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RESEARCH

A Model for Prediction of Outer Race Defects of Rolling Contact Bearing based on Vibration Data Using Machine Learning Algorithms

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A B S T R A C T

The detection of bearing defects while the machinery is in use is essential for predicting the incipient failure and thereby providing an opportunity to take remedial measures for preventing the costly downtime and ensuring the safe and efficient operation of rotating machinery. With the increasing availability of vibration sensor data and the development of machine learning techniques, the ML methods have become a popular approach for automated fault diagnosis in bearings. In this paper, an attempt has been made to detect the faults in the outer race of bearing using different ML algorithms. An experimental setup has been designed and fabricated to conduct experiments on healthy and faulty bearings and the vibration signals were captured. The captured vibration signals were directly employed as images for training the ML algorithms without the need for conducting the spectral analysis. Six machine learning algorithms, namely, Linear Regression (LR), Decision Tree (DTR), KNN Regression (KNNR), Random Forest Regression (RFR), Convolution Neural Network (CNN), Naive Bayes (NB) were separately applied to classify the location of defects within the outer race of the ball bearing. The accuracy table are used to find the best suitable algorithm for the predictions. The methodology includes data preprocessing techniques, network architectures, training strategies, and evaluation metrics. It has been established that the use of ML technique is very effective in detecting the bearing defects and CNN is able to achieve 100% accuracy.

1. INTRODUCTION

Rolling contact bearings are essential components in many machines and equipment. They are used to support rotating shafts and allow for smooth and efficient operation. However, bearings can fail due to a variety of factors, including wear, corrosion, and fatigue. When a bearing fails, it can cause significant damage to the machine and lead to costly downtime.

Early detection of bearing faults is essential to prevent catastrophic failures. Traditional methods for detecting bearing faults include vibration analysis, oil analysis, and ultrasonic testing. However, these methods can be time-consuming and labor-intensive, and they may not be able to detect all types of faults.

Machine learning methods offer a promising alternative for detecting bearing faults. Machine learning algorithms can be trained on data from healthy and faulty bearings to learn to identify the patterns that are associated with different types of faults. This allows machine learning algorithms to detect faults more quickly and accurately than traditional methods. In one study by Upadhyay et al [1], an integrated model and data driven-based methodology for the diagnosis of bearing defect is utilized and statistical time domain features are calculated from the data to train the artificial neural network, support vector machine and decision tree. It was established that the integration of model and machine learning-based technique provides good diagnosis efficiency. Pandarakone et al [2] proposed a diagnostic method to detect the minor fault using SVM and DL algorithm. Delgado et al [3] proposed a novel diagnosis methodology applied to bearings faults using information in time-domain from the vibration data. Kumar et al [4] converted the acquired vibration signals into 2D greyscale images with continuous wavelet transform (CWT) and employed it in deep convolutional neural network to assess the defect severity. Fu et al [5] proposed a bearing fault diagnosis method based on wavelet denoising and machine learning. The wavelet denoising algorithm was used to reduce the noise and five machine learning models, including K-means clustering, decision tree, random forest, and support vector machine were evaluated to classify the bearing faults. Barai et al [6] highlighted the recent trends in research on the diagnosis of faults in bearing. It was surveyed that several vibration measurement and other signal processing methods were utilized for diagnosis of bearing faults such as Fast Fourier transform (FFT), wavelet packet transform (WPT), Short-time Fourier transform (STFT), Principal Components Analysis (PCA), continuous wavelet transforms (CWT), Ensemble Rapid Centroid Estimation (ERCE) etc. Samanta et al [7] compared the performance of bearing fault detection using three types of artificial neural networks (ANNs), namely, multilayer perceptron (MLP), radial basis function (RBF) network, and probabilistic neural network (PNN) from time-domain vibration signals.

Many studies in the past have been utilizing the traditional methods for detecting bearing faults which includes capturing of vibration signals followed by signal analysis [8-14]. The working condition of the bearings have a very significant effect on its performance and the generation of faults and its consequent propagation is greatly influenced by it, this issue has been addressed in many studies, but by using the traditional methods [15-23]. Several research studies have focused on the early fault detection of rolling contact bearings using the vibration signals [24-30]and machine learning methods [31].

In particular, machine learning methods have been shown to be effective in detecting faults in the outer race of rolling contact bearings. It is a common location for faults to occur, and early detection of outer race faults can help to prevent catastrophic failures.

Machine learning methods are a powerful tool for detecting bearing faults. They can be used to improve the reliability of machines and equipment, and they can help to prevent costly downtime.

The application of ML algorithms in detecting defects in rolling contact bearing using only the vibration signal data has not been attempted and is thus explored in the present work. The raw vibration data signal in time domain is used and ML techniques are applied to detect defects.

2. EXPERIMENTAL SETUP

An experimental setup was designed and fabricated to carry out the experimental investigations. The schematic diagram of the experimental setup is shown in Figure 1. It consists of a shaft mounted on support bearings and connected to an electric motor through a flexible coupling as shown in Figure 2. A test bearing is mounted at the over hanged condition. The radial load is applied through dead weights. An accelerometer is attached on the outer race of the rolling contact to capture the vibration signals of healthy and faulty bearings. The NI-9250 data acquisition module is used for signal acquisition. The specifications of the test bearing are given in Table 1.

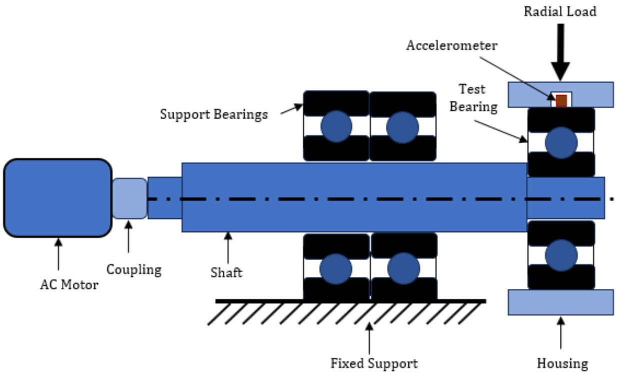

Fig. 1. Schematic of the experimental setup.

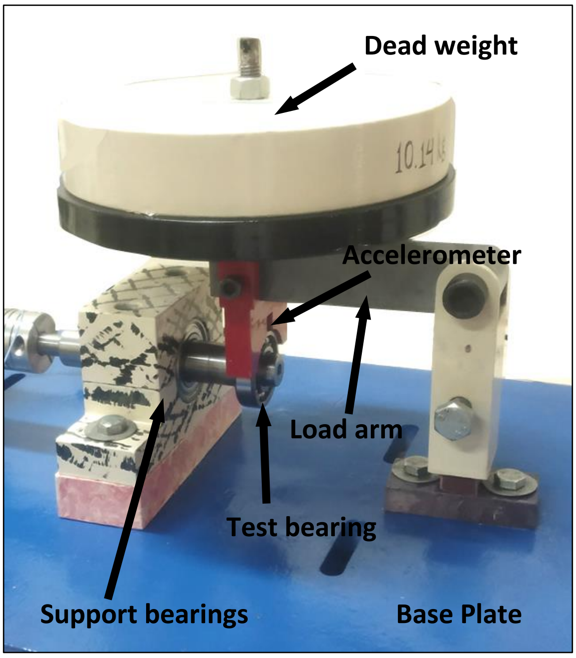

Fig. 2. Experimental setup.

Table 1 Bearing parameters [8].

Bearing type SKF BB1B420204	
Pitch diameter, Dp (mm)	32.94
Ball diameter, db (mm)	8.7
Diametral clearance, pd (µm)	10
Number of balls, Z	7
Angular spacing between balls, ϕs (deg)	51.42
OR fault frequency ratio, $\varpi o = f_{OR}/fs$	2.576
Mass of ball, mb (kg)	0.0027
Mass of OR and housing, mh (kg)	0.445+0.890
Mass of IR and overhung shaft, ms (kg)	0.210+0.165
Housing stiffness, kh (N m− 1)	1.451e+10
Shaft stiffness, ks (N m− 1)	4.667e+8
Housing damping, ch (N s m− 1)	769.78
Shaft damping, cs (N s m− 1)	24.76
Applied radial load, Fr (N)	100
Shaft speed, Ns (rpm)	1500
BPFO (theoretical) at Ns = 1500 rpm	64.38

Table 2 Defect parameters [8].

Angular location of defect (degree)	20° to 40° in steps of 5°
Length of defect	1 mm
Depth of defect	> $h_{d, crit}$
Radius of defect edge	0.01 mm

Fig. 3. Defect in outer race [8].

The vibration signals acquired by the accelerometer for different locations of the defect in the outer race of the ball bearings is recorded and is given in figures 4 to 8. The Figure 4 depicts the acceleration signal acquired in the time domain for the outer race defect located at a span of 20°.

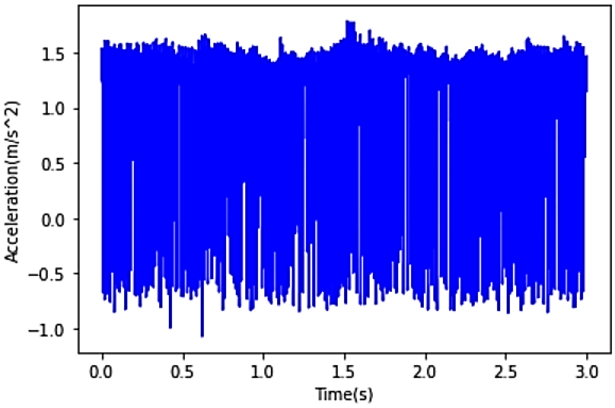

Fig. 4. Outer race defect at a span of 20°.

The Figure 5 depicts the acceleration signal acquired in the time domain for the outer race defect located at a span of 25°.

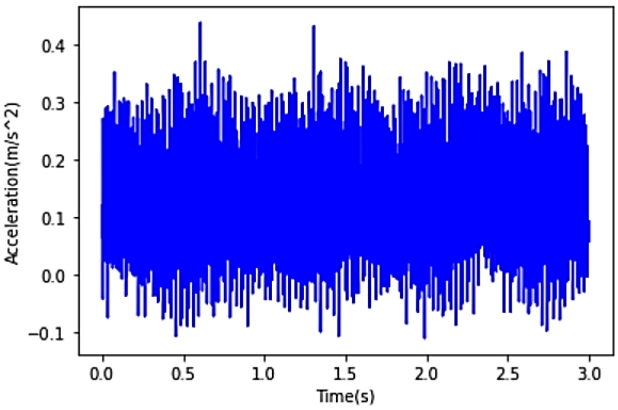

Fig. 5. Outer race defect at a span of 25°.

The Figure 6 depicts the acceleration signal acquired in the time domain for the outer race defect located at a span of 30°.

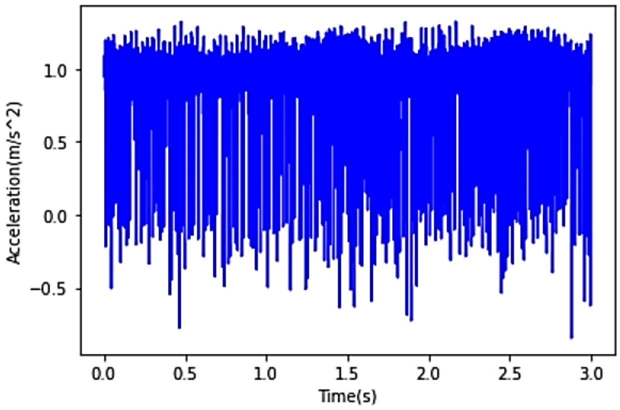

Fig. 6. Outer race defect at a span of 30°

The Figure 7 depicts the acceleration signal acquired in the time domain for the outer race defect located at a span of 35°.

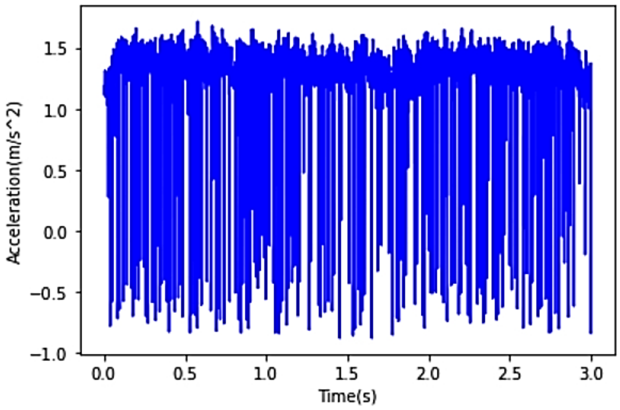

Fig. 7. Outer race defect at a span of 35°

The Figure 8 depicts the acceleration signal acquired in the time domain for the outer race defect located at a span of 40°.

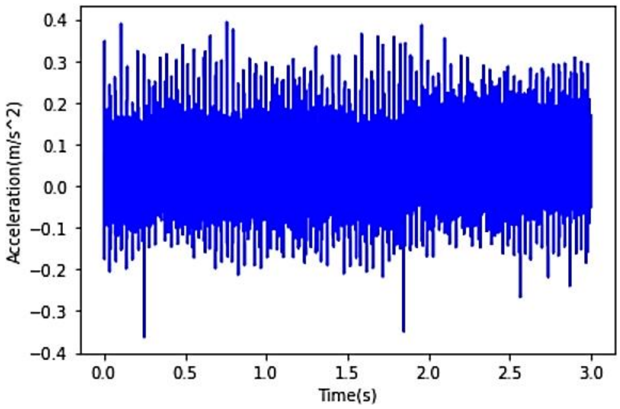

Fig. 8. Outer race defect at a span of 40°.

The following methodology was adopted to implement the machine learning algorithms.

3. METHODOLOGY

The accelerometer was used to acquire the vibration data of healthy and faulty bearing. The local defects on the outer race of the rolling contact bearing were created at an angle of 20°, 25°, 30°, 35° and 40° from the load line. The acquired data from the vibration sensor was mix of signal and noise. It is required to de-noise the data for extracting the useful information. Six machine learning algorithms, namely, Linear Regression (LR), Decision Tree (DTR), KNN Regression (KNNR), Random Forest Regression (RFR), Convolution Neural Network (CNN), Naive Bayes (NB) were separately applied to classify the location of defects within the outer race of the ball bearing. The accuracy table are used to find the best suitable algorithm for the predictions. A brief description of the ML algorithms used are given below.

3.1 Logistic regression

Logistic Regression serves as a statistical technique for binary classification. In regression analysis, where the dependent variable is categorical (typically binary), and independent variables can be either continuous or categorical, logistic regression finds its application. Despite its name, its primary use is in classification tasks.

To simplify, logistic regression models the probability of an input belonging to a specific class. The outcome transforms through the logistic function (sigmoid function), mapping input to a value between 0 and 1. This transformed outcome indicates the likelihood of input associating with a particular class.

$P(Y=1|X)=1/(1+e{-}(\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta nXn))$
P(Y=1|X) is the probability that the dependent variable Y is 1 given the input X.

Coefficients β_0, β_1, …, βn derive from training data using techniques such as Maximum Likelihood Estimation (MLE). The logistic function confines output between 0 and 1, enabling probability estimation and classification.

For classification, a threshold (e.g., 0.5) distinguishes inputs with predicted probabilities above from those below. Logistic Regression finds utility across medicine, economics, social sciences, and machine learning. Multi-class scenarios extend via multinomial logistic regression or one-vs-all approaches.

In the present work, LR is utilized to classify the different types of ball bearing defects and achieved accuracy of 82% which is shown in Figure 9.

3.2 Decision tree

The Decision tree, a popular machine learning algorithm, handles classification and regression. Its structure resembles a tree, where internal nodes denote feature-based decisions, branches indicate outcomes, and leaf nodes convey class labels (classification) or predicted values (regression).

The Decision Tree process unfolds as follows:

Feature selection: Optimal features derive from dataset using defined criteria. The goal is pure subsets regarding the target. For classification or regression, Gini impurity, entropy, or mean squared error guide.

Splitting: Selected features segment data into subsets by value. Child nodes emerge from splits.

Recursive steps: Process recurs as each child node repeats feature selection and splitting. Stopping occurs at criteria like depth or uniform class samples.

Leaf node labels: Terminal nodes gain class labels (classification) or predicted values (regression) based on majority or average.

Visualizing results showcases the root node atop branches to leaf nodes. Decision Trees mimic human decision-making.

Overfitting risk motivates techniques such as pruning and ensemble methods (Random Forests, Gradient Boosting). In sum, Decision Trees prove versatile across domains like finance, healthcare, and marketing, performing tasks such as customer segmentation and medical diagnosis.

To achieved better accuracy further DT is utilized for classification and shows results with 99.9% of accuracy which is shown in Figure 10.

3.3 Naïve Bayes

Naive Bayes, grounded in Bayes' theorem, is a probabilistic algorithm for classification. Simplicity, speed, and effectiveness characterize it, even with high-dimensional data. Naive acknowledges the assumption of feature independence given the class. Despite this simplification, Naive Bayes performs well.
Naive Bayes operates as follows:

Bayes' theorem: Core to Naive Bayes, Bayes' theorem calculates class posterior probability using likelihood, prior probability, and evidence probability.

Independence assumption: Naive Bayes simplifies by assuming feature independence within the class. Likelihood calculates via product of individual feature probabilities given the class.

Class prediction: For classification, Naive Bayes computes posterior probabilities for classes, predicting the class with the highest probability.
Variants include Multinomial Naive Bayes (text), Gaussian Naive Bayes (continuous features), and Bernoulli Naive Bayes (binary data). While effective for quick predictions, it might not outperform complex models for correlated features or independence violations. With utilization of Gaussian Naïve Bayes algorithm different ball bearing defects are classified with accuracy of 79.1% which is shown in Figure 11.

3.4 KNN

K-Nearest Neighbors (KNN) stands as an intuitive algorithm for classification and regression. It relies on nearby training data points.

The KNN process unfolds as:

Training phase: Data memorization occurs during training.

Classification phase: For classification, KNN examines k nearest neighbors, determining class by majority vote.

Regression phase: For regression, KNN computes average of k nearest neighbors' target values.

Considerations include choosing k, distance metric, feature scaling, and computational cost. KNN is a starting point for simple tasks. Complex data or imbalances might affect performance. In the present work KNN classified different ball bearing defect with 94.9% of accuracy which is shown in Figure 12.

3.5 Random forest

Random Forest combines decision trees for robustness. It handles classification and regression, combating overfitting.

The Random Forest process involves:

Bootstrap aggregating (bagging): Multiple trees arise via bagging, random training data subsets per tree reduce overfitting.

Feature randomness: Random subsets of features per tree diminish dominance.

Voting or averaging: Classification outcomes vote, regression averages.

Random Forest benefits include overfitting reduction, high accuracy, feature importance, handling missing values, and nonlinearity capture. Complexity and interpretability concerns exist. Applied broadly, Random Forest excels across tasks which is shown in Figure 13.

3.6 CNN

CNNs excel in visual data analysis. Convolution, pooling, and fully connected layers constitute its core.

CNN components include:

Convolutional Layers: Convolution filters detect edges, textures, shapes.

Pooling Layers: Down sampled feature maps.

Activation Functions: Nonlinearity introduction.

Fully Connected Layers: Merge learned features for predictions.

Flattening: Preceding fully connected layers, 1D transformation.

CNN advantages encompass hierarchical learning, translation invariance, parameter sharing, accuracy, data augmentation. CNNs revolutionize domains like medicine, style transfer, and extend to non-visual tasks. With the advantage of automatic feature extraction from the sample images CNN achieved 100% accuracy in classifying different ball bearing defects with the help of signal images utilized to trained the CNN model and the accuracy which is achieved by CNN model is respectively represented in Figure 14, 15 and 16.

The Bearing Defect is estimated by following the below mentioned pre-processing steps.

i) The entire datasets are divided into training and testing set in the ratio of 80:20 (Table 3).

Table 3. Training and Testing Set of 3 different datasets

Dataset	Training Set	Testing Set
1	307200	76800

ii) After dividing the training set, the training and testing input parameters are separately standardized by subtracting the mean and scaling each feature to unit variance considering the standard normal distribution.

iii) Then the features were fed to into the different machine learning algorithms to predict the location of the defect in the outer race of the ball bearing.

iv) In the next step, different machine leaning regression algorithms were applied to predict the defects. The hyper parameters of the different models are presented below in the Table 4.

Table 4. Hyper parameter of the different machine learning models.

Model	Hyper parameters
LR	-
DTR	CART Algorithm
KNNR	K =5
RFR	bootstrap=False, max_features=1, n_estimators=50
CNN	• 3 Hidden layer with Relu activation function • Each Hidden Layer contains 10 hidden neurons • Batch Size =32 • Epoch = 100 • Adam Optimiser
NB	Gaussian

4. RESULT AND DISCUSSIONS

The different machine learning algorithms were applied and the screenshots of the output of these algorithms are given below:

```
    Please also refer to the documenta
        https://scikit-learn.org/stabl
      n_iter_i = _check_optimize_resul
Out[6]: LogisticRegression()

In [7]:  model.score(X_test,y_test)
Out[7]: 0.8235677083333334
```

Fig. 9. Output of logistic regression algorithm.

The Logistic Regression model is tested in the conducted experiment and it is observed that it achieved accuracy of 82.2 % and the predictive output is not every time correct, it is not the best fit model for this experimental environment.

```
In [14]:  model.fit(inputs, target)
Out[14]: DecisionTreeClassifier()

In [15]:  model.score(inputs,target)
Out[15]: 0.9997916666666666

In [16]:  model.predict(inputs)
Out[16]: array([20, 20, 20, ..., 40, 40, 40], dtype=int64)
```

Fig. 10. Output of decision tree algorithm.

With outstanding accuracy of 99% and with every time correct prediction, its show that decision tree is one of the best fit model and can be utilized as a solution for this kind of problems.

```
In [28]:  from sklearn.naive_bayes import GaussianNB
          model = GaussianNB()

In [29]:  model.fit(X_train,y_train)
Out[29]: GaussianNB()

In [30]:  model.score(X_test,y_test)
Out[30]: 0.7944401041666667
```

Fig. 11. Output of Naïve Bayes algorithm.

With least accuracy of 79.1 % Naïve Bayes shows its unsuitability for the prediction of different defects with this kind of data distribution.

```
In [24]:  knn.fit(X_train, y_train)
Out[24]: KNeighborsClassifier(n_neighbors=45)

In [25]:  knn.score(X_test, y_test)
Out[25]: 0.9493619791666666

In [26]:  knn.predict(X_test)
Out[26]: array([40, 20, 30, ..., 30, 40, 20], dtype=int64)
```

Fig. 12. Output of KNN algorithm.

KNN perform well in the experiment with accuracy of 94.4% and its predictive output is also correct most of the time but not always. This shows that it can be utilized for this application with less precision.

```
          model = RandomForestClassifier(n_estimato
          model.fit(X_train, y_train)
Out[29]: RandomForestClassifier(n_estimators=25)

[30]:     model.score(X_test, y_test)
Out[30]: 0.9443619791666666
```

Fig. 13. Output of random forest algorithm.

Similar to KNN model, the RF model too perform well with good accuracy and prediction but with less precision.

```
Epoch 11/20
10/10 [==============================] - 10s 1s/step - loss: 2.9430e-08
racy: 1.0000
Epoch 12/20
10/10 [==============================] - 11s 1s/step - loss: 1.1548e-08
racy: 1.0000
Epoch 13/20
10/10 [==============================] - 12s 1s/step - loss: 1.9744e-08
racy: 1.0000
Epoch 14/20
10/10 [==============================] - 12s 1s/step - loss: 1.4529e-08
racy: 1.0000
Epoch 15/20
10/10 [==============================] - 11s 1s/step - loss: 2.1979e-08
racy: 1.0000
```

Fig. 14. Output of CNN algorithm.

With the higest accuracy of 100% CNN model proves that it is capable of automating the prediction system by automatic extracting the important features from input data and it is best fit model for prediction in this kind of environment.

The loss and accuracy vs epochs curves are plotted and the same are given below:

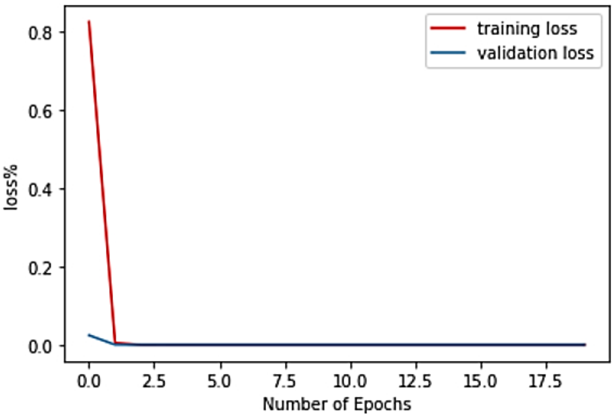

Fig. 15. The loss vs epochs curve.

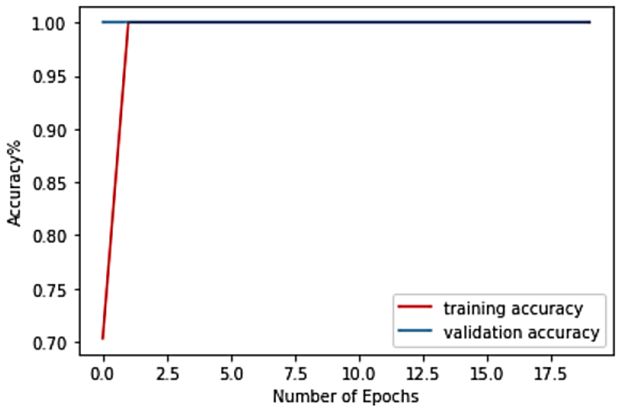

Fig. 16. The Accuracy vs epochs curve.

The results are summarized in Table 5.

Table 5. Results.

Algorithm	Predicted output	Dataset	Accuracy
LR	Bearing Fault	Dataset for 20deg, 25deg, 30deg 35deg, 40deg	82%
DTR			99.9%
KNNR			94.9%
RFR			94.4%
CNN			100%
Naive bayes			79.1%

Table 5 represents a comparison between different models utilized in the experiment based on their accuracy. It is observed from the results that CNN achieves 100% accuracy in detecting the defects. Here, LR abbreviation is utilized for Logistic Regression, DTR for Decision Tree regression, KNNR for K-Nearest Neighbor Regression, RFR for Random Forest Regression and CNN for Convolutional Neural Network respectively.

5. CONCLUSION

It has been established that different ML algorithms can be utilized effectively in detecting the faults in the outer race of the rolling contact bearing without the need to conduct the spectral analysis of the acquired vibration signals. The captured vibration signals were directly employed as images for training the ML algorithms obviating the need of spectral analysis. These methods offer a very effective data driven way to detect faults in the outer race of rolling contact bearings. Linear Regression (LR), Decision Tree (DTR), KNN Regression (KNNR), Random Forest Regression (RFR), Convolution Neural Network (CNN) and Naive Bayes (NB) methods were separately applied to classify the location of defects within the outer race of the ball bearing. The existing model are optimized and customized with different optimizing parameters to achieve improved accuracy. It is established that the CNN algorithm is able to detect the fault with 100% accuracy. It will be useful in predicting the incipient failure of rolling contact bearing and will prevent costly downtime.

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