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Early Detection of Ball Bearing Faults Using the Decision Tree Method

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Abstract

Bearings are one of the important components in the machine that functions as a holder and positions the shaft alignment radially when rotating. Statistics show that about 50% of failures in electric motors are related to bearings. Therefore, monitoring bearing performance and efficiency before damage occurs is necessary to avoid more serious damage and save repair costs. This research aims to build a classification model that can identify bearings in normal condition and 6 types of damage (inner crack, outer crack, ball crack, and a combination of both) using the HUST dataset. The model building process begins with collecting datasets, processing and extracting dataset features, building classification models and evaluating the models that have been made. A decision tree is a type of supervised machine learning used to categorize or make predictions based on how a previous set of questions were answered. The model is a form of supervised learning, meaning that the model is trained and tested on a set of data that contains the desired categorization. The results of the decision tree model that has been built are able to identify bearing damage with an accuracy of 94.47%.

Keywords: Bearing, machine learning, decision tree, HUST dataset

1. INTRODUCTION

Bearings are one of the important components in rotating machines that function as a holder and position the shaft alignment radially when rotating [1], [2], [3]. Statistics show that faults in rotary motors related to bearings account for nearly 50% of the total number of common faults that occur[4]. Therefore, the performance and efficiency of bearings greatly affect the successful operation of a machine[5]. In principle, if the use of the bearing has been in accordance with the specified load, speed and temperature as well as

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adequate lubrication, it can be assumed that damage to the bearing can be caused by its own material fatigue[6]. Several innovative techniques have been proposed for fault detection using vibration signals. Bearing failure, usually resulting in abnormal vibration caused by unsuitable materials, maintenance factors, and improper design and use, can affect the reliability of the mechanical system and may even cause costly accidents[7], [8], [9], [10]. Some purely mechanical techniques used in the past such as temperature monitoring[11], [12], electric motor current monitoring[13], wear analysis, vibration measurement[14] have been reviewed[15]. However, vibration analysis is popular at the moment, as it can do a lot of damage detection without stopping the machine[16].

Industry 4.0 is a transition phase in industry that utilizes the integration of digital technology in various aspects of the production process. In this context, it provides a great opportunity to implement predictive maintenance, where data analysis and artificial intelligence are used to predict potential damage to equipment before the damage actually occurs[17].One method that is very relevant in predicting bearing failures based on vibration signals in bearings using machine learning decision tree method[18].

Ball bearing fault detection by using Feature Representation and Alignment Network (FRAN) was done by[19]. The purposed algorithm shows improved transfer and diagnostics performance between identical machines in different operating conditions, and it is computationally lighter than its original counterpart. The ball bearing fault detection by using Minimum variance cepstrum (MVC) has been introduced to detect the ball bearings in automotive wheels by[20]. The MVC was able to detect incipient faults in 4 out of 12 normal bearings which passed acceptance test as well as in bearings that were recalled due to noise and vibration. Modified the Hilbert-Huang traform Algorthm for early fault detection of ball bearing was done by [21].

The ball bearing fault detection in the previous result was done by using FRAN, MVC adn Hilbert Huang transform. The decision tree algoritm to detect ball baring fault is rarely used. Therefore, combining the analysis of vibration signal data in the HUST bearing dataset and the decision tree algorithm, this research can make a valuable contribution in modeling that can learn related patterns and classify bearing defects with a high percentage of accuracy.

This reseach focus on the ball bearing foult detection by using the decision tree algorithm. The dataset contains 99 raw vibration data of 6 types of defects in 5 types of bearings at 3 working conditions with a high sample rate of 51,200 samples per second. This research can make a valuable contribution in modeling that can learn related patterns and classify bearing defects with a high percentage of accuracy.

2. RELATED WORKS

Dhakar, et al [22] Decision tree-based J48 classification algorithm more accurately identifies healthy and damaged bearing conditions in air compressors with the help of all statistical indicators. The dataset consisted of

360 examples having 17 attributes with 2 classes (healthy and damaged). A higher classification accuracy than the J48 algorithm (96.66%) has been obtained for healthy and damaged bearing conditions.

Alonso, et al [17] bearing damage detection using the decision tree method has been carried out with a percentage of accuracy reaching 100% on the CWRU bearing dataset. However, this research focuses more on comparing models that have been made instead of classifying bearing damage on the CWRU dataset. Envelope analysis used as a feature extraction method also has shortcomings due to the inability of this method to characterize ball defects.

An integrating knowledge transfer via transfer learning to detect servomotor bearing defects in the industrial robot done by[23]. The current signals of the servomotor are utilized to build the model for fault detection . This processed data. The purported algoritm shows an average accuracy of more than 99 %.

An bearing fault detection and diagnostic method for nuclear power plants (NPPs) have been done by[24]. This paper explores various KNN algorithms and proposes a hybrid model—Segmentive Cosine Weighted K-nearest neighbors (SCWK)—to improve FDD in NPPs. The proposed model combines segmentive mechanisms, cosine distance metrics, and weighted KNN to achieve robust and versatile fault detection with minimal signal processing and feature engineering which could benefit efficiency of computational resource. The SCWK model outperforms traditional AI methods, the SCWK model's potential to enhance the reliability and safety of NPP operations by providing an efficient and practical solution for bearing fault detection.

The CWRU (Case Western Reserve University) bearing dataset was analysed by using the Fine-Tuned TabNet Convolutional Neural Network Long Short-Term Memory (FTCNNLSTM) Algoritm to optimized the bearing fault detection by[25]. The FTCNNLSTM model, augmented with TabNet, achieved 96% accuracy, outperforming other methods.

The CWRU (Case Western Reserve University) bearing dataset was analysed by using bidirectional long short-term memory (Bi-LSTM) to predict the bearin fault detection by [26]. The proposed model achieved a final test prediction accuracy of 98.42% and had low computation time, making it an interesting candidate for application in bearing fault prognosis.

The development of aa unsupervised method for constructing the bearing Health Index (HI) using GMM to estimate vibration signal distributions have been done by[27]. The introduced GMM-HI allows for accurate detection of bearing early failures and characterizes the health index of bearings.

3. ORIGINALITY

This study investigates the condition of bearings under normal conditions and when they are damaged such as inner cracks, outer cracks, ball cracks, and combinations of these using machine learning techniques, specifically the decision tree method. By applying the decision tree algorithm to vibration and acoustic emission data taken from the HUST Bearings dataset, this research aims to develop a classification model that can accurately identify different types of bearing damage. The novelty of this research lies in its focus on using decision trees to diagnose and classify 7 complex condition of bearings based on multi-dimensional sensor data, thus contributing to the development of damage detection in mechanical systems.

This study also evaluates the performance of the decision tree model in comprehensively analyzing the HUST Bearing dataset. Through rigorous evaluation, including comparative analysis with other machine learning techniques, this research aims to validate the effectiveness of decision trees in fault diagnosis. This study systematically compares the decision tree method with other alternative models, providing empirical evidence supporting the reliability and suitability of this method for real-world applications in industrial machinery breakdown diagnosis. By addressing these objectives, this study underscores the importance of decision tree algorithms in advancing predictive maintenance strategies and optimizing operational efficiency in mechanical systems.

The HUST Bearing data set give us a complete data with high sampling time. This dataset contains 99 raw vibration data of 6 types of defects (inner crack, outer crack, ball crack, and their 2-combinations) in 5 types of bearings at 3 working conditions with a sample rate of 51,200 samples per second. Therefore, this enables us to to work with real-world data.

4. SYSTEM DESIGN

This study used bearing data sets form Hanoi University of science and technology (HUST)[4], which contains vibration data obtained from sensors on the machine and can provide the information needed to build machine learning models that can predict or detect damage to bearings. This research consists of several stages with the research flow shown in the following figure 1.

4.1 Collecting Data Set

HUST Bearing Data Set

The data was collected using a 750 W (1 HP) induction motor as the prime mover that drives the multi-step shaft and is controlled by an inverter and power supply. The multi-step shaft allows changes in diameter, and Leroy somer brake powder serves as a simulated load. To monitor the load and motor speed, a torque transducer and dynamometer were attached to the shaft. Broken bearings are mounted into various types of flexibly replaceable housing on the multi-step shaft. PCB 325C33 accelerometers are mounted vertically on the bearings to measure vibration.

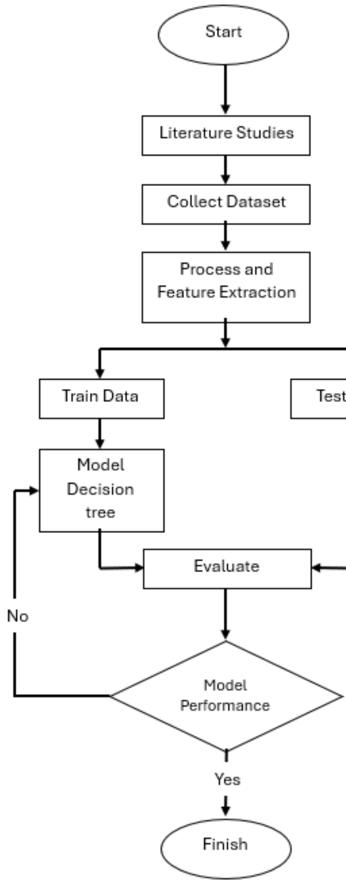

Figure 1. Research Flow

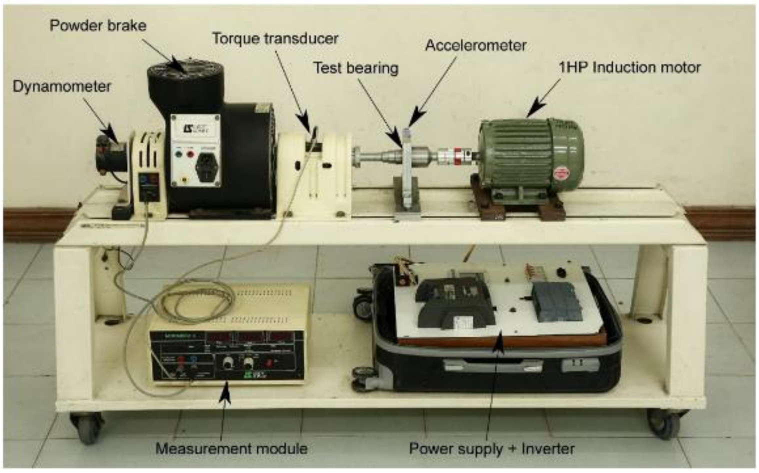

Figure 2. Vibration testing and data collection scheme by hust[4]

This dataset contains 99 raw vibration data of 6 types of defects (inner crack, outer crack, ball crack, and their 2-combinations) in 5 types of bearings at 3 working conditions with a sample rate of 51,200 samples per second. Bearing dimensions are shown in table 1.

Table 1. Description of the file name in the HUST dataset[4]

Bearing ID	*Normal State*	*Inner Fault*	*Outer Fault*	*Ball Fault*	*Inner – Outer Fault*	*Inner - Ball Fault*	*Outer – Ball Fault*
6204	N40x	I40x	O40x	-	IO40x	-	OB40x
6205	N50x	I50x	O50x	B50x	IO50x	IB50x	OB50x
6206	N60x	I60x	O60x	B60x	IO60x	IB60x	OB60x
6207	N70x	I70x	O70x	B70x	IO70x	IB70x	OB70x
6208	N80x	I80x	O80x	B80x	IO80x	IB80x	OB80x
x=0; No load | x=2 ;200 W | x=4 ; 400 W							

4.2 Reprocessing Raw Data Set

Reprocessing raw data is a process that involves a series of steps to correct, clean, and prepare raw data so that it can be used more effectively in further analysis[28]. The purpose of reprocessing raw data involves improving data quality, ensuring accuracy, addressing issues such as missing values or anomalies, and converting data to a format more suitable for descriptive statistical analysis. In descriptive statistics, clean, complete, and structured data allows for more accurate compilation of summary statistics such as mean, median, standard deviation, and others.

4.3 Segmenting Data Set

In this research, dataset segmentation is used to analyze and understand data behavior patterns by dividing data into segments of varying sizes (20, 25, 50, 75, 100, and 200 segments). By dividing large data into specific segments, researchers can observe changes in patterns as the sample data in a segment increases or decreases, which in turn can help in finding the best segment size for classification model analysis[29]. Smaller segment sizes result in more data samples, thus enriching the generalizability of the model. However, small segment sizes also tend to increase the accumulation of noise that can obscure relevant information. On the other hand, larger segment sizes (smaller sample data) allow for reduced noise accumulation as random variations can be averaged over a larger time interval. However, a large size tends to cause the model to overfit the training data due to the lack of variation. In addition to reducing noise, this variation in segment size also tests the reliability of the model as well as computational efficiency. A larger segment size (small sample data) allows for a faster computational process, although it does not always result in the best model performance. By trying these segment size variations, researchers can find the most suitable data group size so that the resulting model has high accuracy and efficient computing time.

The HUST bearing dataset has a sampling rate of approximately 51,200 samples per second, with each data collection session lasting 10 seconds. This means that each class in the dataset contains approximately 512,000 vibration samples. This high sampling rate enables detailed analysis of the vibration signal, making it easier to detect and analyze subtle anomalies or variations in bearing behavior. The following table illustrates the segmentation of the dataset by size variation.

Table 2. illustration of dataset segmentation with size variation

DataFrame Segments	Sample per Segments	Total Samples in Dataset
20	± 25,600	±51,200 samples/s × 10 second = ±512,000 samples
25	± 20,480	
50	± 10,240	
75	± 6,827	
100	± 5,120	
200	± 2,560	

4.4 Feature Extraction

Feature extraction is used to display bearing conditions in time-based signals identified through time domain methods. Descriptive statistic calculation-based analysis, one of several time domain methods available, is used to generate trends from the resulting spectra[30]. Thus, the analyzable patterns can detect any newly emerging bearing defects. In addition, the vibration data of the HUST bearing was also analyzed for stationarity using the statistical calculation method and time domain approach. The statistical calculation follows the following equation:[22].

$$Mean\ Absolut:\ \bar{x} = \frac{1}{N}\sum_{i=1}^{N}|x_i| \quad (1)$$

$$Variance:\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \quad (2)$$

$$Skewness:\ SK = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i-\bar{x})^3}{(\sigma)^3}\ (2) \quad (3)$$

$$Kurtosis:\ K = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i - \bar{x})^4}{(\sigma)^4} \quad (4)$$

$$RMS:\ x_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x^2} \quad (5)$$

$$Maks\ Absolut:\ x_{max} = max(|x_1|, |x_2|, \ldots \ldots . |x_n|) \quad (6)$$

$$Peakt\ to\ peak: x_p = \max(X) - \min(X) \quad (7)$$

$$Crest\ Factor = \frac{\max value}{x_{rms}} \quad (8)$$

$$Shape\ factor = \frac{x_{rms}}{\bar{x}} \quad (9)$$

$$Impuls = \frac{\max value}{\bar{x}} \quad (10)$$

$$Min\ Absolut:\ x_{min} = min(|x_1|, |x_2|, \ldots \ldots . |x_n|) \quad (11)$$

4.5 Decision Tree Classification

A decision tree is a tree-shaped graphical representation, which forms a sequential diagram illustrating all possible decision alternatives and their corresponding outcomes[31], [32]. Starting from the root nodes, each internal node reflects the basis of the decision-making process. Each internal node/branch illustrates how a choice can lead to subsequent nodes. Finally, each final or leaf node represents the outcome that can be obtained.

The perfect attribute to be used as a root node or node is an attribute that has a high purity (homogeneity) value, or in other words, an attribute that has a low impurity (heterogeneity) value. Gini impurity can be calculated using the following equation:[33]

$$Gini(t) = 1 - \sum_{i=1}^{c} {p_i}^2 \tag{12}$$

$$Gini(t) = 1 - (Probabilitas\ "true")^2 - (Probabilitas\ "false")^2 \tag{13}$$

If the “true” and “false” leaves on the root node attribute do not present the same total number of values, it is necessary to calculate the Weighted Impurity of the impurity value of each leaf. Using the following equation :[33]

$$\begin{aligned} Weight\ Impurity(t) \\ = \left(\frac{Total\ \ leaf\ "true"}{Total\ overall\ leaf\ value}\right) Gini\ \text{true} \\ + \left(\frac{Total\ leaf\ "false"}{Total\ overall\ leaf\ value}\right) Gini\ "false \end{aligned} \tag{14}$$

where $\boldsymbol{t}$ is a particular node, $\boldsymbol{c}$ is the number of classes and $\boldsymbol{pi}$ is the probability of a sample at node $\boldsymbol{t}$ belonging to class $\boldsymbol{i}$.

After the features are extracted, the decision tree construction starts by calculating the Gini impurity for each of the eleven identified features. The feature with the lowest Gini impurity value is selected as the root node. After the selection of the root node, the process continues by recalculating the Gini impurity, considering the subsets created based on the root node, using equations (12) and (13). This process is repeated for each subset generated, so that the feature with the lowest Gini impurity can be assigned as the internal node. The Gini impurity calculation will continue until multiple branches are formed, leading to leaf nodes. After all the nodes are calculated, the weighted impurity for each node will also be calculated using equation (14) to provide a clearer understanding of the data purity at each point in the decision tree.

4.6 Comparison of Performance and Computation Time of Decision Tree Models with Comparison Algorithms

In this study, we built a decision tree algorithm as a bearing damage classification model that is expected to have high accuracy and fast computation time. As a reference of success, this research compares the performance and computation time of decision tree algorithm with several other algorithms. The algorithms used for comparison in this study include logistic regression, support vector classifier, random forest, naive bayes classifier, k-nearest neighbor classifier, and gradient boosting classifier.

Some previous studies have used similar approaches for bearing damage diagnosis. Umer Farooq et al. (2024)[34] used various machine learning and deep learning techniques in an effort to detect failures in ball bearings to improve predictive maintenance. Umang Parmar (2021)[35] compared algorithms such as Artificial Neural Network, Support Vector Machine (SVM), and Multinomial Logistic Regression to detect the types of damage in cylindrical roller bearings. Toma et al. (2020)[36] applied the K-Nearest Neighbor, Decision Tree, and Random Forest algorithms for bearing damage diagnosis based on motor current data. Deepam Goyal et al. (2019)[37] used Discrete Wavelet Transform and statistics in feature extraction, followed by Support Vector Machine (SVM) for bearing condition classification. Given these previous studies, our research seeks to provide further evaluation of the performance of specially selected algorithms to support the development of fast and efficient models for bearing fault diagnosis.

5. EXPERIMENT AND ANALYSIS

The research is conducted to obtain a bearing damage classification model based on its vibration signal. After processing the data set and continued with model building and evaluation. The ready data set is divided into 2, namely 70% train data and 30% test data with random_state=1 to get consistent results[38]. The results of model building and evaluation are shown in Figure 3.

Table 3. Decision Tree Model Evaluation Results for each data frames

	Accuracy	Precision	Recall	F1-score
df_20	92,30%	92,31%	92,30%	92,27%
df_25	93,69%	93,67%	93,69%	93,67%
df_50	**94,47%**	**94,48%**	**94,47%**	**94,47%**
df_75	94,26%	94,35%	94,26%	94,29%
df_100	93,77%	93,79%	93,77%	93,77%
df_200	89,44%	89,46%	89,44%	89,44%

Figure 3 is model performance metrics of the model corresponding to Table 3, used to evaluate the performance of the classification model by visually presenting the number of correct and incorrect predictions for each data class.

The model evaluation results show excellent performance with an accuracy value of 94.47% shown in Table 4. The precision value indicates how well the model classifies positive data, where the highest value is in class 'N' with a precision of 1.00, which means the model is completely correct in identifying class 'N'. This shows that the model has a very good ability to distinguish class 'N' from other classes. In addition, the 'IO' and 'I' classes also have high precision values of 0.97 and 0.94 respectively, indicating that the model is quite reliable in classifying these classes with little error.

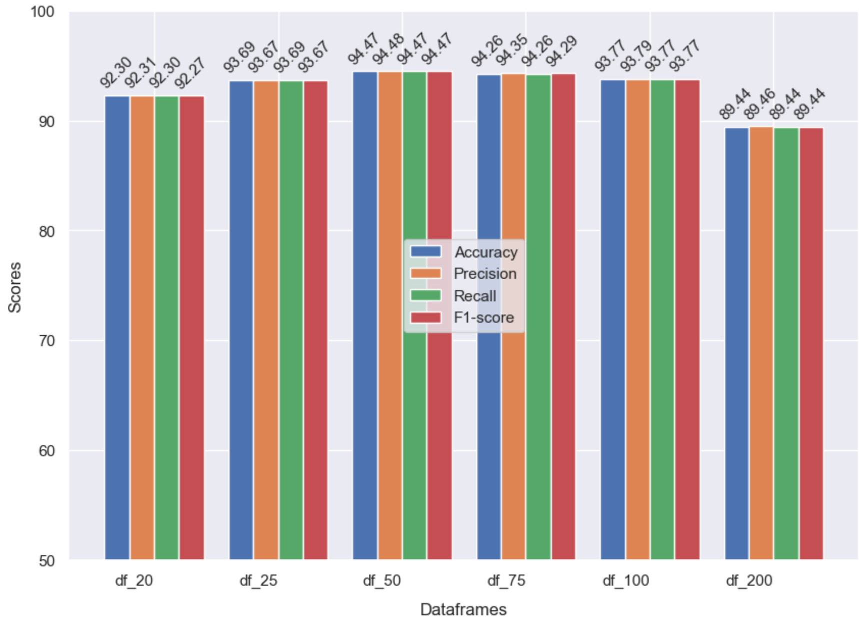

Figure 3. Model Performance Metrics

Table 4. Details of Classification and Prediction Results df_50

	Label	Precision	Recall	F1-Score
	B	91%	90%	90%
	I	94%	98%	96%
	IB	97%	94%	96%
	IO	97%	97%	97%
	N	100%	100%	100%
	O	92%	92%	92%
	OB	88%	87%	88%
Weighted Average		94,48%	94,47%	94,47%
Accuracy		94,47%		

Recall, or sensitivity, measures the ability of the model to find all instances of the class that are actually positive. A high recall value indicates that the model is able to find most instances of each class correctly. In the results of this evaluation, class 'N' also stood out with a recall value of 1.00, indicating that the model was able to find all instances of class 'N' without missing any. In addition, classes 'I' and 'IO' also had high recall values of 0.98 and 0.97, indicating that the model was able to find most instances of both classes.

F1-score is a measure that combines precision and recall in a single metric that presents the overall classification performance. A high f1-score value indicates that the model has a good balance between precision and recall. In this evaluation result, all classes have high f1-score values, with class 'N' having the highest value of 1.00, followed by classes 'I' and 'IO' with 0.96 and 0.97 respectively. This shows that the model performs very well in classifying each class with high precision and sensitivity. Thus, the results of this evaluation provide confidence that the decision tree model developed is able to effectively perform early detection of bearing damage very well.

Figure 4 shows the visualization of the most important features in the decision tree model. Mean, RMS, form factor, and kurtosis are influential features in the decision tree model as each provides important insights into the characteristics of the underlying data, especially in the context of bearing condition prediction. The mean feature has the highest importance score of 28.01%, serving as the average value of the data that describes the central position of the distribution and can indicate normal conditions or changes in wear. Small changes in the mean value often indicate significant trends. RMS (Root Mean Square) measures fluctuations in the data signal, scoring 22.17%, making it particularly useful for detecting increased vibrations that are a sign of damage. RMS is responsive to drastic changes, providing important information regarding the intensity of variation that can be attributed to bearing condition. Form factor, with a score of 12.20%, describes the structure or shape of the signal and indicates the stability of the signal; high form factor values often indicate disturbances in the signal. Kurtosis, with a score of 10.64%, measures the sharpness of the data distribution, where high kurtosis values can indicate the presence of peaks or significant outliers in the vibration signal, being an early signal of damage. The combination of information from these features helps the decision tree model to make more accurate decisions and provide insight into the patterns and conditions of the underlying data.

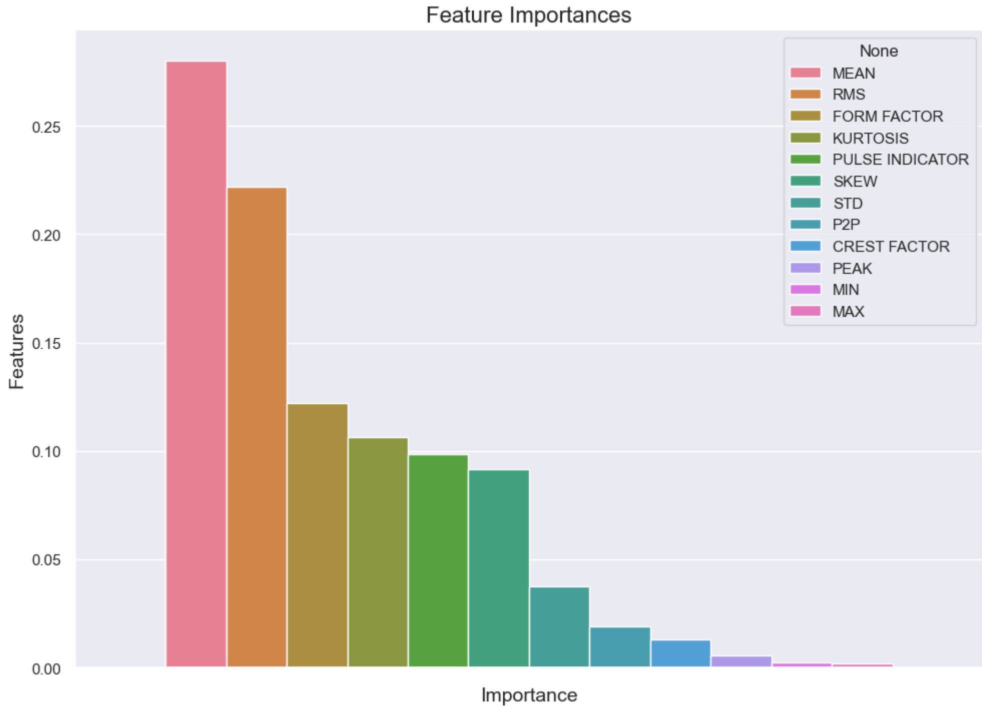

Figure 4. Visualization of the Most Important Features in the Decision tree Model

Once the model evaluation is done, the next step is to compare the performance of the model with alternative models that may have been explored. This comparison helps researchers to understand the relative performance of different approaches or algorithms used in solving the same problem. By comparing the values of evaluation metrics such as accuracy, precision, recall, and f1-score between different models, it can be determined which model provides better performance in solving the problem at hand. In this study, 2 comparisons will be made, namely

5.1. Model performance comparison

Some of the evaluation metrics used to compare model performance include accuracy, precision, recall, and f1-score. By comparing the values of these metrics with different models, we can determine which model provides better performance in solving the problem at hand. Based on Table 2, it is found that the division of the dataset into 50 data frames showed the best evaluation results, so the model variation comparison will use the same dataset division. Take a look at Table 5 which shows the comparison of the evaluation results of the model variations made.

Table 5. Model Variation Performance Evaluation Results

Model Variation	Accuracy	Precision	*Recall*	*F1-score*
Decision Tree	94,47%	94,48%	94,47%	94,47%
Support Vector Classifier	79,24%	81,93%	79,24%	78,93%
Logistic Regression	73,30%	74,24%	73,30%	72,47%
RF Classifier	96,50%	96,51%	96,50%	96,50%
Kneighbors Classifier,	89,93%	89,69%	89,93%	89,72%
Gaussian NB	56,32%	57,89%	56,32%	53,93%
Gradient Boosting Classifier	96,22%	96,23%	96,22%	96,22%

It can be seen in Table 5 that the RF classifier and gradient boosting classifier models have higher accuracy than the decision tree model. So it needs to be continued by comparing the computation time of the model variations that have been made.

5.2. Computation time comparison

Although the comparison results of other models have better performance as shown in Table 5, the decision tree model itself is easy to understand and interpret and has faster computation time as shown in Table 6.

Table 6. Computation Time Comparison of Model Variations

Model Variation	Time (s)
Decision Tree	0,102 ± 0,007
Support Vector Classifier	12,31 ± 1,998
Logistic Regression	0,12 ± 0,016
RF Classifier	6,55 ± 0,581
Kneighbors Classifier,	8,16 ± 1,932
Gaussian NB	0,23 ± 0,006
Gradient Boosting Classifier	2,01 ± 0,504

Decision tree has the advantage of faster computation time due to the simple nature of the algorithm and the fast-training process. The decision tree formation process only involves splitting the data based on the most significant features and only involves the formation of one decision tree without the need for additional model building as in Random Forest and Gradient Boosting. Ultimately, model selection depends on the balance between the need for model interpretation, performance, complexity, time, and available resources, as well as the specific characteristics of the problem at hand.

The Decision Tree model achieved high results with an accuracy of 94.47%, there are several factors that may cause errors in prediction. Firstly, the data on certain classes may lack specificity, making it difficult for the model to distinguish between similar classes. This data insufficiency may result in the model not having enough information to make accurate predictions. Secondly, the model may follow the patterns in the training data too closely, leading to the phenomenon of overfitting. In this case, although the model performs well on the training data, its performance degrades when faced with unfamiliar data. In addition to the above factors, there is also the possibility that the complexity of the model does not match the available data. For example, a Decision Tree model could be too complex or too simple for the characteristics of the dataset. This mismatch can result in errors in classification, especially if the selected features are irrelevant or there are important interactions between the features that are not captured by the model. Therefore, it is important to evaluate the characteristics of the data and the model as a whole. To improve the performance of the model, several potential steps can be taken. The application of cross-validation can help in evaluating the stability of the model and reducing the variance in the results. In addition, performing more careful feature selection and hyperparameter tuning can also improve model accuracy. By improving feature selection and tuning hyperparameters, it is expected that the model can generalize to unseen data and improve accuracy in class prediction.

6. CONCLUSION

The resulting decision tree model is able to determine and classify bearings in normal conditions and when they are damaged (inner crack, outer crack, ball crack, and a combination of both). Based on the evaluation results, the decision tree model produced is reliable in detecting early bearing damage according to the data set given with an accuracy percentage of 94.47% with the fastest computation time compared to other methods, namely 0.102 ± 0.007. In the future work, feature selection and a hyperparameter tuning will be added to improve the performance of the decission tree algorithm.

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