Estimation of Remaining Useful Life of Bearings Based on Nested Dichotomy Classifier – A Machine Learning Approach

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***Abstract* - Rolling element bearings play a vital role for maintaining the reliability metrics in all rotating machineries. The downtime due to these bearing failures are now in increasing trend. In general manufacturing environment most of the time the bearings are replaced only after an indication or symptom due to the complexities of deployments for condition monitoring techniques. This paper emphasis on estimating the remaining useful life of bearing using Nested dichotomy classifier. Vibration signals were acquired for a bearing from day one of its operation till it fails naturally through a piezoelectric accelerometer and the features are extracted using the defined statistical features. The best contributing features are selected and classified using the Nested dichotomy, data near balanced nested dichotomy and class balanced nested dichotomy classifiers. The effectiveness of these classifiers was analyzed and compared.**

Keywords : Remaining Useful Life (RUL) ; Nested Dichotomy (ND), Statistical Features

I. INTRODUCTION

In a manufacturing industry a high amount of capital cost is incurred on improving the uptime of the machineries. Preventive maintenance is a common tool deployed across the industries to reduce the downtime and improve the health condition of the machines. However there are instances that the breakdowns occur due to variable unpredicted conditions. Bearing failures alone contributes to a reasonable sum in the total breakdowns. This failures shows up usually in the quality parameters. There are already number of conditional monitoring techniques for assessing the health condition of the bearings under study. However, these techniques have their own limitations to the real time applications. A bearing failure is associated with various reasons like mis-alignment,temperature, load conditions,lubrications etc., however,the present study is focused on assessing the health condition of a bearing under real time conditions.

Palmgren. A and G.Lundberg [1]-[3] have laid the basics in estimating the lifetime of the bearing. This has given way to establish the standard for predicting the lifetime of the bearings with respect to the loads and speed of the application [4]-[6].Zhigang Tian,Lorna Wong and NimaSafaei [7] has detailed the deployment of Artificial Neural Networks (ANN) for estimating the remaining useful life of a bearing with age and condition monitoring data as input and the remaining life as the resultant output. This model was built with the past failure histories. The main drawback of using ANN is the associated complexities in designing all the failure histories in the real time applications. Nathan Bolander,Haiqiu and Neil Eklund [8] summarizes a physics based remaining useful life predictions for a aircraft engine bearing. The model was built with spall propogation theories by which the remaining life is assessed based on the future operating conditions and the spall propogation.

Francesco Di Maio, et.al., [9] used a Naïve baysian classifier for estimating the remaining useful life of bearings. This method is based on the bearing degradation patterns that are already stored in the database. The new acquired vibration signals are compared with reference to the similar degradation patterns and the remaining useful life is predicted. Paula J. Dempsey, et.al.,[10] presented the remaining life by correlating it with the condition indicators. Spall propogation data was used to generate the condition indicators. A damage progression model was thus built with the said data. Data fusion analysis technique was used to map the condition indicator to the damage level and thus the current state of the transmission component is assessed.

Sugumaran V. andRamachandran K. I [11]-[13] and V.Muralidharan and V. Sugumaran [14],[15] detailed the process of acquiring the vibration signals, feature extraction ,feature selection and feature classification through a machine learning approach. Statistical parameters like standard deviation, mean average, minimum and maximum values forms a set of features and the best contributing features are selected and further classified using various classifiers. Decision tree was used as one of the tool for selecting the best contrubting feature for the given data set.

This paper presents a predictive method to estimate the remaining useful life of the bearings based on nested dichotomy clasifiers. This method is based on the supervisedmachine learning approach. Run-to-failure tests were conducted on the bearings that are similar to real time applications. The vibration signals thus acquired at defined intervals were used for feature extraction through descriptive statistical methods.

II METHODOLOGY

This paper proposes the step by step process to estimate the remaining useful life of the bearings as shown in Fig. 1. The said methodology follows data driven approach wherein the data collected from the experiments are used to learn about the systems and to infer the current state of the system. The experiments were conducted on dedicated test rigs with real time conditions. The selected bearings were tested on these experimental setups and the vibration signals are acquired at defined intervals. The signals are later converted to data for further analysis.

Fig. 1. Methodology of RUL estimation

Statistical features were deployed for feature extraction. These features are dealt in detail in the next sections in this paper. From the listed features the best performing and contributing features are selected. This selection is done using decision tree algorithm. The selected features are further used for constructing a model which will be used for assessing the current state of the bearings and thus estimating the remaining useful life of the bearings in the test.The model is initially constructed with training data set and further validated for precise results. This paper details about the effectiveness of Nested Dichotomy Classifiers for model construction. Nested dichotomy (ND) is a method used for studying a multi class classification problem. A nested dichotomy organizes the classes in a tree , each internal node has a binary classifier. A set of classes can be organized in a different ways in an nested dichotomy. An ensemble of nested dichotomy is formed by several dichotomies. Hence an attempt has been made in the present study to classify the selected features using different types of nested dichotomy classifiers.

III EXPERIMENTAL STUDIES

The main objective of this experiment is to assess the health condition of the bearing at defined intervals.The experiments were conducted with the selected bearings in a controlled environment andrun-to-failure test data is aquired to validate the effectiveness of the proposed model for predicting the remaining life of the bearing. In general, most of the bearing tests will be done in an accelerated conditions toshorten the test time. This paper is built around to overcome the limitations set in the previous studies. The experiments on these bearings are continued at real time environments till the bearing fails naturally. The complete experimental setup used for data acquisition is shown in Fig. 2. This setup consists of a bearing, accelerometer, motor, DAQ card and LABVIEW software loaded into a computer to acquire the vibration signals.

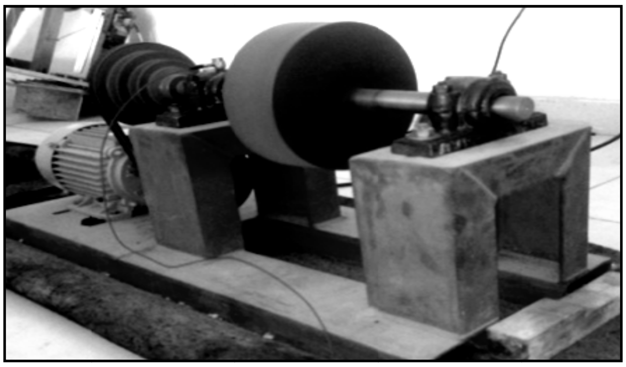


Fig. 2. Experimental setup

The bearings are mounted on a shaft with housing and in-turn connected to a variable speed motor. Few major parameters like speed, load, temperature, lubrication, *etc.,* are simulated at real time conditions. The brand new bearing (ball bearing 6205) was made to run to failure at rated speeds (1400 RPM)and rated radial load (0.2 kN). The vibration signals from the bearings are collected through the piezo electric accelerometers placed on the either side of the housings and acquired via DAQ system (Model NI USB 4432).The card has a 5 anolog input slots with a sampling rate of 102.4 kilo samples per second and 24 bit resolution. These accelerometers(40Hz resonant frequency) have a large frequency response and it can detect very small vibrations. These signals were processed in the LabVIEW. The vibration signals acquired from the experimental set-up follows the below sampling parameters.

Sample length : 1024

Sampling frequency :24 kHz

Number of samples : 200 samples every 08 hrsof running

The experiment was run in real time conditions matching to the said bearing application. Adequate measures were taken to avoid bearing faults or damages due to fitments, misalignments etc,.All researches done on bearing life time mostly opts with Vibration signalas it is most effective and suitable for reflectingactual bearing running condition. There are other methods other than vibration signals such as temperature, oil or debris,acoustic methods etc., to assess the health condition of the bearings. However vibration signals are less complex when compared to others. The amplitude of the vibration signals is monitored on a daily basis for estimating the current health condition of the bearings. The amplitude reflects the age of the bearing under study. The amplitude of the vibration is small and smooth when the bearing is under normal condition. The amplitude of the vibration signal gradually increases with respect to the time as shown in Fig.2. Meanwhile any defects or damages on the bearings during the process can also be easily identified, if the acquired signals are contuniously monitored. Thus, vibration signal becomes the suitable variable to asses teh health condition of the bearings. The collected data from the bearings were categorized into different stages with respect to the time. The stages are defined asstage 1, stage 2, stage 3, stage 4 and stage 5 etc.... Signals acquired from a new bearing were placed on stage 1. Stage 2 and 3 includes the signals that are extracted from the bearing after 1000 hours and 1250 hours respectively. Stage 4 includes the signals that are extracted after 1500 hours of running the bearing at rated load and speed conditions. Signals from damaged bearing are placed in stage 5. The variations in signals, thus acquired from the bearings in various stages is shown in Fig. 3 (a), 3 (b), 3 (c), 3 (d) and 3 (e) respectively.

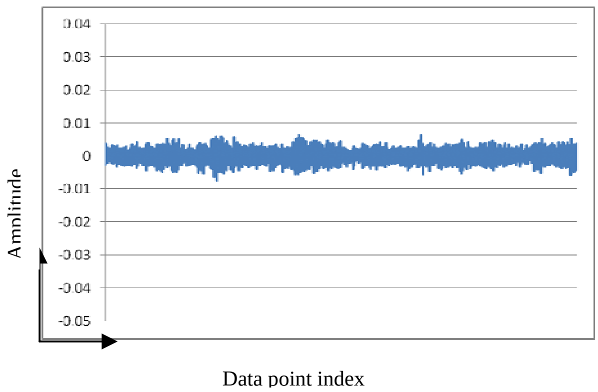


Fig. 3 (a). Satge-1: Vibration Signals at Start

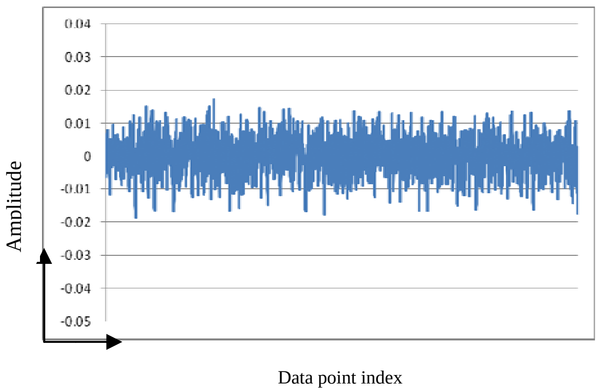
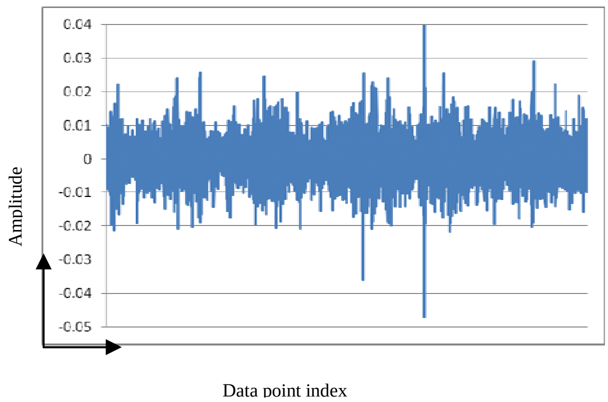


Fig. 3 (b). Satge-2: Vibration signals@1000 Hrs



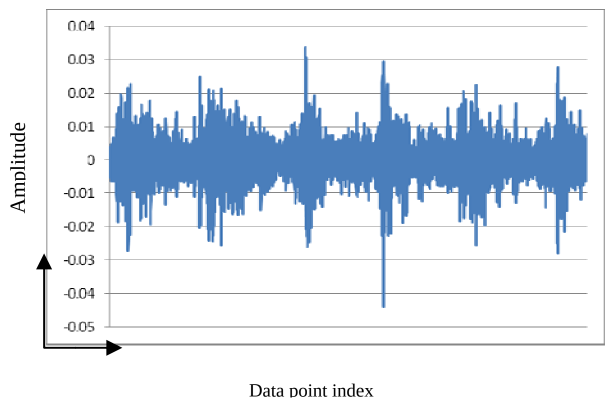


Fig. 3 (c). Stage-3:Vibration Signals@1250Hrs Fig. 3 (d). Stage-4:Vibration Signals@1500Hrs

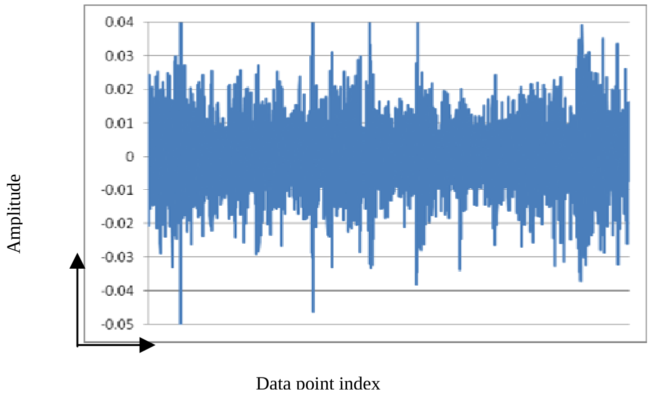


Fig. 3 (e). Stage-5: Vibration Signals @1800 Hrs.

IV FEATURE EXTRACTION AND FEATURE SELECTION

The signals acquired for the experiments will be too large for the algorithm to be processed and it is suspected to be redundant and hence they are reduced set of features. This process is called as feature extraction. Descriptive statistical parameters such as mean, median, mode, sample variance, kurtosis, skewness, standard error, standard deviation, minimum, maximum, sum, and range were computed to serve as features. They are named as 'statistical features' here. Brief descriptions about the extracted statistical features as detailed by Jegadeeshwaran & Sugumaran [16]-[18].

A. Feature selection

Feature selection is the process of selecting well contributing features among the available features. In the present study 12 descriptive statistical features have been extracted and out of 12 features the well contributing features have to be identified. Decision tree was used for feature selection. Satishkumar and Sugumaran [19] detailed the feature selection using J48 decision tree algorithm. The feature which appears on the top of the decision tree is the best feature for the classification problem and coming down the next level, the next best features will be available. In this way a threshold is cut manually to select the number of features required for classification. All 12 features are ordered in the descending order of importance. Out of which only 8 features are appearing in the decision tree and rest of the 4 features are taken in the random order. An experiment was carried out by using only the top most features and classification accuracy was noted down, then top two features were selected and corresponding classification accuracy was noted. The process was continued till the classification accuracy for all the features were noted It is found that 7 features namely standard deviation, maximum, minimum,sum, skewness, kurtosis and range was found to be the best contributing features.

V. FEATURE CLASSIFICATION

In this paper, nested dichotomy classifiers are used for feature classification. The selected features are further classified using the below detailed nested dichotomy classifiers. Jegadeeshwaran and Sugumaran [17] have detailed the deployment of this classifiers.

A. Nested Dichotomy (ND)

A system of nested dichotomies is a hierarchical decomposition of a multi-class problem with c classes into $c - 1$ two-class problems and can be represented as a tree structure. Ensembles of randomlygenerated nested dichotomies have proven to be an effective approach to multi-class learning problems. The decomposition canbe represented as a binary tree (Figure. 4). Each node of the tree stores a set of class labels, the corresponding training data and a binary classifier. At the very beginning, the root node contains the whole set of the original class labels corresponding to the multi-class classification problem. This set is then split into two subsets. These two subsets of class labels are treated as two "meta" classes and a binary classifier is learned for predicting them. The training dataset is split into two subsets corresponding to the two meta classes and one subset of training data is regarded as the positive examples while the other subset is regarded as the negative examples. The two successor nodes of the root inherit the two subsets of the original class labels with their corresponding trainingdatasets and a tree is built by applying this process recursively. The process finally reaches a leaf node if the node contains only one class label.It is obvious that for any given c-class problem, the tree contains c leaf nodes (one for each class) and $c-1$ internal nodes. Each internal node contains a binary classifier. Dong, Frank andKrammer [20-21] explicitly detailed the nested dichotomy classifier.

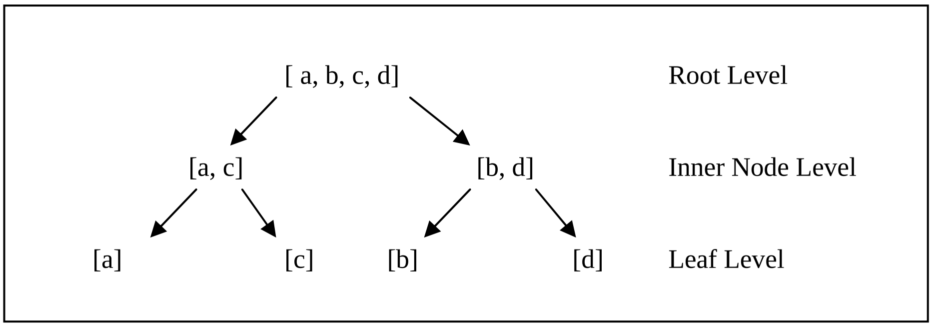


Fig. 4. Nested Dichotomy Tree

B. Class-balanced nested dichotomies

In light of these observations considered two different sampling strategies inthis paper. The first method is based on balancing the number of classes ateach node. Instead of sampling from the space of all possible trees, sample from the space of all *balanced* trees, and build an ensemble of balanced trees.The advantage of this method is that the depth of the tree is guaranteed to belogarithmic in the number of classes. This is referred as an ensemble of class-balancednested dichotomies (ECBND).The number of possible class-balanced nested dichotomies is obviously smallerthan the total number of nested dichotomies. The following recurrence relationdefines the number of possible class-balanced trees:

$$T(c) = \begin{cases} \frac{1}{2}\binom{c}{c/2}T(\frac{c}{2})T(\frac{c}{2}) & : \text{ if } c \text{ is even} \\ \binom{c}{(c+1)/2}T(\frac{c+1}{2})T(\frac{c-1}{2}) & : \text{ if } c \text{ is odd} \end{cases}$$

where$T$ (1) = 1 and T (2) = 1.

Dong, Frank &Krammer [20] has explicitly detailed the algorithm for building a system of class-balanced nested dichotomies as below.

if|*C*| = *1* ***then return***

P = subset of C, randomly chosen from all subsets of size [|C|/2]

N = C \ P

Dp= all instances in D apart from those pertaining to classes in P

buildClassBalancedNestedDichotomies(Dp, P)

Dn= all instances in D apart from those pertaining to classes in N

buildClassBalancedNestedDichotomies(Dn, N)

D' = a two-class version of D created based on N and P

classifierForNode = buildClassifier(D')

C. Data-balanced nested dichotomies

The most common problem with the class-balanced approach is that some multi-class problems are very unbalanced and some are much more populated thanothers. In that case a class-balanced tree does not infer that it is also databalanced.This can negatively affect runtime if thebase learning algorithm has time complexity worse than linear in the number ofinstances.

The data-balanced nested dichotomies randomly assignsthe classes to two subsets until the size of thetraining data in one of the subsets exceeds half the total amount of trainingdata at the node. One motivation for using this simple algorithm was that it isimportant to maintain a degree of randomness in the assignment of classes tosubsets in order to preserve diversity in the committee of randomly generatedsystems of nested dichotomies. Dong, Frank &Krammer [20] has explicitly detailed the algorithm for building a system of data-balanced nested dichotomies. Even with our simple algorithm diversitysuffers when the class distribution is very unbalanced. However, it is difficult toderive a general expression for the number of trees that can potentially generated by this method because this number depends on the class distribution in thedataset.

if|*C*| = *1* ***then return***

C = random permutation of C

Dp= Ø, Dn= Ø

do

if(|*C*| >*1*) ***then***

add all instances from D pertaining to first class in C to Dp

add all instances from D pertaining to last class in C to Dn
remove first and last class from C
else
add all instances from D pertaining to remaining class in C to Dp
remove remaining class from C
while$(|Dp| < \lceil |D|/2 \rceil)$ ***and*** $(|Dn| < \lceil |D|/2 \rceil)$
if$((|Dp| \geq \lceil |D|/2 \rceil)$ ***then***
add instances from D pertaining to remaining classes in C to Dn
else
add instances from D pertaining to remaining classes in C to Dp
P = all classes present in Dp,
N = all classes present in Dn
buildDataBalancedNestedDichotomies(Dp, P)
buildDataBalancedNestedDichotomies(Dn, N)
D'= a two-class version of D created based on N and P
classifierForNode = classifier learned by base learner from D'

VI. RESULTS AND DISCUSSIONS

The experiments were conducted on atest rig wherein the bearings were made to run under real time conditions till it fails naturally. The data thus collected from this experiments are discussed in the below sections.

A. Effect of number of features on Clasification accuracy

The vibration signals acquired at regular intervals are further extracted into 12 descriptive statistical features like standard deviation, mean, mode, median, kurtosis, skewness, sample variance, standard error,minimum,maximum, sum and range. Decision tree algorithm was used to select the best contributing features for the given data set. The effect of number of features on the classification accuracy is listed in the Table I. This data reveals that the classification model performs at its best with top 07 selected features.

TABLE I. Effect of number of features on Classification Accuracy

No. of Features	**Classification Accuracy (%)**		
	ND[1]	**CBND[2]**	**DNBND[3]**
1	80.00	79.88	79.88
2	89.94	90.26	90.30
3	94.59	94.07	94.27
4	94.71	94.79	94.87
5	94.87	94.91	94.91
6	95.07	94.99	94.75
7	**94.91**	**95.19**	**95.19**
8	94.55	94.59	94.83
9	94.59	95.03	95.19
10	95.11	94.87	94.55
11	94.67	94.71	94.59
12	94.79	94.83	94.27

[1]ND= Nested Dichotomy ; [2]CBND= Class Balanced Nested Dichotomy ;
[3]DNBND= Data Near Balanced Nested Dichotomy

B. Nested Dichotomy Algorithm

The selected features were further taken-up for the classification using the Nested Dichotomy classifier. The results of the algorithm for the given experimental data sets are shown via confusion matrix on Table III and detailed accuracy by class on TableII. TP Rate and FP Rate are the important terms when detail the class by accuracy. 'TP rate' stands for true positive which measures the proposition of positives that are correctly identified and 'FP rate' stands for false positive rate which measures the proposition of positives that are incorrectly identified. True positive should be close to 1 and false positive rate should be close to 0 for better classification accuracy. In the present study, from Table II, the closeness of 'TP rate' to '1' and 'FP rate' to '0' describes the classification accuracy. Similarly Table III represents the results via confusion matrix. The diagonal elements in the confusion matrix are the correctly classified instances and the other elements in that row are the incorrectly classified instances. The overall classification accuracy for the given data set using the Nested dichotomy classifier is 94.91%.

Total number of instances	2496
Correctly classified instances	2369 (94.91%)
Incorrectly classified instances	127 (5.08%)
Kappa statistic	0.936
Mean absolute error	0.028
Root mean squared error	0.135

TABLE II. Detailed accuracy by class for Nested Dichotomy

	TP Rate	FP Rate	Precision	Recall	F-measure	ROC Area	Class
	0.996	0	1	0.996	0.998	0.999	Stage-1
	0.91	0.033	0.873	0.91	0.891	0.967	Stage-2
	0.868	0.024	0.902	0.868	0.885	0.964	Stage-3
	1	0.007	0.973	1	0.986	0.998	Stage-4
	0.972	0	1	0.97	0.98	0.99	Stage-5
Weighted Average	0.949	0.013	0.95	0.949	0.949	0.984	

Stage-1:New ; Stage-2:1000 hrs ; Stage-3:1250 hrs ; Stage-4:1500 hrs ; Stage-5:1800 hrs

TABLE III. Confusion Matrix for Nested Dichotomy

Category	a	b	c	d	e	
a	494	0	2	0	0	a = Stage-1
b	0	455	45	0	0	b = Stage-2
c	0	66	434	0	0	c = Stage-3
d	0	0	0	500	0	d = Stage-4
e	0	0	0	14	486	e = Stage-5

C. Class Balanced Nested Dichotomy Algorithm

Class balanced nested dichotomy algorithm yeilds best results with the top selected 07 features as shown in the Table I. The overall classification accuracy of this classifier for the given data set is 95.19%. Table IVand Table Vdetails the accuracy by class and confision matrix results for the class balanced nested dichotomy clasifier. The precision value indicates the fraction of retrieved instances that are relevant whereas the recall value indicates the fraction of relevant instances that are retrieved. The value of precision and recall is close to 1 which indicates the data is correctly classified.

Total number of instances	2496
Correctly classified instances	2376 (95.19%)
Incorrectly classified instances	120 (4.80%)
Kappa statistic	0.939
Mean absolute error	0.026
Root mean squared error	0.129

TABLE IV. Detailed accuracy by class for Class Balanced Nested Dichotomy

	TP Rate	FP Rate	Precision	Recall	F-measure	ROC Area	Class
	0.994	0	1	0.994	0.997	0.999	**Stage-1**
	0.89	0.029	0.885	0.89	0.887	0.969	**Stage-2**
	0.884	0.029	0.886	0.884	0.885	0.972	**Stage-3**
	1	0.003	0.99	1	0.995	0.999	**Stage-4**
	0.992	0	1	0.992	0.996	0.997	**Stage-5**
Weighted Average	0.952	0.012	0.952	0.952	0.952	0.987	

Stage-1:New ; Stage-2:1000 hrs ; Stage-3:1250 hrs ; Stage-4:1500 hrs ; Stage-5:1800 hrs

TABLE V. Confusion Matrix for Class Balanced Nested Dichotomy

Category	a	b	c	d	e	
a	493	0	2	1	0	a= Stage-1
b	0	445	55	0	0	b= Stage-2
c	0	58	442	0	0	c= Stage-3
d	0	0	0	500	0	d= Stage-4
e	0	0	0	4	496	e= Stage-5

D. Data Near Balanced Nested Dichotomy Algorithm

Data near balanced nested dichotomy algorithm yeilds best results with the top selected 07 features as shown in the Table I. The overall classification accuracy of this classifier for the given data set is 95.19%. Table VI and Table VII details the accuracy by class and confusion matrix resuls for the data near balanced nested dichotomy clasifier. F-measure is the balanced mean between precision and recall. The value of F-measure closeness to 1 as per the below table 6 determines the accuracy of the classifier.

Total number of instances	2496
Correctly classified instances	2376 (95.19%)
Incorrectly classified instances	120 (4.80%)
Kappa statistic	0.939
Mean absolute error	0.026
Root mean squared error	0.128

TABLE VI. Detailed accuracy by class for Data Near Balanced Nested Dichotomy

	TP Rate	FP Rate	Precision	Recall	F-measure	ROC Area	Class
	0.996	0	1	0.996	0.998	0.999	**Stage-1**
	0.88	0.027	0.891	0.88	0.885	0.969	**Stage-2**
	0.892	0.031	0.878	0.892	0.885	0.974	**Stage-3**
	1	0.003	0.992	1	0.996	0.999	**Stage-4**
	0.992	0	1	0.992	0.996	0.997	**Stage-5**
Weighted Average	0.952	0.012	0.952	0.952	0.952	0.987	

Stage-1:New ; Stage-2:1000 hrs ; Stage-3:1250 hrs ; Stage-4:1500 hrs ; Stage-5:1800 hrs

TABLE VII. Confusion Matrix for Data Near Balanced Nested Dichotomy

Category	a	b	c	d	e	
A	494	0	2	0	0	a= Stage-1
B	0	440	60	0	0	b= Stage-2
C	0	54	446	0	0	c= Stage-3
D	0	0	0	500	0	d= Stage-4
E	0	0	0	4	496	e= Stage-5

E. Comparitive Study

The classification accuracy of the nested dichotomy classifiers are listed in the Table VIII. Data near balanced nested dichotomy classifier performs best for the given data set with 95.19%. However the class balanced nested dichotomy classifier performed equally the same with respect to the DNBND. Table 1 reflects the classification accuray of the classifiers against the number of features. The kappa statistic, mean absolute error and root mean squared error are the key performance metrics for comparing the performance of the classifiers. The kappa statistic is a metric that compares anobserved accuracywith anexpected accuracy. The kappa statistic is used to evaluate classifiers amongst themselves. The above results shows that the kappa value for CBND and DNBND is higher that the ND classifier. Mean Absolute Errors (MAE) measure, the closeness value of predictions to the eventual outcomes. Root Mean Squared Error (RMSE) is the measure of difference between the predicted values and observed values.The MAE and RMSE analyzes the variation in the errors in predictions. The RMSE will always be higher in value or equal to the MAE; the greater difference between them, the greater the *variance* in the individual errors in the sample. The MAE and RSME for CBND and DNBND is lower than the ND classifer for the given data set.

TABLE VIII. Comparion Study

S. No.	Name of the Classifier	Classification Accuracy (%)
1	Nested Dichotomy	94.91
2	**Class Balanced Nested Dichotomy**	**95.19**
3	**Data Near Balanced Nested Dichotomy**	**95.19**

VII. CONCLUSION

Estimating the life time of bearings and monitoring the health condition of the bearings are widely accepted by the industries and well received in the recent times. This paper presented a predictive method to estimate the remaining useful life of the bearings based on nested dichotomy clasifiers. This method is based on the machine learning principles. The bearings are made to run at stated conditions that are similar to real time applications. The vibration signals are acquired at defined intervals till the bearing fails naturally. Statistical features were extracted and top contributing features were selected using the decision tree algorithm. Thus selected features were used to construct the model based on the ND,CBND and DNBND classifiers. The predictive model built on the CBND and DNBNDyieldsbetter classification accuracycompared to the Nested Dichotomy Classifier. This model that was tested with the bearing life data can also be horizontally deployed for predicting the remaining life of all other critical components.

NOMENCLATURE

ND	Nested Dichotomy
CBND	Class Balanced Nested Dichotomy
DNBND	Data Near Balanced Nested Dichotomy

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