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PREDICTING THE FAULTS IN INDUSTRIAL METALS USING SUPPORT VECTOR MACHINE

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ABSTRACT

Ball-bearing faults are one of the main causes of the breakdown of industrial machines. The main objective of this paper is to build a predictive model for identifying the bearing fault. Dataset collected from the Prognostic Centre of Excellence is used for prediction. Using the WEKA tool, the dimensionality of the features is reduced using Principal Component Analysis (PCA) and the chosen features are ranked in order using the Sequential Floating Forward Selection (SFFS) for decreasing the number of information elements and observing the most relevant feature set. At last, these chosen features are passed to Support Vector Machines (SVM) and Artificial Neural Networks (ANN) for predicting and grouping the different bearing imperfections. The trained model is tested with the testing dataset. The results compare the effectiveness of the classifiers based on the selection and the reduction of features, the classification accuracy of SVM is better than ANN. With the help of the proposed method, bearing faults will be identified earlier which will improve the productivity of the machines.

Keywords: WEKA, Support Vector Machine, Artificial Neural Network, Sequential Floating Forward Selection, Principal Component Analysis.

I. INTRODUCTION

This paper chooses Ball-Bearing as the main component Because it is a part that is present in every industrial machine. Ball-bearing is an important part of every industrial machine. Due to environmental impacts and the longer rotation time of the machine, the bearing's thickness will get reduced, resulting in inner race defect, outer race defect, and complete ball defect. According to machinery statistical data, 90 % of the machinery faults occur due to bearing faults and it will affect the productivity of the machines. So, it is important to predict the faults at the early stages to avoid unnecessary failure of the machine.

The dataset has been collected from PCOE (Prognostic Centre of Excellence) which is widely used for machinery fault prediction. The effective performance of fault prediction is not only based on the signals collected, feature selection and feature reduction play a crucial role in making predictions accurate. First, the collected vibration data are analyzed with Exploratory Data Analysis [EDA]. The null values and missing values are replaced by analyzing the scoring strength of every independent feature. Then, the Categorical Encoding process is done using the label encoding method for changing the categorical values to real numbers to make the prediction easier. The processed data set is given for principal component analysis to reduce the dimensionality of the features. The feature strength is identified using Pearson Correlation Analysis. The Sequential Forward Floating Search algorithm is used for feature selection.

This paper mainly focuses on building a predictive model for identifying the faults in bearings such as inner race defect, outer race defect, and complete ball defect at a very early stage using a support vector machine. The obtained features are given to Support Vector Machines (SVM) for predicting the faults. The trained SVM model is tested using the remaining dataset. The accuracy score proves to be better than the existing model. The derived results are useful for preventing unexpected machine breakdowns resulting in financial losses.

II. RELATED WORK

Choosing suitable algorithms and techniques for different purposes is a vital part of the domain of Machine Learning. Various works related to machine learning prediction are carried forward as follows. In [1], The paper compares three different datasets with a single machine learning algorithm- RNN to check the efficiency of that particular algorithm. In [2], The paper suggests a low-cost non-contact optimal sensor placement (NC-

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OSP) methodology to know similar features and quality related to this device. Experiments were carried out using different circumstances under various work levels and placement orientations. Careful selection and setting of position finders are the most important part of constructing and implementing an effective condition monitoring system. There is a continual call for depletion and operational worth of rotating elements. Keeping an eye on the health of bearings is the crucial component of this machinery. The effectiveness and reliability approach for observing the state of gait is influenced by signal processing techniques and the location of the detector chosen for fault characteristic extraction. In [3], Using Deep neural networks, the remaining life of the ball bearing is predicted. A demonizing auto encoder-based DNN is used to differentiate the gain signals of the seen stance into a variety of degradation stages. The representative attribute is taken directly from the raw wave by coaching the DNN. In [6], The prediction of fault is carried out by various algorithms such as Artificial neural networks, Computational Neural Networks, and Random forests. The result shows that Artificial Neural Networks have better accuracy. Finally, in [7] the remaining useful life of the bearing is predicted using the computational frameworks by analyzing the electric current discharge.

III. PROPOSED METHOD

The predictive model is designed to predict the faults in ball bearings and provides classifications such as Inner race defect, outer race defect, and total ball defect. The results are obtained using the data collected from the sensors placed at different locations in an industrial machine. This will improve the productivity of the machines and prevent breakdowns. The predictive model is built using a Support Vector Machine. The model is built using a Support Vector Machine. This algorithm works well with a greater number of features in the dataset. SVM works well as there is a clear separation between classes. It is more memory efficient for classification problems.

Motor_Load_(HP)	Time	Amplitude	Raw/Envelope_Spectrum	Frequency	pk_pk1	pk_pk2	pk_pk3	pk_pk4	pk_pk5
1	17	1	1	69	2	1	2	2	1
1	10	2	1	76	2	1	2	1	1
1	43	2	2	71	1	1	2	1	1
1	6	2	1	81	1	1	1	1	1
4	20	2	1	78	1	1	1	1	1
1	39	2	1	54	1	1	2	1	1
1	4	2	2	77	1	1	1	1	1
1	24	2	1	23	1	1	2	1	1
1	18	2	1	47	1	1	1	1	1
1	13	2	1	81	2	1	1	1	1

Figure 1: Overview of the dataset

Dataset collected from the Prognostic Centre of Excellence is used for prediction. The bearing dataset table consists of 96 features, classified into three categories. The attributes include motor load, Time, Frequency, raw envelope spectrum, normal baseline, drive end fault, fan end fault, etc., fig 1 shows an overview of the PCOE Dataset. The fault condition values are visualized in fig 2.

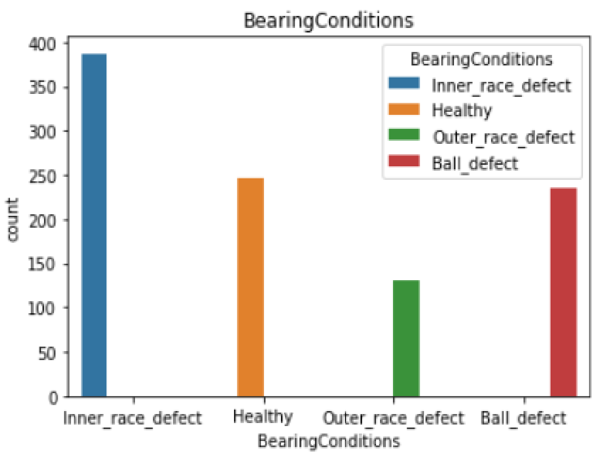

Figure 2: Bearing conditions in the dataset

The dataset is loaded initially and it is split into training and testing data using the Holdout cross-validation method. The libraries are imported from the weka tool. These are used for availing the functionalities within the java code. In the preprocessing step, the data is handled for missing data. The missing data is replaced with the average mean values. This is done to improve the algorithm's performance.

These training and testing datasets with and without target variables are loaded into the environment for prediction. The artificial Neural Network model is built for comparison. The proposed predictive model built using a Support Vector Machine is compared against the model built with an Artificial Neural Network. The models are compared in terms of recall, f1 score, accuracy, and precision. The comparison proved that the model built using Support Vector Machine performs better than Artificial Neural Network.

IV. EVALUATION

Evaluating the model is the most important part of building a machine learning model. It works on a constructive feedback model. After building a model, feedback from performance metrics is considered to make improvements. This process is continued until a desirable accuracy is achieved. The performance of the model is measured by evaluating it. It is vital to check the accuracy of the model before computing predicted values.

- Accuracy is a metric that gives the fraction of results that the model predicted right.
- Recall, precision, and f1-score are the most important classification metrics and are plotted for proposed and existing models for comparison.
- The recall is the true positive rate and gives the fraction of positive values we identified correctly with the total values (True Positive + False negative).
- Precision gives the fraction of correctly identified true positive values with all predicted positive values (True positive + False positive).
- The average value of recall and precision is the fi-score. Thus, the proposed model proves to be the best at giving better accuracy.

The Proposed algorithm gives better accuracy. Table 1 shows the Performance comparison of classifiers with feature reduction and feature selection.

Table 1. Performance comparison of classifiers with feature reduction and feature selection

PARAMETERS	FEATURE SET	ANN	SVM
Accuracy	4-82	0.8065(±0.05)	0.9543(±0.03)
Precision	4-82	0.7899(±0.02)	0.9719(±0.01)
Recall	4-82	0.7632(±0.06)	0.9632(±0.01)
F measure	4-82	0.8165(±0.05)	0.9178(±0.05)
Execution Time	4-82	0.09 sec	0.04 sec

From the below graph, It is proved that the model built using Support Vector Machine has higher accuracy than Artificial Neural Networks.

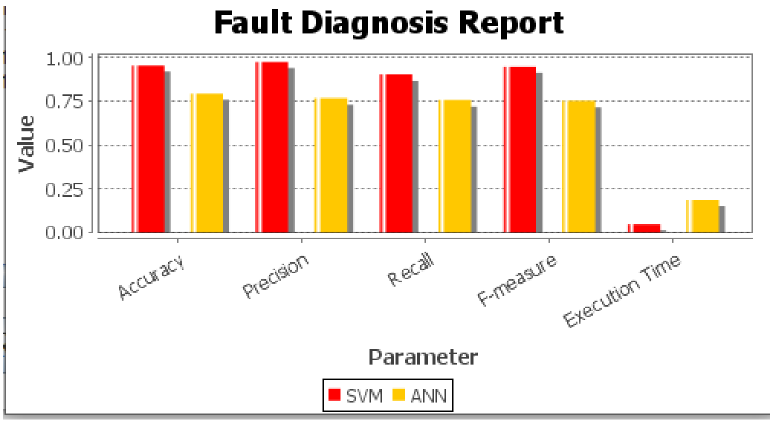

Figure 3: Comparison between ANN & SVM

V. CONCLUSION

This study presents a procedure for the detection of bearing faults by classifying them using a machine learning method, namely, SVM. Attributes are hauled from hour-land shivering gestures using different ways. The procedure incorporates the most appropriate features selected by a filtering algorithm, which uses a Principal Component analysis and Sequential Forward Floating Search. The pulse responses observed for different fault conditions of a motor show that severe disturbances occur under them with rough inner race surface and ball with corrosion hole. The effect of combined defect has also signed on the vibration of a rotor-bearing system. It is also picked out that the ranking precision for SVM is superior to that of ANN. The results show the potential application of a machine learning algorithm for developing a knowledge base system that can be useful for early diagnosis of defects for applying condition-based maintenance to prevent catastrophic failure and diminish intervention value.

VI. FUTURE WORKS

In upcoming work, proxy methods for collapse sensing can be investigated (e.g., based on other computational models such as spiking neural networks which seem to be resilient to missing data), as well as methods for estimating the information content in the data concerning solving a particular machine learning task. Also, alternative sampling methods are often investigated, where the great samples are taken just after a machine was maintained, instead of just before a traditional power.

- In the future, the dimension of the fault location will be identified.
- Testing of the model can be done with different datasets acquired from various machine parts.

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