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MACHINE LEARNING BASED FAULTY BEARING DIAGNOSIS IN CNC MACHINE

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Abstract: **The prediction of faulty bearing in rotating machineries like CNC machine, induction motor, wind turbine etc. is very important. Bearings are essential parts of such machines and mechanical systems to reduce friction between moving parts and to support the weight of rotating machineries. The noise produced by the machine can make it difficult to detect a fault or diagnose a problem. This is because the noise can mask or obscure the signal that would indicate a fault. To overcome this challenge, researchers may need to use advanced signal processing techniques to separate the signal of interest from the background noise. In this proposed work the vibration signal responses of CNC machine bearing was studied during faulty and normal bearing conditions. Early faulty bearing diagnosis was made using Support Vector Machines (SVM) to identify whether a bearing is faulty or not, what type of fault it has (inner race, outer race, or rolling element fault). This model is effective when there is a clear boundary between the classes by finding a hyper plane that separates the data into different classes. To decompose the signal Fourier transform is used to analyze signals in the frequency domain. It decomposes a signal into its constituent frequencies. Once the model is trained and tested, we can visualize the accuracy, precision, recall, and F1 score using confusion matrix to show how many normal and faulty behavior instances were correctly or incorrectly classified by the model.**

Keywords: **Vibration signal, CNC machine tools, bearing fault diagnosis, SVM, Fourier transform**

I. INTRODUCTION:

CNC (Computer Numerical Control) machines are widely used in industry for a variety of purposes, including manufacturing, prototyping, and engineering. These machines are highly automated and operate with precision and accuracy, making them a popular choice for industrial processes that require high levels of precision and repeatability. Bearings are used in a wide variety of applications, from large industrial machinery to small household appliances. Some common uses of bearings include in automobiles, airplanes, industrial equipment etc. Bearing fault diagnosis is a common task in machine condition monitoring, where the goal is to detect and classify faults in bearings based on their vibration or acoustic signals. The application of machine learning have been successfully applied to this task, but some of the most popular ones are used by several researchers are Support Vector Machines (SVM), Random Forest (RF), Neural Networks, K-Nearest Neighbors (KNN). Machine learning models are algorithms that enable computers to learn from data and make predictions or decisions based on that data. These models are built using statistical and mathematical techniques to find patterns and relationships in the data, and then use those patterns to make [1-3]. Bearing is a basic mechanical component in rotating machines such as CNC machine, wind power production, high-speed electric multiple unit (EMU) etc. [4]. Bearing fault diagnosis using vibration signals to predict bearing failure various rotating machines in industry [5]. Artificial neural network (ANN) used in automated detection and diagnosis of machine conditions, Support vector machine (SVM), has applications in the areas of machine learning, computer vision and pattern recognition because of the high accuracy and fine generalization ability [6-7]. Data-driven shallow ML approach like artificial neural network (ANN), hidden Markov model (HMM), and support vector machine (SVM), and other offers distinct fault feature extraction models for different problems and have limited generalization capacity [8-9]. Recently HSD was implemented along with gentle Adaboost for bearing fault diagnosis in CNC [10]. A fault diagnostic technique based on cascading failure is presented to assure the safe functioning of CNC machines. [11]. Iqbal and Madan [12] proposed a CNC machine bearing fault diagnosis based on Convolution Neural Network (CNN) approach. In this study two type of signal vibration and acoustics are taken into consideration and STFT technique is used to handle the raw data. Because of the long-term use of CNC machine tool abrasions and fatigues of its mechanical components are unavoidable, due to which various types of failures occur in the manufacturing environment during the operation of machine tools. Teti et al. [13] investigated that in today's digital manufacturing almost 79.6% downtime of machine tool is caused by the mechanical failures. Recently another technique to predict the CNC machine bearing fault diagnosis using HSD and Gentle Adaboost learning is presented [14].

From the literature, it has been observed that most of researchers used vibration signals for bearings in rotating machine, there is lack of research work of fault diagnosis for CNC machine bearings, except few, most researchers have worked on CNC machine bearing fault diagnosis. Therefore it has been also observed from the literature, the noise produced by the machine can make it difficult to detect a fault or diagnose a problem. This is because the noise can mask or obscure the signal that would indicate a fault. For example, if a bearing is worn out and producing a high-pitched whine, the noise of the machine or other components may make it difficult to hear the whine or identify its source. To overcome this challenge, researchers may need to use advanced signal processing techniques to separate the signal of interest from the background noise. This may involve filtering out specific frequencies or using Fourier transform and SVM algorithm to identify patterns in the data that indicate a fault whether a bearing is faulty or not, and if so, what type of fault it has (inner race, outer race, or rolling element fault).

The noise produced by the machine can make it difficult to detect a fault or diagnose a problem. In this paper PCA can help remove noise from the data by identifying and removing the principal components that correspond to noise.

This paper is organized in the following manner: section 2 Machine learning work, section 3 methodology of the CNC machine bearing fault diagnosis, section 4 briefly describes experimentation used in the proposed work. Section 5 Feature Extraction methods. In the last, the results and conclusion are summarized in section 6.

II. MACHINE LEARNING (ML)

ML is the method of developing an inductive model that learns from a narrow amount of data without the involvement of an expert. This learning entails identifying an underlying set of structures that can be used to understand relationships in data that may not be identical to the data on which the learning happened. The SVM algorithm works by finding a hyper plane that separates the normal and faulty behavior in the feature space. In the classification of ML models, two types of learning are, supervised learning that predicts an output variable using labelled input data. Whereas unsupervised learning draws conclusions from data without labeled inputs. Supervised learning differentiate predict a quantitative variable called regression and models that predict a categorical variable called classifiers.

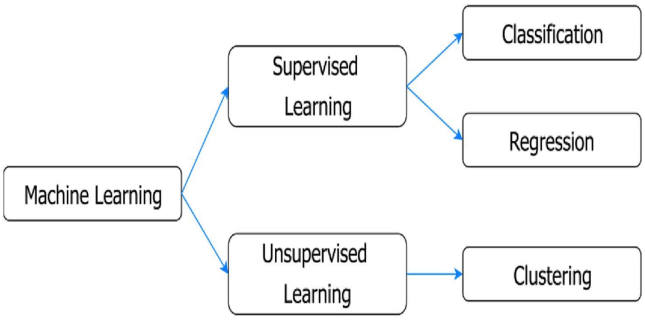

Fig. 1 description of ML

The ML method can be broken down into several steps:

Data acquisition and data transformation: where various data sets and modalities may be joined and outliers cleared.

Feature selection and extraction: From the data, essential signals and attributes are recognized and taken out.

Model selection: based on the job to be performed an effective model is selected.

Validation: At the last a task-specific performance measure, is used and assessed on a validation set of data. The performance measures are classification accuracy, mean absolute error and regression.

III. METHODOLOGY OF THE PROPOSED WORK:

A brief explanation of the proposed work will provide the basic information regarding the proposed work. CNC machine bearing fault detection using machine learning (ML) is a promising approach to detect and diagnose faults in real-time. ML algorithms can be trained to analyze vibration and other sensor data from CNC machines to identify patterns indicative of bearing faults.

The steps to follow to implement a CNC machine bearing fault detection system using ML:

1. Collect data: First, we need to collect vibration and sensor data from CNC machines by using sensors such as accelerometers, tachometers.
2. Pre-process data: Once we have collected the data, need to preprocess it to remove noise and prepare it for ML algorithms. This can include filtering, resampling, and feature extraction.
3. Train the SVM machine learning model using preprocessed data. The model should be trained on data from healthy bearings and bearings with faults.
4. After training the model, we need to test it on new data to check the performance matrices such as accuracy, precision, recall, and F1-score to evaluate the model's performance.
5. Deploy it to the CNC machines once we satisfied with the model's performance. The model can continuously monitor the sensor data from the CNC machines and alert operators when it detects a fault in the bearings.

Implementing a CNC machine bearing fault detection system using ML can improve machine reliability, reduce downtime, and increase productivity.

IV. EXPERIMENTAL SETUP

The experiment for defect detection is conducted out on the test rig and the experimental setup is depicted in Figure 4. Due to the complicated structure of the CNC machine servo axis and weak signs of incipient deterioration the traditional health evaluation approaches are challenging in the in-service context. The proposed method for detecting incipient servo axis deterioration in CNC machining centers is presented to overcome this restriction. The experimental setup is made out of an encoder signal acquisition system. The experiments are performed on 1.5KW spindle type AC induction motor. The highest spindle speed of MCL-12 is 2800 rpm. The experimental setup for encoder signal acquisition system is shown in Figure 2. During the operation on CNC machine tool several torque loads, including 60, 90, and 110 Nm, were tested at a constant input shaft speed of 18 Hz. It was usual to check the bearings in multiple configurations (outer race, normal bearing, inner race, and ball defected bearing states). In each inspection, the vibration signatures for both the exterior and internal accelerometers were acquired. Table 1 shows the data collected from the test settings. Vibration data for internal and external vibration tests acoustic noise of bearing is acquired by using a B&K 4394 IEPE-type and LM393 microphone accelerometer. The specifications of bearing are illustrated in table 1. Both the sensor was installed radially on the ring gear's outer surface; a Michigan Scientific B6-2 slip ring was utilized to transmit the acceleration signal from the internal accelerometer to the signal.

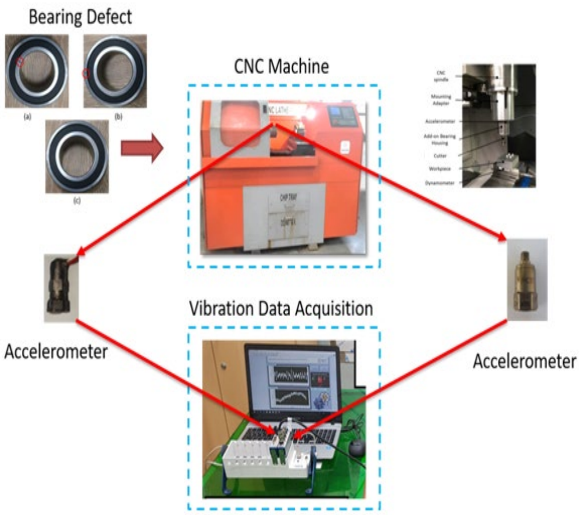

Fig. 2 Experimental setup of data acquisition for CNC machine fault diagnosis system

Pitch diameter	37.9 mm	Outer diameter	52 mm
Ball diameter	8.7 mm	Contact angle	0
Bore diameter	25 mm	No. of ball (z)	8

Table 1 Specification of bearing

V. THE FOURIER TRANSFORM:

The Fourier Transform is a mathematical technique that allows us to represent a signal or function in terms of its frequency components. Fourier analysis breaks down a signal into frequency components and evaluates how strong they are. The Fourier Transform decomposes a signal into its constituent sinusoidal waves, which can be represented as a sum of sine and cosine waves of different frequencies, amplitudes, and phases.

The Fourier Transform is defined as follows:

$F(\omega) = \int f(t)\, e^{(-i\omega t)}\, dt$

where $F(\omega)$ is the frequency-domain representation of the signal, $f(t)$ is the time-domain representation of the signal, i is the imaginary unit, ω is the frequency variable, and the integral is taken over all time.

The inverse Fourier Transform allows us to convert the frequency-domain representation of a signal back into its time-domain representation:

$f(t) = (1/2\pi) \int F(\omega)\, e^{(i\omega t)}\, d\omega$

where $f(t)$ is the time-domain representation of the signal, $F(\omega)$ is the frequency-domain representation of the signal, and the integral is taken over all frequencies.

5.1 Feature Extraction Using PCA:

PCA (Principal Component Analysis) is a statistical technique used to reduce the dimensionality of a dataset by identifying the most important variables that explain the maximum variance in the data. PCA is not typically considered a machine learning algorithm, but rather a data preprocessing technique that can be used in conjunction with machine learning algorithms. PCA is often used to preprocess data in machine learning tasks, such as image recognition or natural language processing. In these cases, PCA can help to reduce the dimensionality of the data and improve the performance of the machine learning algorithm.

VI. RESULTS AND CONCLUSION:

SVM can effectively classify different types of bearing faults, such as inner race fault, outer race fault, and rolling element fault. To obtain accurate results using SVM, it is essential to use appropriate features that can capture the underlying characteristics of bearing vibration signals. To predict the bearing fault a confusion matrix of 2x2 was generated for a SVM classifier. For this train the SVM classifier on a labeled training dataset, use the trained SVM

classifier to make predictions and then compare the predicted labels to the true labels in the test dataset.
In table 2 showing fault detection accuracy for different approach for this proposed work. It has been found that the SVM is an effective machine learning algorithm for bearing fault detection, and it can provide accurate and reliable results when trained and evaluated properly. The following hyper-parameters are adjusted as mini-batch (128), epochs (100), learning rate (0.0001) with adaptive moment estimation (adam) optimizer.

Method	Accuracy Rate	Computational Time
Logistic Regression	89.85	0.290
Random Forests	92.30	0.201
Decision Tree	96.60	0.190
SVM	98.50	0.154

Table 2 bearing fault detection using different approaches

The motivation of this paper is to provide a machine learning-based feature extraction from the input signals as manual features could not give better accuracy. The comparison of different classifier and feature extraction methods is showing in table 3. In this proposed work PCA based feature extraction was implemented and then SVM model was trained on the basis of extracted features.

Classifier/ feature	HOG	LDA	ICA	PCA
	59	40	16	89
SVM	97.20	80.3	75.2	98.50
Decision Tree	96.75	79.7	64.8	96.60
Random Forests	92.70	71.6	64.5	92.30
Logistic Regression	85.80	68.9	57.3	89.85

Table 3 Comparison of different classifiers

The performance of model was evaluated after training of SVM model by calculating performance metrics such as accuracy, precision, recall, and F1 score.

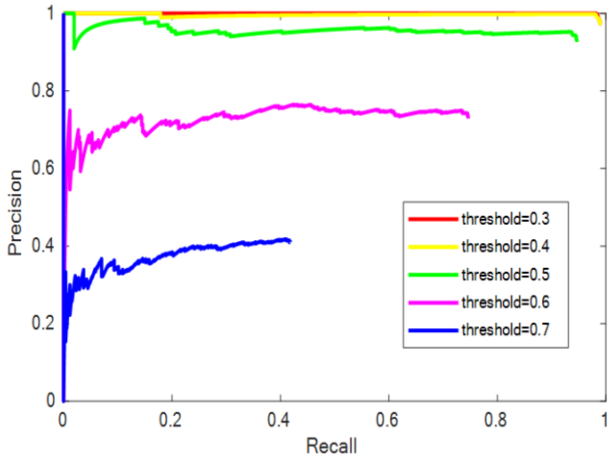

Fig. 3 Precision vs. recall graph for proposed model

- **Accuracy**: It is the ratio of the number of correct predictions to the total number of predictions made by the model. It is a measure of how well the model can correctly predict the classes.
- **Precision**: It is the ratio of the true positive predictions to the total number of positive predictions made by the model. It is a measure of how often the model correctly predicts a positive class when it actually is.
- **Recall**: It is the ratio of the true positive predictions to the total number of actual positive instances in the data. It is a measure of how well the model can identify the positive class instances.
- **F1 Score**: It is the harmonic mean of precision and recall. It provides a balance between precision and recall by giving equal importance to both. The F1 score is a better measure of the model's performance when there is an imbalance in the class distribution.

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