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DEFECT RECOGNITION AND CLASSIFICATION IN ROLLING ELEMENT BEARINGS USING A NOVEL MACHINE LEARNING TECHNIQUE

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A B S T R A C T

The rising advancements in Industry 4.0 technologies have made more usual to acquire significant volumes of machine operating data in real time. In response to inconsistent data distribution and label scarcity in target domains, this work suggests a machine learning (ML) approach for rolling element bearing failure identification under a variety of circumstances. This study presents, a new method called Composite coyote optimized resilient linear regression (CCO-RLR) for defect recognition and classification in rolling element bearings. Early rolling bearing failure diagnosis is a crucial and time-sensitive operation that guarantees the dependability and security of mechanical fault systems. Initially, the rolling element bearings dataset is collected and preprocessed using Min-max normalization. For extracting the feature, Fourier transform (FT) is employed. The result shows that the CCO-RLR accuracy is 97.8% when compared with those existing methods. Our suggested method offers an effective means of quantifying flaws and significantly improving classification effectiveness.

1. INTRODUCTION

The rolling element bearings reduce a friction between parts, support the shaft, and absorb weight, making them a vital aspect of spinning equipment. Industrial machinery availability and performance are significantly impacted by their health. Bearing problems are one of the most common causes of machine malfunctions since they are the most delicate parts of rotating machinery. Significant device damage and the loss of essential equipment as a result of bearing failure pose serious safety concerns and financial losses. Early failure identification is crucial to the availability and functionality of rolling element bearings (Tayyab et al., (2022)). The most frequent reason for bearing failure usually starts at the surfaces. The primary causes of problem are contamination and wear debris in the lubricants. The revolving machine surface experiences extremely severe abrasive wear as the temperature of the contaminant's medium rises. A useful tool for tracking the performance of spinning machinery used is vibration measuring (Tran et al., (2023)). The fast rise in vibration spectrum of rolling bearings is a sign of impending failure. Additional monitoring methods, such as oil analysis, thermography, temperature analysis and motor current signature analysis, etc., give early warning of faults in the rotating equipment (Sahu et al., (2022)). The bearing is the

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most important component of rotating machines. In motion, it serves two main purposes, it lowers the machine's coefficient of friction and supports the rotating mechanical body. Rolling bearings are utilized for load transfers from shifting to stationary elements and the other way around, along with determining the relative movement circumstances of spinning components. For the mechanical system to operate smoothly, effective bearing problem identification is necessary (Mishra et al., (2022)). As rolling element bearings (REBs) are frequently exposed to severe working conditions, such as high loads, high speeds, and high temperatures in aero-engines, they are among the most important parts of contemporary rotating equipment. Bearings deteriorate with time due to defects that cause greater clearance, friction torque, overheating, and other issues. Finding the reasons behind malfunctioning bearings and other parts of complicated equipment, as well as the connections between monitoring data and REB health, are made possible by fault diagnostics (Kiakojouri et al., (2022)). A number of benefits are available to mechanical systems using rolling element bearings, such as roller and ball bearings. By decreasing the amount of friction that exists between moving elements, they maximize wear and energy efficiency. In applications involving heavy machinery, these bearings are essential because of their exceptional ability to distribute loads that handle high radial and axial loads. Their precise and accurate movements make them ideal for tasks requiring controlled motion, including those in robotics or machine tools (Lee et al., (2022)). In this study, we present a brand-new method for fault identification and categorization in rolling element bearings dubbed CCO-RLR. A critical and time-sensitive process that ensures the dependability and security of mechanical fault systems is early rolling bearing failure diagnosis.

2. RELATED WORKS

Kumar and Upadhyaya, (2023) described the acquisition of vibration signals for three distinct deep groove ball bearing conditions Normal (N), Inner Race (IR) defect, and Outer Race (OR) defect at varying loads and top speeds using a specially designed test setup. The collected signal was subjected to Continuous Wavelet Transform (CWT), and from the CWT coefficients, seventeen Time-Frequency Domain (TFD) statistical characteristics were identified. Mohiuddin et al., (2023) provided an exclusive method that reliably detect the bearing flaw and fix the issue with classic convolutional neural network (CNN). Tran et al., (2023) presented a revolutionary deep learning and Internet of Things (IoT) based fault Recognition and correction (FRC) approach for instant messaging. Bearing fault characteristics are generated from vibration signals during motor operation and fed into a deep learning model that successfully detects bearing problems. Grover and Turk, (2022) established on bispectrum images of defect signals via transfer learning, deep CNNs yield fault diagnostic results that are comparable to state of the art. Saha et al., (2022) created an intelligent fault detection system to identify different types of flaws in deep groove ball bearings. An experimental configuration was created to provide incorrect information to the healthy condition under a number of scenarios, such as cage fault, external race error, and inner race fault. Hakim et al., (2023) used bearing defect diagnostics, and this study attempts to provide an introduction to Deep Learning (DL). The most popular DL approaches for identifying bearing faults are generative adversarial networks, CNN, auto encoders, and recurrent neural networks (RNNs). Hati et al., (2022) proposed a transfer learning based bearing defect recognition technique, making use of DL benefits. A basic model for creating an efficient fault detection approach for bearing defects is the pre-trained ResNetV2 model. Creating an efficient fault detection model involves the various bearing problems, such as the ball defect, inner race fault, and outer race fault. Liu et al., (2022) developed a defect diagnostic approach based on random forest (RF) and refined composite multiscale reverse dispersion entropy (RCMRDE). Afia et al., (2023) proposed an intelligent technique for bearing fault diagnosis, which enhance the condition monitoring of external ball bearings. Kulevome et al., (2022) provided a reliable defect classification model by utilizing the power and effectiveness of a pre-trained CNN. This approach has a high-performance rate in the absence of enough data. To extract differentiating characteristics from fresh data and feed them into a classifier, a modified VGG16 architecture is first employed. Qi et al., (2024) proposed a novel prognosis approach for Rolled Elements Bearings (REB) that combines the multi-step Movable Horizons Estimate (MHE) estimate technique with a resilient detection of anomalies technique called the Support Vector Data Description (SVDD). Fifteen experimentally-derived deteriorated bearing show that the MHE performs superior to both the traditional Kalman and Particle filters. Furthermore, when combined with the MHE, the polynomial model outperforms the two traditional exponential methods in terms of RUL estimates. Yang et al., (2024) presented a hybrid forecasting method to solve the adaptable prediction model of element deterioration. First, the Theil-sen estimation (TSE) was proposed as the containing functioning health indication, and its good trendability, monotony, and resilience have validated. Finally, bearing expedited deterioration experiments and the XJTU-SY bearing dataset were used to validate the efficacy of the suggested approach. Iunusova et al., (2023) presented two methods for bearing defect diagnostics and contrasted. The first strategy was based on knowledge. It applied previous understanding of the bearing properties and parameters for testing and relied on mechanical concepts for understanding the observed signals from vibrations. The second strategy was data-driven, meaning that only the vibration signal was used to collect data. In order to evaluate and contrast each approach's unique advantages in terms of implementation time, domain expertise, data processing-related knowledge, data demands, diagnostic accuracy, and usefulness, the diagnostic capabilities of the two methods were examined. To accelerate the incidence of cracking and splitting, a rotating bearing-rotor testing setup with enforced lubricating was built up by Zhao et al., (2023). Nonferrous impurities with increased toughness were deliberately supplied. It was not possible to detect early breakdowns and unusual wear of bearings that roll alone by using a vibration signal, simultaneous data collection regarding temperature and oil particulate tracking was also required. Finally, the various machine learning algorithms, the significance of the characteristics based on oil detritus for the identification of improper bearing wear was examined. The experiment results, using an SVM classifier as a model, demonstrate that adding features based on oil debris raises the diagnostic accuracy level attained. Skariah et al., (2021) improved wideband crossing spectra (IWCS) technique for rolling element bearings health tracking. The radial the preload, the lubricant circumstance, and the interaction surfaces' roughness at the surface were the variables that are being examined. These factors affect a ballbearing's life and efficiency, particularly in space applications where minimal torque noise was required while the bearing was operating under variable speed and temperature circumstances. The suggested method extracts feature from the irregular signatures of vibration by utilizing the benefits of the wavelet cross spectral technique. The validity of the IWCS was tested by experiments, which show that it was a highly useful tool for assessing bearing health issues.

3. PROPOSED METHOD

Rolling element-bearing defect detection and classification entails employing cutting-edge sensing technologies to identify anomalies like fractures and wear patterns, then classifying the results to determine the probable severity of problems. The dataset collected, preprocessing numerical data to a specified range using min-max normalization, preserves the relative connection between values and improves machine learning model performance by limiting the dominance of individual features. Fourier transform is used to extract features when it comes to fault identification in rolling element bearings. To improve the precision and robustness of linear regression models that are specially designed for identifying and classifying defects in bearing systems, rolling element of bearing defect detection and classification using CCO-RLR entails the use of a sophisticated optimization technique, evaluated the result section, as shown in figure 1.

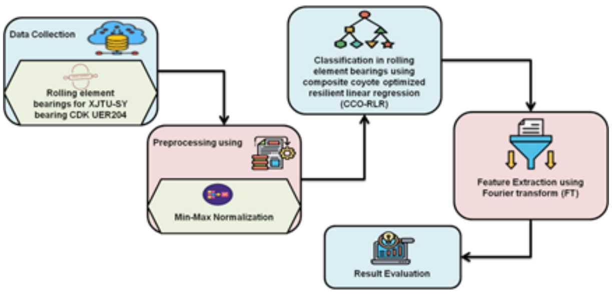

Figure 1. Overall framework for the proposed methodology

3.1 Data collection

The XJTU–SY bearing's LDK UER204 rolling element bearings of experimental dataset (Wang et al., 2018) were utilized to examine the outcomes. Figure 2 shows the outer-ring fracture and bearing configuration for an accelerated life testbed. Vibration signals were collected during the experiment utilizing a pair of unidirectional acceleration sensors positioned horizontally and vertically, together with a portable dynamic signal collector. 32,769 samples were collected overall, with 1 minute and 26.5 kHz as the sample frequency and interval settings, respectively. The $bearing1\_1$ dataset's horizontal vibration signals were selected for the investigation.

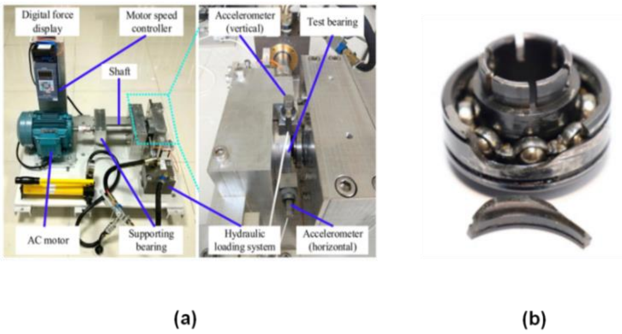

Figure 2. Bearing with an outer ring fracture and an accelerated life test bed. (A) Testbed for accelerated life bearings. (b) A bearing's outer-ring fracture

3.2 Data pre-processing using min-max normalization

The procedure known as normalization keeps the original data's associations intact. A straightforward approach called min-max normalization allows the data to be precisely fitted inside a predetermined limit. The Min-Max normalizing approach states that,

$$A' = \left(\frac{A - \min of\ value\ of\ A}{Max\ value\ of\ A - min\ value\ of\ A}\right) * (D - C) + C \quad (1)$$

A'-Includes one set of Min-Max Normalized data. Assuming $[C, D]$ is the predefined border. Given an initial data range A and a mapped dataset (B).

3.3 Feature extraction using Fourier transform (FT)

The Fourier transform (FT) is designed and simplified in FT, which helps in calculation. The frequency domain details may be obtained more easily when the FT transformation is applied to the bearing's time-domain vibration signal. Comparing the frequency domain signal to the original vibration signal, it is more capable of fault identification since diverse frequency bands include distinctive fault patterns. To help with bearing defect diagnostics, vibration data were subjected to an FT transformation, and characteristics were extracted from the resulting spectrum signals. Early bearing failure detection was achieved by applying an FT generative adversarial network (GAN) for the analysis of the generated spectrum information after transformation to a bearing vibration signal. Using DFT, the spectral function $W(l)$for a discrete vibration time-domain signal with finite length bearing$w(m)$ is found:

$$W(l) = \sum_{m=0}^{M-1} w(m)\omega_M^{lm}, 0 \leq l \leq M-1 \quad (2)$$

Where$M$ is the sample length$\omega_M = f^{-i\frac{2\pi}{M}}$

The sequence $w(m)$ is split into two pieces by FFT: an odd sequence and an even sequence, $w_2(m).w_1(m) each with the length \frac{M}{2}$Consequently, we get

$$W(l) = \sum_{M=0}^{\frac{M}{2}-1} w_1(m)\, \omega_M^{2lm} + \sum_{m=0}^{\frac{M}{2}} w_1(m)\, \omega_M^{2l+1)m} \quad (3)$$

$$W(l) = \sum_{M=0}^{\frac{M}{2}-1} w_1(m)\, \omega_M^{2lm} + \sum_{m=0}^{\frac{M}{2}} w_2(m)\, \omega_M^{2lm} \quad (4)$$

While$\omega_M^{2l} = f^{-i\frac{2\pi}{M}2ln} = f^{-i\frac{2\pi}{M/2}ln} = \omega_{M/2}^{lm}$, Equation (5), after integrating it, produces

$$W(l) = \sum_{M=0}^{\frac{M}{2}-1} w_1(m)\, \omega_M^{lm} + \omega_M^{lm} \sum_{m=0}^{\frac{M}{2}} w_2(m)\, \omega_M^{lm}$$
$$= W_1(l) + \omega_M^{lm} W_2(l) \quad (5)$$

Given an odd sequence $w_1(m)$, its output is $W_1(l)$, whereas an even sequence $w_2(m)$yields $W_2(l)$

3.4 Rolling element bearings using Composite coyote optimized resilient linear regression (CCO-RLR)

To improve the accuracy and resilience of linear regression models that increase the system's capacity to identify and categorize bearing component problems, rolling element bearings of a benefit from the deployment of CCO-RLR, which involves an advanced optimization technique. The mapping of correlations between input and output parameters is linear in the case of linear regression. The following is the formulation of the connection for o input parameters mathematically:

$$\gamma = \beta_0 + \beta_1 W_1 + \beta_2 W_2 + \cdots . \beta_O W_O \quad (6)$$

The linear dependency between the various input parameters X_i and the output parameter Y is described by the parameters $\beta_i$for $i = 1 \ldots p$. These need to be optimized using the dataset. Owing to the linear nature of Equation (2), an optimal solution is assured. Lasso regression is one of the sophisticated linear approaches that may be utilized for regression issues that have multiple input parameters. This regression contains input parameters that have a strong correlation with the result. The regularization parameter λ is used. As stated in, the optimization issue as follows:

$$Find\ \beta_j\ such\ that\ (\gamma - \beta_O - \sum_{i=1}^{o} \beta_i \beta_j)^2 + \lambda \sum_{i=1}^{o} |\beta_i| \rightarrow Min \quad (7)$$

In the first summand, the regularized regression parameters are represented, and the root-squared mean error. Regressions in higher dimensions also achieved by using polynomial regression to regress correlations, as physical events are not always linear. The type of linear regression used is distinctive. The following equation is applied to the one-dimensional situation, adapts a d-order polynomial to the available data. The root-squared mean error is represented by the first summand and the regularized regression parameters by the second. Polynomial regression allows correlations to be regressed in higher dimensions, which is useful as physical events are nonlinear. This kind of linear regression is exclusive. In the one-dimensional situation, the following equation is used to adapt a d-order polynomial to the available data:

$$\gamma = \beta_O + \beta_1 W + \beta_1 W^2 + \cdots . + \beta_c W^c \quad (8)$$

The parameter optimization remains a convex optimization issue and solved using iterative techniques, such as gradient descent, much like linear regression. A novel intelligent optimization algorithm called COA was introduced in 2018. It has the ability to replicate the social life, development, death, rejection from the group, and acceptance of coyotes. By means of random grouping, COA partitions the population into many subgroups. Results from benchmark function optimization show that COA might produce superior optimization outcomes. These four elements an impact the coyote population's growth, and we may modify the growth process in response to the coyotes' social adaptation. Environmental variation and two selected death have an impact on coyote births.

From a social adaption point of view, the newborn coyote perishes outlives the senior coyote, and its opposite occurs. Certain likelihood among the subgroups dictates that a portion of the coyotes was chased across groups and accepted by other groups, changing a coyote's status as a group. Every optimal answer to the optimization issue is found to be the coyote that is most suited for the social context through the ongoing development of the processes of growth, death, expulsion, and acceptance. The method COA represents a potential solution, and the coyote social state components make up each solution vector. Coyote internal and external aspects are included in this state element; D state factors comprise a solution vector with D choice variables; each state component is a decision variable; and social adaptation is used to measure each coyote. The four primary phases of the COA are as follows:

suburban wolves randomly initialized and grouped, coyote population development, the coyote life cycle, and the coyote acceptance and expulsion from the group.

- Set up and organize at random in this case, Ib_i the defined parameters like the total count of suburbs wolvesN_p, the number of residential wolves overall in the group Nc, along with the total number of repetitionsN_{gen}. Because COA is an algorithm that is random, every coyote's basic social state components are instantaneously set. The following groups were randomly assigned all coyote's basic social state components are instantaneously set:

$$soc_i = Ib_i + q_i \times (ub_i - Ib_i) \quad (9)$$

In the case when q_i is a distributed random number in [0,1], and Ib_i, ub_i correspond extending below and upward, respectively, $i$state component of the coyote s$i = 1, 2, \cdots, C$.

- Coyote numbers in the group are increasing. The research calculates a group's of cultural trends, choose two coyotes at random, and use these four criteria to influence the coyotes' growth to establish the ideal coyote alpha. The group's cultural tendencies are calculated.

$$cult_i = Median(B_i) \quad (10)$$

During the coyote development process, calculate the contrast (δ_1) between the optimal coyote alpha for the group and a randomly selected coyote, as well as the cultural tendency (δ_2) between the CCO picked at random and the group. Then, a result of $\delta_1$andδ_2, the coyotes in the group develop.In this case, A_j stands for matrix are j's A column; median denotes the median; and columns indicate $N_c$and $N_c$rows and D rowsexplanation vectors in matrix A. Subsequently, the group's coyotes grow as a result of the consequences of $\delta 1$,$\delta 2$ an indicated by Formula (11):

$$\delta_1 = K_{best} - soc_{q1}, \delta_2 = cult - soc_{q2} \quad (11)$$

Where L_{bset} is the group's best coyote *alpha* coyote and $r1$,$r2$ are two different arbitrary coyote markers:

$$new_{soc_d} = soc_d + t_1 \times \delta_1 + t_2 \times \delta_2 \quad (12)$$

Where $s1, s2$ are random values with uniform distribution in $[0, 1]$, and $s1$, $s2$ are random weights of δ1 and δ2, respectively. Formula (13), which illustrates how the algorithm determines social adaptation and uses greedy selection, is applied once in each group coyote matures. The algorithm's convergence speed is enhanced by keeping the superior coyotes around to contribute to the groups other coyotes were developing:

$$soc_d = \begin{cases} new\_soc_d, new\_fit_d < fit_d \\ soc_d, otherwise \end{cases} \quad (13)$$

- **The coyotes' life and death**: In nature, birth and death are two significant evolutionary processes. The coyote ages in COA are expressed in years. A young coyote is born after each group of coyotes matures. Algorithm 1 displays the coyote births and deaths. The social settings and circumstances of two randomly chosen parents have an impact on the birth of young coyotes. The process outlined in Formula (14) shows how newborn coyotes are produced:

$$pup_j = \begin{cases} soc_j^{cr1}, rnd_j < p_s or j = j_1 \\ soc_j^{cr2}, rnd_j \geq p_s + P_a or j = j_2 \\ R_j, otherwise \end{cases} \quad (14)$$

Where $Ps$the likelihood of dispersion is, $Pa$is the possibility of connection and $cr1$,$cr2$are two sporadically different coyotes in group p. Formula (15) is used that illustrates$J1$, $J2$are two wildly different newborn coyote realities. The variety of newborn coyotes is influenced by the scattered association probability in this case; Algorithm 1 illustrates Rj is an arbitrary number of the $i$the choice variable's dimension, and $rndj$is the uniformly distributed random integer on$[0, 1]$.

$$o_t = \frac{1}{C}, o_t = \frac{1-o_t}{2} \quad (15)$$

- Coyotes are accepted and chased away. The coyotes are first divided into each group at random, but some of them break away to join other groups. $Pe$is used in Formula (16) to describe the likelihood that coyotes be banished and accepted by the group. This system encourages relationships between coyotes within species and improves information flow among COA groups:

$$o_t = 0.005 \times M_d^2 \quad (16)$$

Algorithm 1: The coyotes' birth and death

Start

Calculate ω and φ

If$\varphi = 1$

The youngest coyote then lives, the lone coyote in ω perishes, and the age of the superior coyote is=0.

If$\varphi > 1$

The coyote that was born lived, the coyote that was the oldest and had the weakest social adaption in ω passed away, and the coyote that was doing well was age 0.

Else

The young coyote passed away.

End

Following the beginning and randomness at startup, coyotes endure a complex life cycle that includes their survival, mortality, removal, and acceptance. Iteratively, this process continues until the predetermined termination requirements are satisfied. Coyote behaviors and interactions are influenced by a variety of elements throughout each iteration which aids in the population's evolution. The result of these repetitions is the recognition and development of the ideal coyote, which is a person or collection of traits that best satisfy the predetermined standards or goals in the environment of the particular system or simulation.

4. EXPERIMENTAL RESULTS

4.1 Result and discussion

The comparison and evaluation of outcomes, quality, and proposed CCO-RLR technique are investigated. To demonstrate that a recommended methodology is successful, its effectiveness is measured against those of modern approaches like Decision tree (DT) (Fu et al., 2023), Adaboost (Fu et al., 2023), and double SVM(Fu et al., 2023). The simulated findings that recommended strategy produce an improved identification of outcome than other current methods regarding Recall (%), accuracy (%) measurements, Precision (%) and F1-score (%).The simplest statistic is accuracy, which is calculated by the number of accurate forecasts divided by the entire number of forecasts. Here, FP stands for false positive, TN for true negative, TP for true positive, and FN for false negative.

$$Accuracy = \frac{tp+tn}{tp+tn+fp+fn} \tag{17}$$

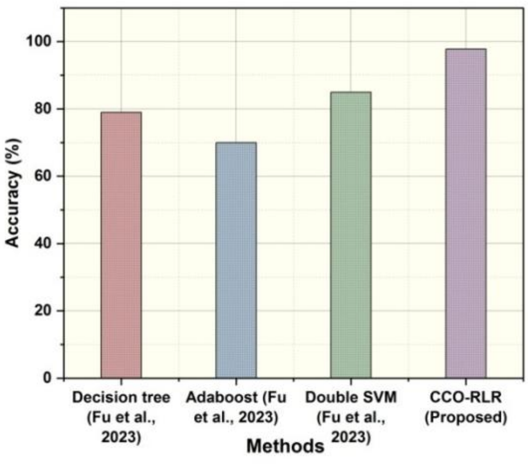

Figure 3. Comparison of the accuracy

Figure 3 presents an accuracy-based comparison of the classifiers under consideration. Table 1 demonstrates that the suggested classifier (97.8%) attained the highest classification accuracy; it outperformed the three current algorithms, decision tree (79%), Adaboost (70%), and double SVM (85%), by a significant amount. This confirms that the CCO-RLR method we proposed was highly accurate.

Table 1. Outcomes of the accuracy

Methods	Accuracy (%)
Decision tree (DT) (Fu et al., 2023)	79
Adaboost (Fu et al., 2023)	70
double SVM (Fu et al., 2023)	85
CCO-RLR (Proposed)	97.8

A model's accuracy in recognizing the positive class is measured by its precision. The number that really indicates how many of the forecasts for the positive class were accurate and it ranges from 0 to 1. An accuracy score that is near 1 indicates that the model accurately classified claims about frauds, for example, and did not overlook any true positives. Eliminating false positives would be the result of optimizing a model based on this statistic.

$$Precision = \frac{tp}{tp+fp} \tag{18}$$

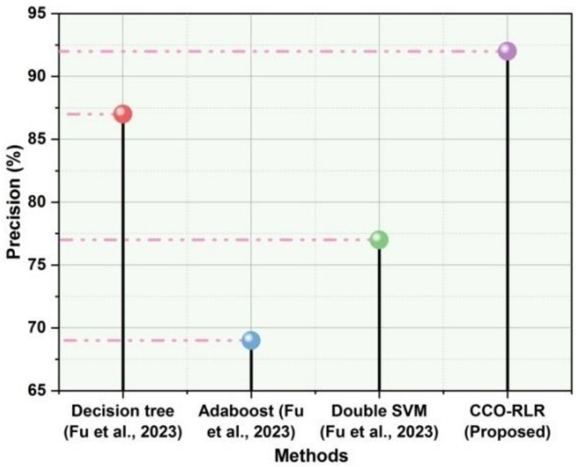

Figure 4. Comparison of the precision

In comparison to the precision percentages of the DT, Adaboost, and double SVM, Figure 4 and Table 2 demonstrate that the suggested classifier achieved the highest percentage. This suggested that there were much less false-positive (FP) rolling elements detected in the classifier that was displayed. Predictions of accuracy utilization for the proposed system and existing systems are explored. A 77% precision is achieved by double SVM, a 69% precision by Adaboost, 87% precision by decision tree, and a 92% precision by the proposed method. It proves that the recommended approach outperforms than other existing methods.

Table 2. Outcomes of the precision

Methods	Precision (%)
Decision tree (DT) (Fu et al., 2023)	87
Adaboost (Fu et al., 2023)	69
double SVM (Fu et al., 2023)	77
CCO-RLR (Proposed)	92

Recall measures that accurately anticipate the dataset's positive observations. It provides no details on the false positives. Recall values around 1 indicate that the model did not overlook any true positives and accurately detect with inaccurate labels. Furthermore, the recall is a value of less than 1. A precision-recall curve is created to examine accuracy and recall simultaneously. The visualization of the trade-offs between the two measures at various threshold values.

$$Recall = \frac{TP}{TP+FP} \tag{19}$$

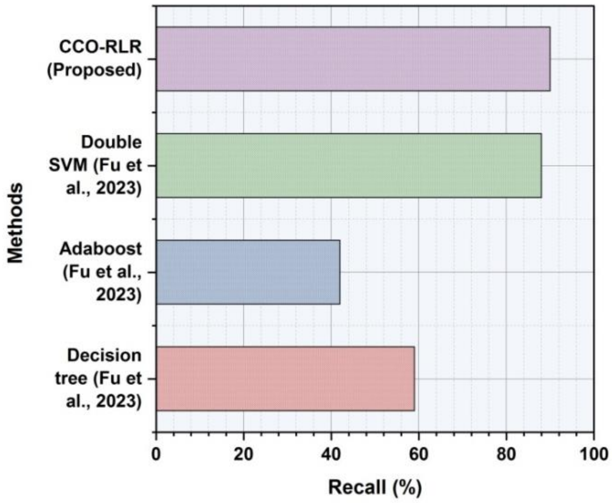

Figure 5. Comparison of the recall

Figure 5 and Table 3 show the recall of the proposed system. The recall utilization estimate is analyzed for both the proposed and current systems, where FN stands for genuine positives and TP for false positives. This research provides perspectives on the effectiveness of each system and possible areas for improvement by highlighting the way it detects false positives and finds positive situations.The suggested technique, CCO-RLR, yields 90% recall as opposed to double SVM's 88%, 59% achieved for the decision tree and 42% for Adaboost. It proves the proposed strategy is more effective than the present methods.

Table 3. Outcomes of the recall

Methods	Recall (%)
Decision tree (DT) (Fu et al., 2023)	59
Adaboost (Fu et al., 2023)	42
double SVM (Fu et al., 2023)	88
CCO-RLR [Proposed]	90

An integer between 0 and 1 known as the F1-score is obtained by taking the harmonic mean of accuracy and recall. If the F1 score is 1, it denotes perfect memory and precision; if the score is 0, it denotes either perfect recall or precision as shown in Figure 6.

$$F1\ score = \frac{2 \times precision \times Recall}{Precision+Recall} \tag{20}$$

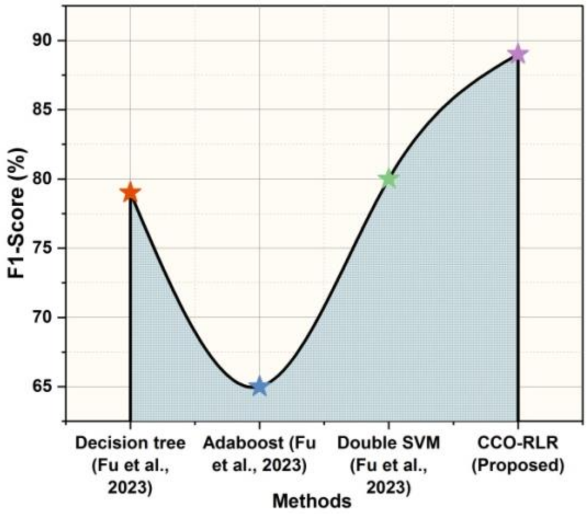

Figure 6. Comparison of the F1-score

Table 4 and Figure 6 display the suggested system of f1-score. Forecasts of recall consumption are displayed for both the recommended and existing systems. The CCO-RLR suggested technique obtains 89% f1-source, whereas double SVM, Adaboost, and decision trees score 80%, 65%, and 79%, respectively. This illustrates how effective the suggested strategy is in comparison to the current strategy.

Table 4. Outcomes of the F1-score

Methods	F1-Score (%)
Decision tree (DT) (Fu et al., 2023)	79
Adaboost (Fu et al., 2023)	65
double SVM (Fu et al., 2023)	80
CCO-RLR [Proposed]	89

5. CONCLUSION

The purpose of the current work is to examine the relative effectiveness of several machine learning models, as well as the impact of data sample size on classification accuracy and training time for bearing fault classification. They provided an exclusive method for classifying and identifying defects in rolling element bearings dubbed CCO-RLR. The evaluation data supports the recommended approach's 97.8% accuracy rate in locating and classifying bearing faults. The inherent constraints of rolling element bearings are tiredness, wear, and vulnerability to failure at high speeds or with heavy loads. Because of these difficulties, routine maintenance is required to minimize wear-related problems and maintain overall performance, highlighting the significance of preventative maintenance for the best possible bearing endurance and effectiveness.Future work on improved machine learning techniques and sensor integration techniques may improve rolling element bearings fault diagnostics. By using cutting-edge fusion techniques to integrate data from many sensors, system resilience can be increased by improving defect identification and categorization. The utilization of advanced machine learning algorithms augments the accuracy and efficacy of bearing defect identification. An important tactic for improving the precision and reliability of rolling parts bearing defect identification and classification is the integrated approach.

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