FAULT DIAGNOSIS OF BALL BEARING USING MACHINE LEARNING

Ajay Pratap Sharma M.Tech Research Scholar Department of Mechanical Medicap's University Indore, Madhya Pradesh India
Avinash Sharma Assistant Professor Department of Mechanical Medicap's University Indore, Madhya Pradesh India

Abstract:

The most integral segment about any rotating machine is its rolling element bearings. In many circumstances, fatal effects will follow sudden bearing failures. As a result, bearing condition monitoring is crucial. Artificial intelligence approaches are employed in this work to forecast and analyse bearing defects. For a wide range of speeds, experiments being conducted on rolling bearings with localized flaws on the various bearing components, and vibration signals were recorded. The two key components of condition monitoring systems are feature extraction and diagnosis using the derived characteristics. Since the Daubechies wavelet is well known for signal filtering, it was used to reduce vibration signal ambient sound. Decomposed time velocity signals are used to extract the reasonable date domain properties Kurtosis, RMS, Crest factor, and Peak difference. In order to categories bearing failures, this study examines the selection of fault features using principal component analysis and multi-class support vector machines (SVM). With the following conditions: normal bearing, bearing with inner race fault, bearing with outer race fault, and bearings with balls defect, the bearings vibration signal is acquired experimentally. The principal component analysis (PCA) is used to extract the best features and reduce the dimensionality of the original parts from the statistical parameters of the vibration signal, such as mean, standard deviation, sample variance, kurtosis, and skewness. For bearing multi-class fault diagnosis, the support vector machine (SVM) multi-class classification technique and the exploratory data analysis (EDA) like versus one approach are utilized. The execution of the suggested strategy was quite precise and efficient.

Key words: SVM, ANN, LDA and Random Forest Method

Introduction:

Every rotating component is said to have a bearing at its core, and industrial facilities, the automation industry, and the aerospace industry all depend on bearing performance. One of the crucial components of rotating machinery for modern, precise information about the defect is the bearing. Large loads and difficult working circumstances are frequent reasons of barring failure because of the high operating speed. In order to avoid machine performance degradation, malfunction, or even catastrophic failures, a variety of initiatives in a wide range of industries using rotary machinery have focused on developing dependable monitoring systems. Since this vibration signals contain dynamic features of the equipment performance and can thus be easily identified rapid recognition of early demise, vibration information is frequently employed for the diagnosis of an unhealthy condition. The implementation of the defect diagnostic process requires two crucial steps: signal processing for feature extraction and noise control in the first phase, and signal segmentation in the second step based on the features identified in the first step. Because different problems may present common characteristics and because numerous faults may occur at once, diagnosis is typically more challenging than detection. The two phases of feature extraction and decision-making are used sequentially in fault identification and diagnosis (diagnosis). In order to establish a methodology for the monitoring and diagnosis of vibrating components, Alguindigue et al. (1993) employed low- and high-frequency spectra to identify early faults and severe flaws. [1] A multi-layered feed-forward neural network trained using the supervised Error Back Propagation technique and an unsupervised Adaptive Resonance Theory-2 (ART2) based neural network were employed by Subrahmanyam et al. for the

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automatic detection and diagnosis of localized problems in ball bearings. [2] For five different major defects and their combinations, neural networks were employed by Vyas N. S. et al. in 2001. To prepare the network, statistical moments of the rotor-bearing system's vibration signals are used. [3] Tse P. W. et al. conducted a thorough comparison of ED and wavelet analysis and concluded that wavelet analysis was the most practical approach for machine operators to employ for diagnosing bearing faults. [4] The input layer comprises of five nodes, one for each of the root mean square, variance, skewness, kurtosis, and normalized sixth central moment of the time domain vibration signals. The features are derived via direct processing of the signal. Prior to feature extraction, the impacts of different pre-processing methods for vibration signals are examined and reported. These include high-pass, band-pass filtration, envelope detection (demodulation), and wavelet transform. [5] The APF-K closest neighbor approach was utilized by Pandya D. H. et al. (2013) to classify faults using time domain parameters such as the Crest factor, Kurtosis, skewness, and Shape factor. The accelerometer data were processed and feature vectors were produced using the wavelet technique by Lou et al. [6]. [7] Jun sheng et al approach's to extracting fault features for roller bearings, which uses the empirical mode decomposition (EMD) method and the autoregressive (AR) model. [8]. The three parameters are excellent fault features for pattern recognition fault patterns, according to Peng et al wavelet's modulus maximal technique modelling of the vibration signals. [9] Sreejith et al. employed the kurtosis value and normative negatively log probability value extracted from the time- domain vibration signals as input characteristics for the neural network. to diagnose a rolling element bearing fault. [10] To predict the bearing of wave fronts in smart antenna systems, Gharavolet et al. used spectrally condensed data based on the discrete wavelet transform and truncated fast Fourier transform for the first time. [11] A mathematical model has been proposed by Upadhyay S. H. et al. to explore the nonlinear dynamic response of a high-speed rotor bearing system caused by rolling element flaws. [12] Chebil J. et al. have covered the selection of the mother wavelet, the discrete wavelet packet transforms, and some of the frequently retrieved characteristics for the Detection and Diagnosis of Faults in Rolling Element Bearings. [13] Using failure and suspension condition monitoring records, Tian Z. et al. created an ANN method. [14] In order to extract the most important characteristics from signals in a first phase and to utilize those features as inputs of a supervised neural network (NN) for classification in a second phase for automatic detection of rolling bearings, Castelo's et al. used multi resolution analysis (MRA). [15] In this study, wavelet transform is utilized to first denoise the vibration signals, and then time domain features are extracted. These features are then used for further fault classification using ANN and SVM. In this study, defective bearings are normalized for ANN and SVM input signals using an experimental velocity vibration signal. In this discussion, the impact of various loading conditions and fault sizes at a range of speeds has been examined.

Brief review of Wavelet Transform, ANN, SVM:

The wavelet transform, multi-resolution analysis, time-scale analysis, and time-frequency interpretations are just a few of the many instruments that make up this wavelet technique. Statistical analysis or prediction is fundamentally important for temporal domain analysis. [16] In actuality, a signal can be dissected into numerous lower-resolution components by computing successive approximations in turn and iteratively determining the signal's breakdown. This technique is additionally used for signal filtration. Reconstruction filters allow us to remove the constituent noise from the initial signal and ultimately produce a smooth output [17]. Discrete wavelet analysis became feasible with the creation of "compactly supported orthonormal wavelets" by Ingrid Daubechies. No explicit expression exists for these wavelets. In this study, the wavelet was given a smooth signal after applying the Daubechies-6 iteration. For the purpose of removing noise, the "Daubechies-6" wavelet was used to every vibration data gathered from figure 1.

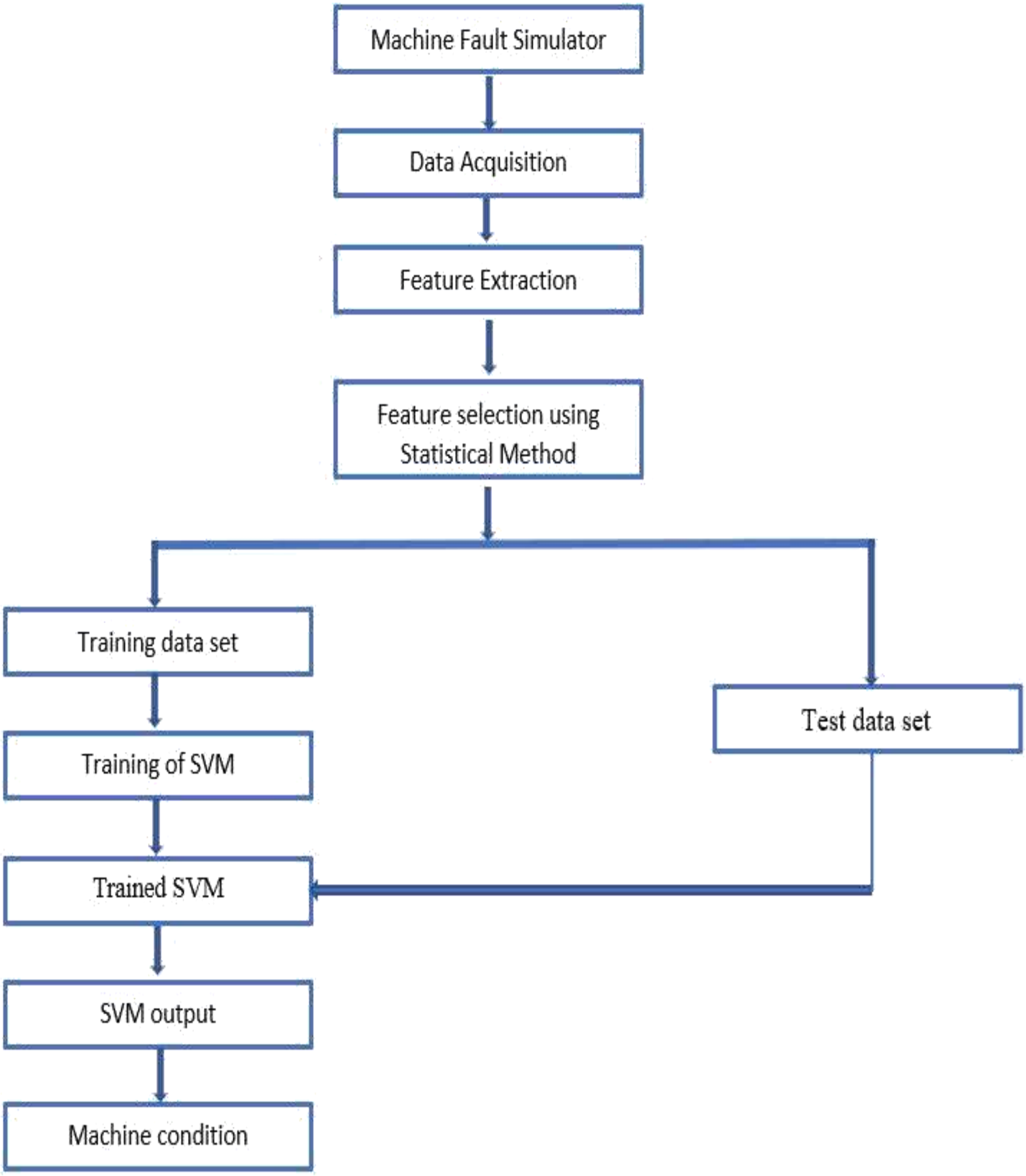

Figure 1. Flow chart of bearing health diagnosis

Support Vector Machine:

In accordance with statistical learning theory, support vector machines (SVM) are a supervised machine learning technique. In situations with a small sample size, like fault identification, it is a highly helpful tool for classification and regression. A supervised machine learning technique built on the statistical learning theory is the support vector machine (SVM). In situations with a small sample size, like defect diagnostics, it is a practical method for classification and regression. A brief description of pattern detection and classification using SVM (Cristianini & Shawe-Taylor, 2000) [18]. Considered is a straightforward situation of two classes that can be distinguished by a linear classifier.

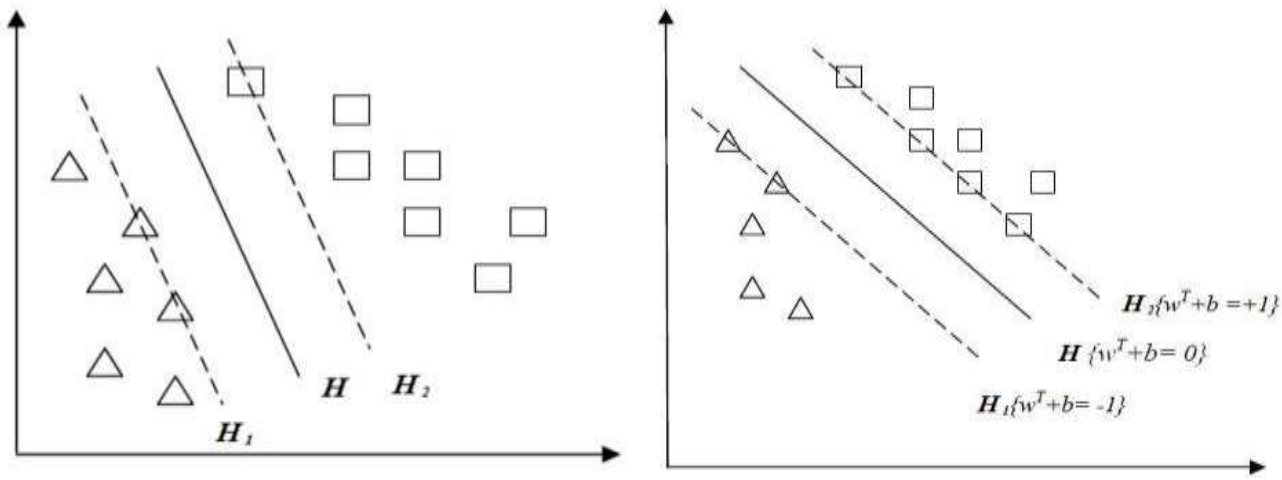

Figure 2. Hyper plane classifying two classes small margin

In Fig. 2, triangles and squares are used to represent these two categories of sample points. One of the splitting planes that divides two classes is the hyperplane H. The parallel planes H1 and H2 (depicted by dotted lines) cross through the sample points in these two classes that are closest to H. The margin is the separation of H1 and H2. The SVM seeks to establish a linear separation between the two distinct classes H1 and H2, orienting it to maximize the margin and minimize generalization error. Support vectors are the closest dataset points that were used to establish the margin. This is accomplished by turning it into a convex optimization problem, which calls for minimizing a quadratic function while subject to limitations imposed by linear inequality (Cristianini & Shawe-Taylor, 2000) [18]. Think about a training sample set (x, y) with i = 1 to N, where N is the overall sample count. The goal is to identify the linear separation plane that divides input data into two classes with the least amount of generalization error. Assume for the moment that the samples can be divided into the triangle class and the square class. Triangle class and square class are denoted by the labels Yi = 1= 1 and Yi = +1, respectively. For non-separable data, slack variables are regarded as ($\xi i \geq 0$). The iterative minimization could be solved to acquire the hyperplane f(x) = 0 that divides the provided data [19].

$$minimize = \frac{1}{2}\|W\|_1^2 + i\Sigma_{i=1}^{N}\xi_i ----------(1)$$

$$Subjected\ to, \begin{cases} y_i(w^T x_i + b) \geq 1 - \xi_i \\ \varepsilon \geq 0\ i = 1,2,3, \ldots\ldots N \end{cases}$$

where C is a constant that stands for the penalty for errors. The issue arises when the aforementioned optimization problem is rewritten in terms of Lagrange multipliers

$$Maximize = w(\lambda) = \sum_{i=1}^{N} \lambda i - \frac{1}{2}\Sigma_{i,j}^{N} y_i y_j \lambda_i \lambda_j (x_i - x_j)$$

$$Subjected\ to, \begin{cases} 0 \leq \lambda_i \leq C \\ \Sigma_{i=1}^{N} \lambda_i y_i = 0 \quad i = 1,2 \ldots . N \end{cases}$$

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This double issue resulting from the SVM's derivation can be efficiently solved using the sequentially minimum optimization (SMO) approach. SMO breaks down the main QP challenge into smaller QP issues.

Time domain Feature Extraction:

The formula 2-4 demonstrated that one of the main variables in bearing diagnosis is frequency.

$$F_b = \frac{1}{2} f \cdot \left[\left(1 - \frac{d}{D}\right)^2 cos^2\, a \right] \frac{D}{d} ----------- (2)$$

$$F_i = \frac{1}{2} f \left[\left(1 - \frac{d}{D} cos\, a\right) z \right] ------------ (3)$$

$$F_0 = \frac{1}{2} f \left[\left(1 + \frac{d}{D} cos\, a\right) \right] z ------------- (4)$$

F_b, Fi and Fo are the frequencies of the outer race fault, inner race fault, and ball spin, correspondingly. As a result, information from the time domain and the frequency domain must be extracted in order to appropriately portray the bearing defect type. Thus, the research's parameters were mean, standard deviation, sample variance, kurtosis, skewness, peak-peak value, and frequency [20]. The following explanations were given for several challenging parameters and formulas.

Peak-peak value:

$$v_{P-P} = maxy_i - miny_i ------------- (5)$$

Mean:

$$V_m = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{1\cdot} \mathrm{y_i} ----------------- (6)$$

Standard deviation:

The bearing condition is plainly deteriorating as the standard deviation, a measurement of the effective energy or power intensity of the vibration signal, increases.

$$SD = \sqrt{\frac{n \sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2}{n(n-1)}} ---------- (7)$$

Sample variance:

Sample variance, which accounts for all potential values and their probabilities or weightings, is a measurement of the degree of variation within the values of that variable.

$$SV = \frac{n\Sigma_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2}{n(n-1)} ----------- (8)$$

Kurtosis:

The effect of the face defect pulse, the kurtosis coefficient of the formation of substantial value that fault pulse the probability, and the kurtosis coefficient of the impulse response amplitude of the fourth power to determine the basis for optimized signal to noise ratio, accuracy vastly enhanced when such bearing surface of the work of fatigue failure.

$$Kurtosis = \frac{\Sigma_{i=1}^{n}(y_i - \mu)^4}{N\sigma^4} ------------ (9)$$

Skewness:

Skewness is a metric for gauging how asymmetrical a distribution is. The function is considered to have negative skewness if the left tail is more obvious than the right tail. It has positive skewness if the opposite is accurate. It has no skewness if the two are equal.

$$Skewness \frac{1}{N} \sum_{i=1}^{n} \left(\frac{y_i - \mu}{\dot{\sigma}}\right)^3 ---------- (10)$$

Frequency1:

Frequency is the key parameter for signal analysis in the signal frequent domain, which carries data on bearing failure frequency. The frequency that matched the power spectrum's greatest amplitudes was frequency 1. In order to gain the power spectrum, the vibration signal first required Fast Fourier Transform (FFT). [21]

Experimental Procedure:

For such following conditions: normal bearing, bearing with inner race fault, bearing with ball fault, and bearing with outer race fault, the time series vibration signal was received from the Case Western Reserve University Bearing Data Centre and was recorded at 48000 samples per second. In this study work, we'll consider data collected at a sample rate of 48 kHz, with a defect that has changing fault depth (0.007inch, 0.014inch and 0.021inch). For the purposes of this study article, we will consider all the data with a 1hp external load despite the fact that the motor can operate with no load, 1HP load, 2HP load, and 3HP load. Study article, we will consider all the data with a 1hp external load despite the fact that there are several loads for the motor (no load, 1HP load, 2HP load, and 3HP load).

Given temporal data, I have categorized these ten forms of fault in this research work. There are numerous ways to solve it; we used the Random Forest method, LDA (Linear Discrete Method), and MSVM (Multiclass Support Vector Machine) as input. Each defect type's initial data is gathered and divided into smaller chunks. In our scenario, there are 2048 data points per segment, one for each defect class. Following that, a feature matrix with the time domain features for each segment is calculated. Each fault has 230 segments, and we have multiplied the domain feature nine times.

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Maximum, minimum, mean value, standard deviation, root mean square value (RMS), skewness, kurtosis, crest factor, and form factor are the temporal domain features. As a result, our feature matrix is (2300*9) in size. The feature matrix also gains a new column for "fault" kind. The final feature matrix is thus 2300*10 in size. The data are initially divided into a training set and test set, with the test set containing 75 rows of fault matrices selected for each fault type, before applying the aforesaid procedure. Its dimensions are (750*10). The remainder are used as a practice set. The training set data is processed using the MSVM (Multiclass Support Vector Machine), LDA (Linear Discrete Method), and Random Forest methods, and the best parameters are selected via cross validation. Then, to forecast the final classification outcome, the best parameters are applied to the test set data. The Multiclass Support Vector Machine (MSVM), Linear Discrete Method (LDA), and Random Forest method are being implemented in this case using Python to plot the confusion matrix.

Table 1. Raw data after extracting mat. Files

	max	min	mean	sd	rms	skewness	kurtosis	crest	form	fault
0	0.35986	-0.41890	0.017840	0.122746	0.124006	-0.118571	-0.042219	2.901946	6.950855	Ball_007_1
1	0.46772	-0.36111	0.022255	0.132488	0.134312	0.174699	-0.081548	3.482334	6.035202	Ball_007_1
2	0.46855	-0.43809	0.020470	0.149651	0.151008	0.040339	-0.274069	3.102819	7.376926	Ball_007_1
3	0.58475	-0.54303	0.020960	0.157067	0.158422	-0.023266	0.134692	3.691097	7.558387	Ball_007_1
4	0.44685	-0.57891	0.022167	0.138189	0.139922	-0.081534	0.402783	3.193561	6.312085	Ball_007_1
...	...	...	...	...	...	...	...	...	...	...
2295	0.21425	-0.19839	0.010769	0.064100	0.064983	-0.212497	-0.119312	3.297037	6.034174	Normal_1
2296	0.21967	-0.20882	0.013136	0.068654	0.069883	-0.061308	-0.295122	3.143410	5.319958	Normal_1
2297	0.20799	-0.21613	0.012571	0.067128	0.068279	-0.154754	-0.071405	3.046161	5.431299	Normal_1
2298	0.21425	-0.22405	0.012608	0.066813	0.067977	-0.326966	0.023662	3.151821	5.391672	Normal_1
2299	0.19610	-0.24721	0.012209	0.063243	0.064396	-0.351762	0.226294	3.045244	5.274392	Normal_1

2300 rows × 10 columns

Linear discriminant analysis (LDA):

A Gaussian distribution over variables is assumed for each class in the classification method known as linear discriminant analysis (LDA). Different means are chosen for various classes, but all classes use the same covariance matrix. Even though using the same covariance matrix for all classes is a restrictive assumption, it works well when it is roughly satisfied and there are fewer data points. Bayes' rule is used to calculate the conditional probabilities that a data point belongs to a certain class after Gaussians have been fitted for each class. The distribution's parameters are determined by data.

Random forest for Bearing Fault Classification:

Bagging and random forest are extremely similar. Similar to bagging, random forest grows a wide variety of trees on bootstrap samples. The number of variables considered while performing a split in the tree differs between the two approaches. A random sample of a few variables is only selected at random forest for each split. If there are p features in the training data, the best feature is typically picked at random from the p features at each split. This lessens the connectivity between the

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trees. Because of reason, bagging typically yields inferior results to random forest. We will employ random forest in this study to categories various bearing defects. According to the wavelet energy value in each packet, the dataset has 8 parameters. We'll utilize four random features while splitting a random forest model.

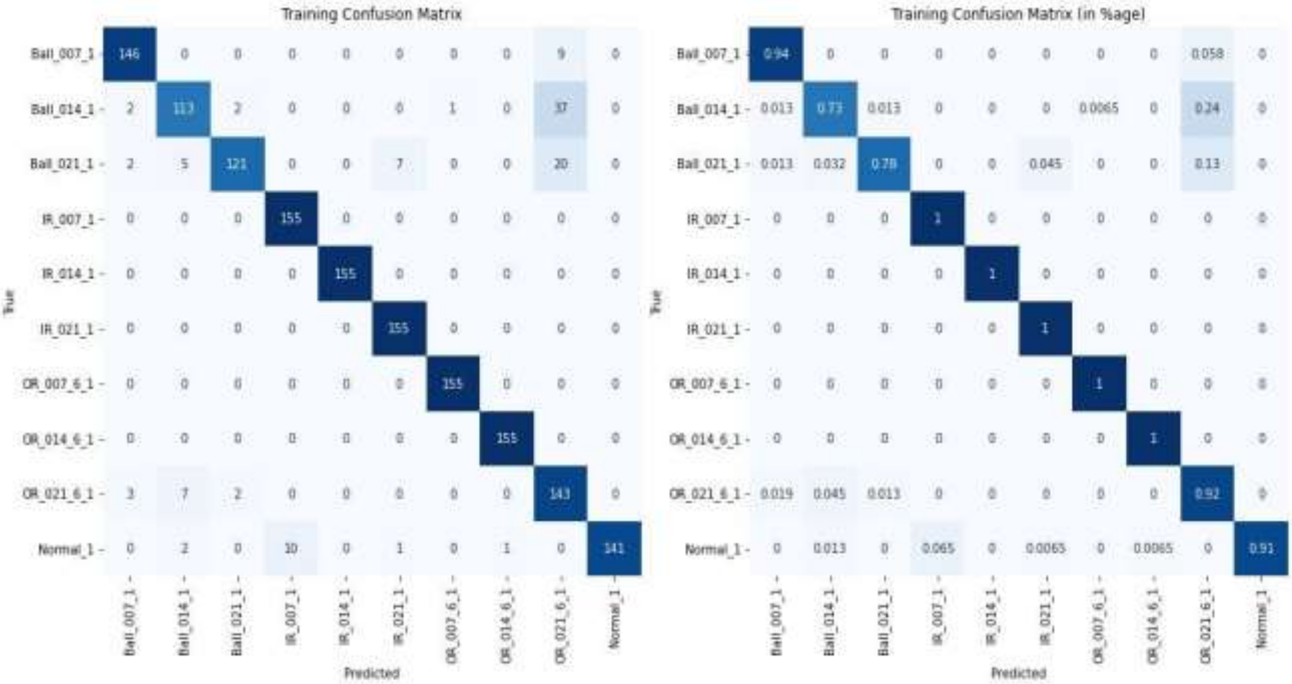

Fig 3 Training Confusion matrix of LDA

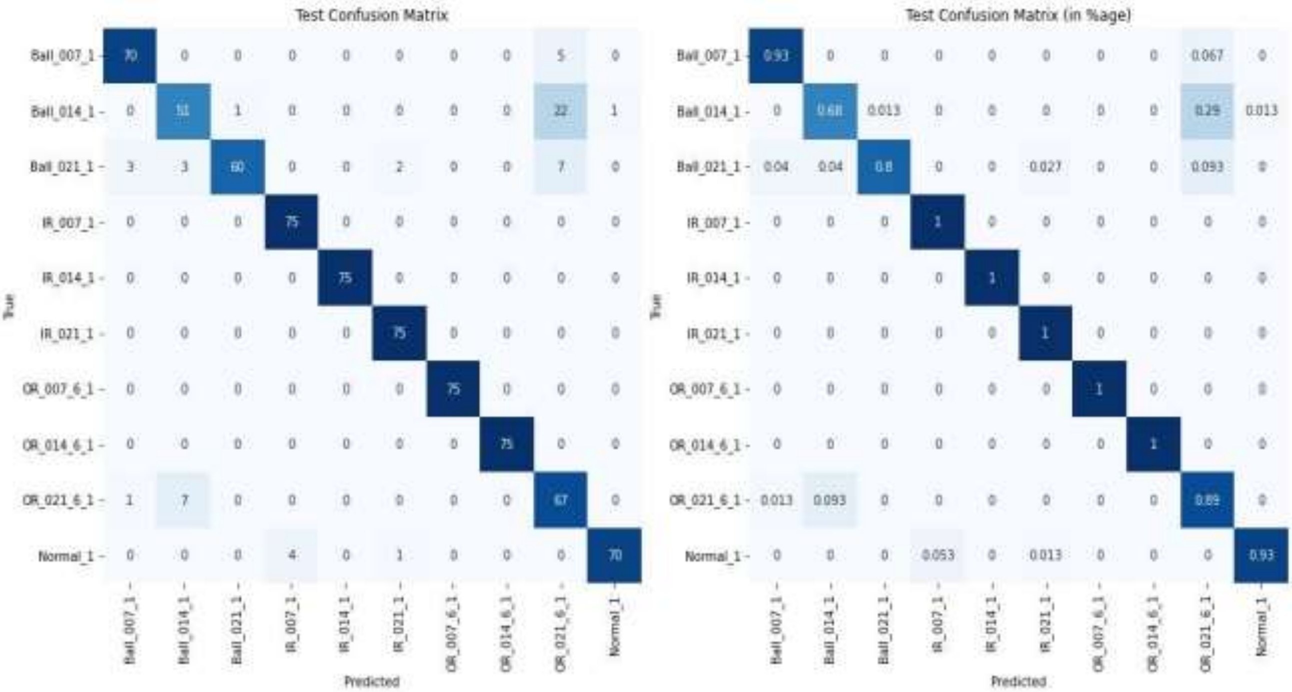

Fig 4 Test Confusion matrix of LDA

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MSVM (Multiclass SVM using time domain feature):

The focus of this work is the existence of a practical technique for multi-fault diagnosis in such systems with time-domain features extracted from vibration signals and multi-class support vector machine (MSVM) utilized for rolling-element bearing fault detection and classification. The characteristics that indicate the source of the roller bearings' vibration can be derived through certain indirect methods. There are two steps to the procedure. Initially, the time-domain aspects from the vibration signals are extracted. These features are frequently employed in defect diagnosis. The features that were successfully retrieved are then successfully classified using the MSVM classifier, together with the roller bearings' working status and fault patterns, and finally, defects are diagnosed in real time based on polling.

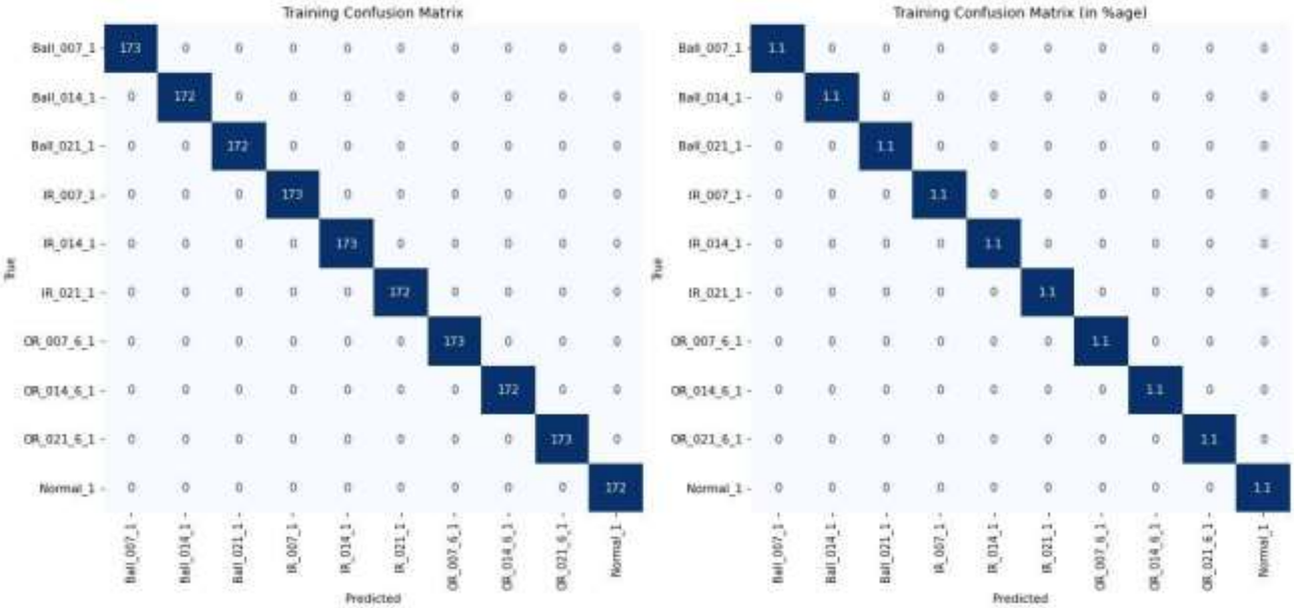

Fig 5 Random Forest classifier Training Matrix

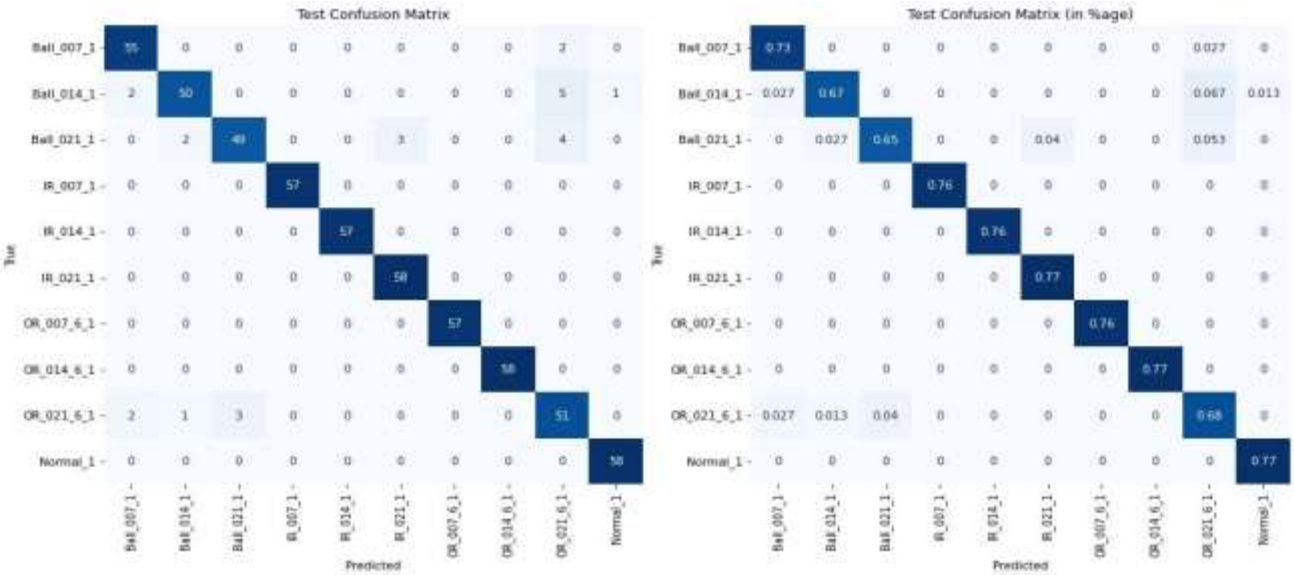

Fig 6 Random Forest Classifier Test Confusion

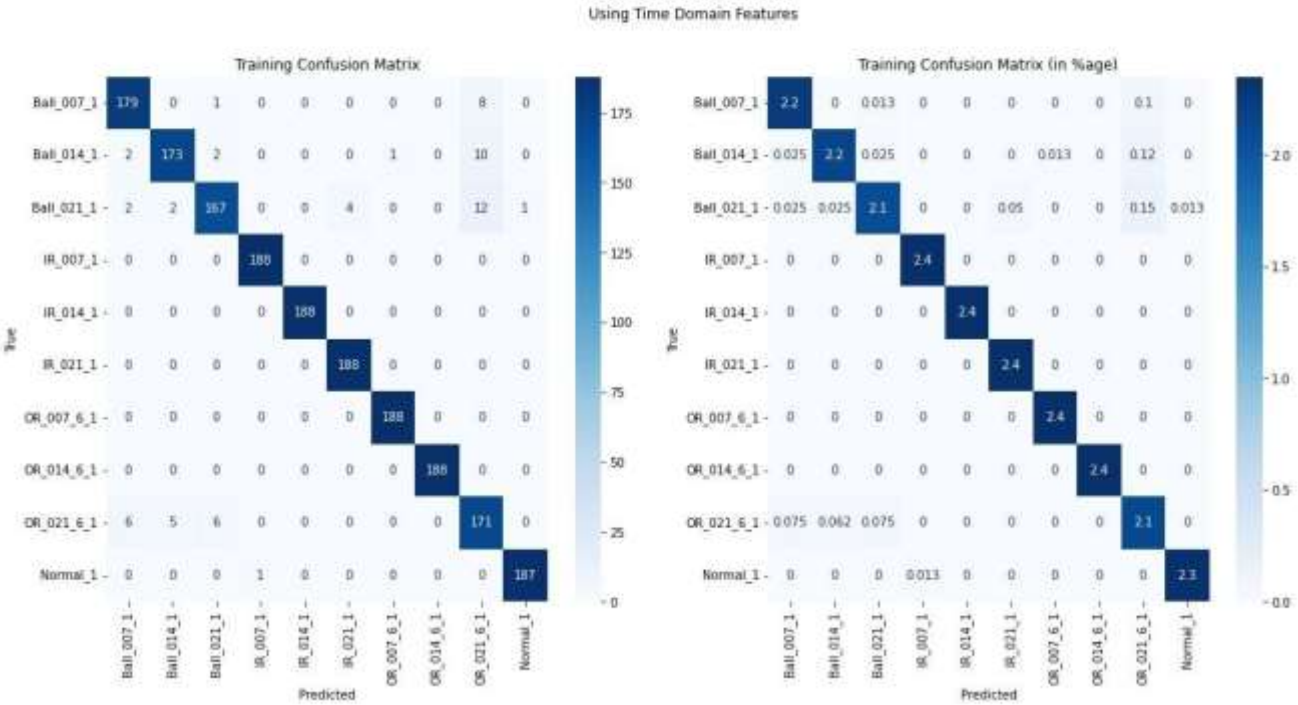

Fig 7 MSVM Training Based confusion Matrix

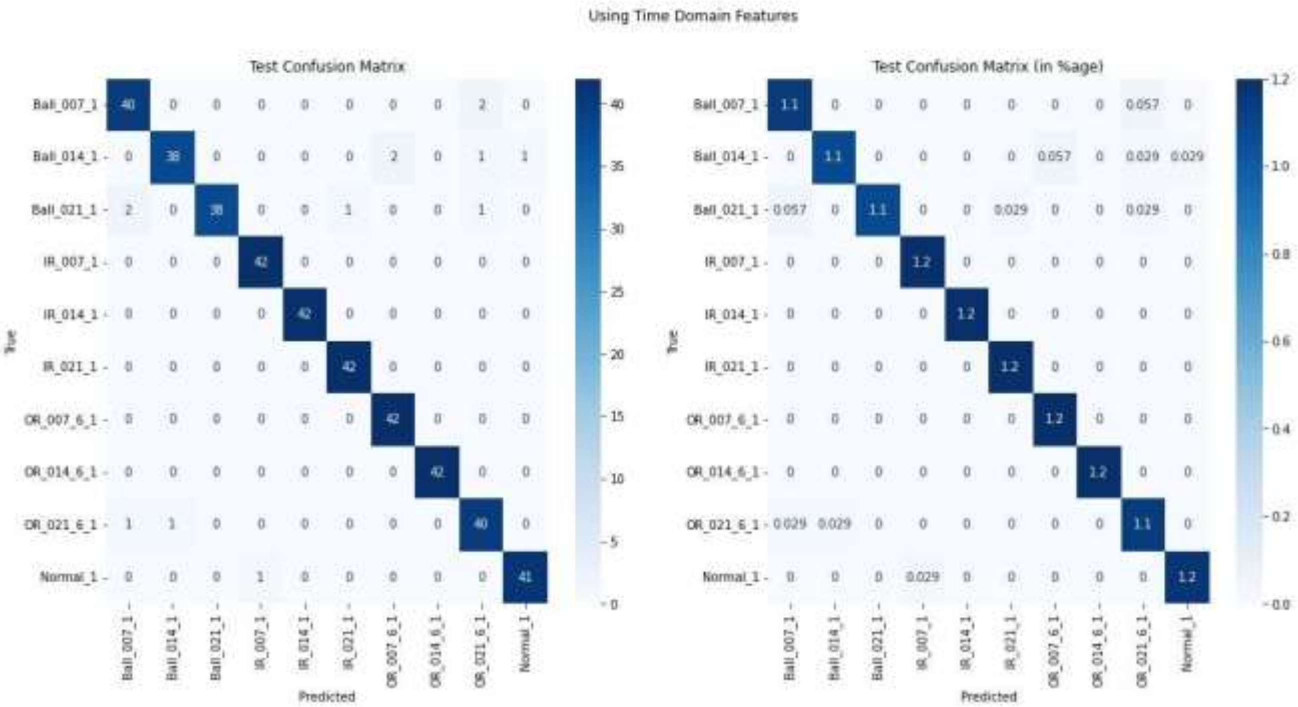

Fig 8 MSVM testing with confusion matrix

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Result:

Table 2 Comparison of LDA-SVM method with K-fold cross-validation with recent related AI fault classification models.

Author	Model	Classification accuracy (%)	Speed
Shuhui Wang, 2018	CNN based Markov model	98.125	Constant
Tang et. al, 2019	Adaptive learning rate deep belief network (ADDBN)	99.75	Constant
Sufi Tabassum Gul, 2018	SVM with 5 K-cross fold validation	91.95	Constant
Liu et al. 2018	1D-CNN	99.999	Constant
M.Pule, O. Matsebe et. al 2022	SVM+ PCA and 10 K-fold CV	97.4	Various speed condition
Our method	MSVM, LDA and Random forest classifier	96, 92 and 95.65	Constant

Conclusion:

This article describes a method for identifying bearing faults through classification utilizing ANNs and SVMs, two machine learning techniques. Statistical methods are used to extract features from time-domain vibration signals. According to the temporal responses that were found for various bearing fault conditions, bearings with rough inner race surfaces and balls with corrosion pitting experience strong (chaotic) vibrations. A rotor bearing system's vibration is significantly impacted by the associated fault. SVM, Random Forest as a classifier, and LDA all use the cross-validation process to achieve classification accuracy. Optimal feature selection is a crucial topic for fault classification but is covered little in the literature. The percentage of cases accurately identified using SVM, LDA, and Random Forest Classifier is 96%, 92.4%, and 95.65%, respectively, according to the results. We discovered that SVM provides the best accuracy compared to all other methods after comparing all the findings. In the future, we can combine this method with other signal decomposition techniques to improve the effectiveness of classification, and we can also use it to diagnose faults.

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