adaptation [25] are examples.

The choice of model for gearbox fault detection depends on several factors, including the amount and quality of labelled data, the complexity of the underlying fault patterns, and the desired performance metrics. A common approach to model selection is to evaluate multiple models using a validation set and select the one with the best performance. Alternatively, an ensemble of multiple models can be used to improve the accuracy and robustness of the fault detection system.

2) Model training: involves training the selected machine learning algorithm using the labeled data. The labeled data consists of the extracted features and the corresponding fault labels.

3) Model validation: involves evaluating the performance of the trained model on a validation set. The purpose of model validation is to estimate the performance of the model on an independent dataset that was not used for training the model.

4) Model testing: involves evaluating the performance of the trained model on new, unseen data. The purpose of model testing is to assess the generalization capability of the model, i.e., how well it can predict the outcome for new data that it has not seen before.

III. Case Study

In this case study a machine learning-based model is developed for analysing vibration signals to monitor the health of gear box in the industrial setup based on the method defined in section II. Gear boxes are prone to defects and failures, which may lead to various undesirable consequences. Therefore, real-time monitoring techniques are essential to mitigate the risk of failures, reduce machinery downtime, and increase productivity by performing efficient maintenance strategies. Vibration signals are widely used for fault detection in industrial/manufacturing machinery, making them the focus of this case study.

A. Data Collection and Feature Extraction:

The dataset [26] used in this study consists of vibration signals collected from a two-stage gearbox under different operational conditions captured using a portable data acquisition system of National Instruments (NI, 356A01). The vibration data used for the present study focuses on the planetary gearbox. Each vibration signal was recorded in three directions (x, y, z), for a period of five minutes, and with a sampling frequency of 10 kHz. The first operating condition included a motor speed of 1500 rpm with a load of 10Nm. The second operating condition in which the data were recorded had a motor speed of 2700 rpm with a load of 25Nm. The features used in the study were extracted from time domain, frequency domain, wavelet analysis and time-frequency domain. The features used for this study includes peak-to-peak, kurtosis, crest factor, skewness, standard deviation, variance, energy spectrum, velocity spectrum (1x, 2x, 3x), Fast Fourier Transform (FFT) (1x,2x,3x,4x), Scale Averaged Wavelet Power (SAWP), Laplace Wavelet Kurtosis, M6A, M8A, Energy Operator and spectral entropy. The features were extracted for the vibrations signal collected across the three directions individually. Five classes of gear state were monitored for this study: - Normal/healthy, surface wear, cracked tooth, chipped and tooth missing. Each of the state had 10,000 signals for which the above-mentioned features were estimated.

This study uses a tree classifier to identify the most important features. Here, a total of 78 features were extracted from the vibration signals, with 26 features extracted from each of the x, y, and z directions. These features were then fed into the tree classifier for feature ranking, which analyzed the features and ranked them according to their importance. After the analysis, the top 60 features were selected based on their feature ranking score and were used as input for the modelling stage. By selecting the top features, the model can focus on the most important information in the dataset, reducing the impact of irrelevant or redundant features, and improving the overall performance of the model.

B. Machine Learning Model Development

Sequential neural networks are employed for this study as they can learn from large amounts of data and have been shown to achieve state-of-the-art results in various applications. Also, they can effectively capture complex patterns and dependencies in data. This makes them a suitable choice for the task of gearbox fault detection, where large amounts of vibration signal data are available for training.

The sequential neural network model has four hidden layers that are stacked one after the other. The layers are fully connected or dense layers. The input layer has 512 units with a rectified linear unit (ReLU) activation function and uses L2 regularization with a strength of 0.001. The dropout layer with a rate of 0.2 is used to prevent overfitting by randomly setting 20% of the input units to 0 at each update during training time. The following layers are also dense layers with ReLU activation functions and have 256, 128, and 64 units, respectively. All of these layers use L2 regularization with a strength of 0.001 and dropout with a rate of 0.2. The output layer has 5 units (one for each gear state) with a softmax activation function to produce a probability distribution over the classes. The hyper parameter learning rate was optimized using the Adam optimizer, and an early stopping criterion was used to prevent overfitting or underfitting. The model was evaluated on the loss function 'sparse_categorical_crossentropy' since the labels used in the study were integers.

The study utilized a data set consisting of 50000 x 60 samples, where each gear state including faults had a size of 10000 x 60 samples for training the model. The data set is normalized prior to being fed into the model. The resulting data set was then split into training and testing sets in an 90:10 ratio. The model was evaluated using 5-fold cross-validation on the training set, which contained 45000 samples. Finally, 10 percent of the data set was reserved for the final testing of the model. A learning rate schedule function lr_schedule() is used to adjust the learning rate during training. This function will keep the learning rate constant for the first 10 epochs, and then decrease it exponentially with a decay rate of 0.1. The code also sets up an early stopping criterion using the Early Stopping callback from Keras. This will monitor the validation loss during training and stop training if the validation loss has not improved during consecutive 5 epochs. This also helps prevent overfitting and ensures that the model does not continue training if it has already reached its optimal performance on the validation set. When using K-fold cross validation, this code will be applied within each fold of the cross-validation loop. Each fold will use a different subset of the data for training and validation, but will use the same initial learning rate, optimizer, learning rate schedule, and early stopping criteria.

IV. Results and Discussion

The developed model based on sequential neural network and feature selection achieved promising results for the task of gearbox fault detection. The model was trained and tested on two different RPM (revolutions per minute) values, 1500 and 2700 RPM. Fig. 1. represents the results of a 5-fold cross-validation study conducted on these two operating conditions (RPMs) of Gear.

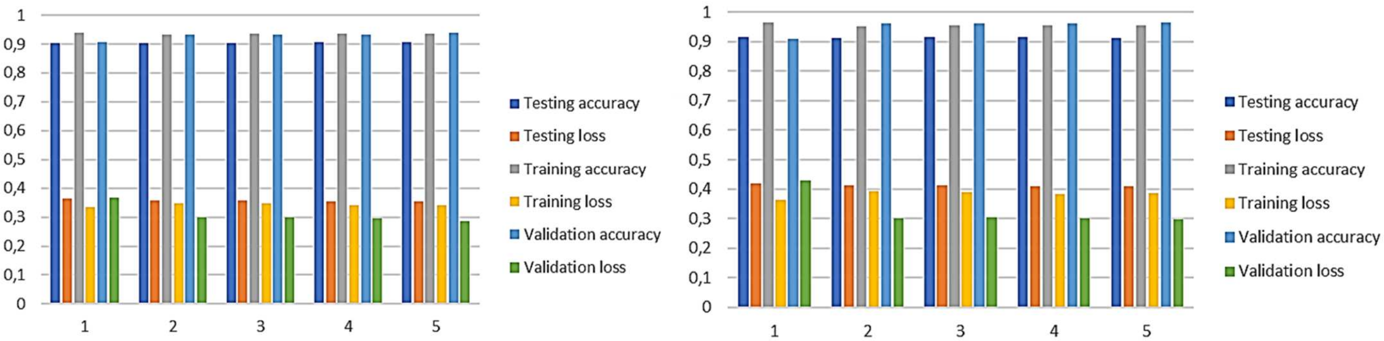

Fig. 1. Five-fold cross-validation results for 2700 RPM (left) and 1500 RPM (right)

For the 2700 RPM operating condition, the training accuracy ranged from 93% to 94% from fold 1 to fold 5. The training loss ranged from 0.3348 to 0.3416. The validation accuracy ranged from 90% to 93%. The validation loss ranged from 0.2969 to 0.365 and the testing accuracy ranged from 90% to 91%. The testing loss ranged from 0.3536 to 0.3647. For the 1500 RPM operating condition, the training accuracy ranged from 95% to 96% from fold 1 to fold 5. The training loss ranged from 0.3631 to 0.3861 and the validation accuracy ranged from 91% to 96%. The validation loss ranged from 0.2967 to 0.4289 and the testing accuracy ranged from 91% to 92%. The testing loss ranged from 0.408 to 0.4184.

Fig. 2 shows the training and validation loss during each epoch for fold 1 for 1500 RPM. The training loss starts from a relatively high value of 1.2 and decreases over time, reaching a final value of 0.4. On the other hand, the validation loss starts from a value of 0.9 and decreases over time, reaching a final value of 0.5. This indicates that the model is learning to generalize well to new data, as the training and validation loss both decrease over time. Fig. 2 suggest that the model is performing well on the testing set, with testing accuracy ranging from 90% to 91%. Additionally, the testing loss is generally lower than the training and validation loss, indicating that the model is not overfitting to the training data.

Fig. 2. Training and validation loss in each epoch for fold 1

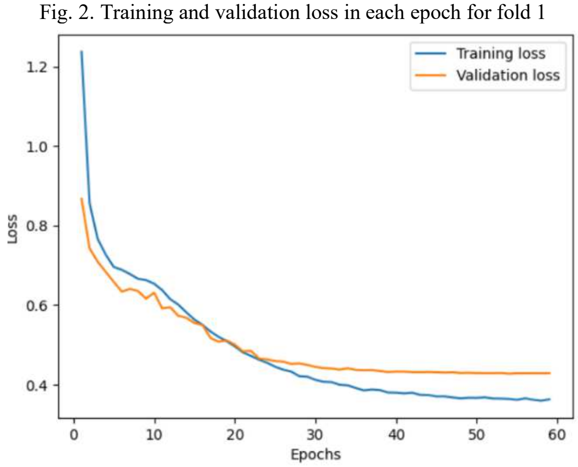

Table. I. shows the final model results after the cross validation. The training accuracy and loss indicate how well the model was able to fit the training data and the model achieved higher accuracy and lower loss on the 1500 RPM training data (92.55% accuracy and 0.3861 loss) compared to the 2700 RPM training data (91.47% accuracy and 0.3146 loss). The validation accuracy and loss indicate how well the model was able to generalize to new data and the model achieved higher validation accuracy on the 1500 RPM data (96.39% accuracy and 0.2967 loss) compared to the 2700 RPM data (93.89% accuracy and 0.2848 loss). This suggests that the model was better at generalizing to new data at the lower RPM. The testing accuracy and loss indicate how well the model performed on a completely new and unseen dataset. The model achieved higher testing accuracy on the 1500 RPM data (91.34% accuracy and 0.407 loss) compared to the 2700 RPM data (90.61% accuracy and 0.3535 loss). This suggests that the model was better at predicting the outcome of new data at the lower RPM.

TABLE I. TRAINING AND TESTING PERFORMANCE

Rpm	**1500**	**2700**
Training accuracy	93%	91%
Training loss	0,3861	0,3146
Validation accuracy	96%	94%
Validation loss	0,2967	0,2848
Testing accuracy	91%	91%
Testing loss	0,407	0,3535

The results of the developed method for fault detection have demonstrated its effectiveness in diagnosing faults in gearboxes. The high training, validation accuracies, and relatively low training and validation losses, indicate that the model can accurately detect and classify faults in the gearbox. The testing accuracies, although slightly lower than the training and validation accuracies, are still relatively high and demonstrate that the model can generalize well to new data and detect five stages of gear heath status simultaneously. The practical implications of these findings are significant for improving the reliability and maintenance of gearboxes in various industrial applications. By accurately detecting various faults in gearboxes, maintenance personnel can proactively address the underlying issues before they become more severe and potentially lead to catastrophic failures. This can help to reduce downtime and maintenance costs and improve the overall reliability and safety of machinery. Additionally, the ability to diagnose faults in gearboxes using a machine learning approach can potentially reduce the need for manual inspection and diagnosis, saving time and resources. Overall, the developed method for fault detection has the potential to improve the reliability and maintenance of gearboxes in various industrial applications, leading to improved safety, reduced costs, and increased efficiency.

V. Conclusion

In conclusion, this paper presents the development of a comprehensive method for fault detection in gearboxes using vibration analysis. The proposed framework includes several stages including feature extraction, and fault diagnosis using machine learning models, which aim to identify and diagnose multiple faults accurately and effectively. The proposed method was applied to a case study involving a gearbox data, and the results demonstrated the effectiveness of the developed framework in detecting and diagnosing faults in gearboxes.

The developed sequential neural network with feature selection has demonstrated promising results in the detection of faults in gearboxes. The model achieved high training and validation accuracies and relatively low training and validation losses, indicating that it can accurately detect and classify faults in gearboxes. The model also performed well on the testing set, demonstrating good generalization ability.

Overall, this paper provides a valuable contribution to the field of fault detection in gearboxes, and the developed framework has the potential to improve the performance and reliability of various systems that rely on gearboxes. The future research in this area can focus on further enhancing the proposed framework's accuracy and efficiency by further optimising the current model, enhancing the dataset and by integrating other advanced techniques, such as machine learning and artificial intelligence.

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