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Creation of a Machine Learning-Based Automated System for the Multi-Component Fault Analysis of Industrial Machines

Abstract: - The efficiency and reliability of industrial machines are paramount for ensuring smooth operations and minimizing downtime in manufacturing environments. However, the complexity of these machines and the multitude of components they consist of pose significant challenges in identifying and diagnosing faults promptly. Traditional fault analysis methods often rely on manual inspection or simplistic rule-based systems, which are time-consuming, subjective, and prone to errors. In this study, we propose the development of a novel machine learning-based automated system for the multi-component fault analysis of industrial machines. Leveraging advancements in artificial intelligence and data analytics, our system aims to revolutionize fault detection and diagnosis by efficiently processing vast amounts of sensor data to identify anomalies and pinpoint potential faults across multiple components simultaneously. The proposed system comprises several key components, including data preprocessing techniques to handle noisy sensor data and extract relevant features, machine learning algorithms for fault detection and classification, and a user-friendly interface for visualization and interpretation of results. Additionally, the system will incorporate techniques for model explain ability to enhance trust and understanding of the automated diagnostic process.

Keywords: Industrial machines, Fault analysis, Machine learning, Automated system, Multi-component faults, Artificial intelligence, Data analytics

Introduction

Virtually every industrial sector makes extensive use of rotating equipment. Machines that spin include things like fans, pumps, compressors, turbines, motors, generators, and so on. Rotating machine components are prone to failure due to continuous operations and different cyclic loading situations, which might result in catastrophic failure. Damages that may occur in rotating machinery include rotor imbalance, shaft misalignment, shaft looseness, bearing inner race fault and outer race fault, fractured gear teeth, and many more. In order to save

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maintenance costs, prevent machine breakdowns, and maximize production, early problem detection is essential. In current industrial age, it is crucial to monitor machine conditions and identify problematic components in a timely manner for maintenance decision making. Predictive maintenance and condition-based maintenance (CBM) are terms that describe this approach to building upkeep. This tactic has been a game-changer in the realm of maintenance technology in the last few years.

Fault Diagnosis

An important part of condition-based maintenance is fault diagnosis, which entails collecting data and then interpreting it technically. Recording the variables for processing, analysis, and interpretation either constantly or occasionally may help identify the error. By monitoring the change in measured or computed variables, both in terms of quantity and rate of change, the malfunctioning machine part may be located. As of right now, the industry makes use of a variety of defect diagnostic methods, such as vibration monitoring, acoustic emission monitoring, oil analysis, wear debris analysis, infrared thermography, sound monitoring, ultrasonic monitoring, etc. There are many different industrial uses for each method, and each has its own set of benefits. One of the most common and effective methods for locating malfunctions in rotating equipment is vibration monitoring. One inexpensive way to diagnose problems with spinning machines is by sound monitoring. The shaft, bearings, gears, rotor, and other spinning mechanical parts generate dynamic forces that cause the system to vibrate. In the event of a malfunction, the machine's vibration pattern will be altered as each component produces increased vibrating forces. Dimensions, rotational speed, etc., allow one to ascertain the distinctive frequency of each component. It is possible to identify a defective component by using its distinctive frequency. A common and fundamental method for studying vibrations, frequency domain or spectrum analysis establishes a relationship between frequency and its constituent parts. In this step, we use the fast-fourier transform (FFT) to convert the collected time-domain data to a frequency-domain signal. For the analysis of sound signals, the same idea works. However, the spectrum analysis method is not very helpful for rotating machines since these machines often have a complicated and extremely non-stationary vibration signature. Vibration analysis methods that are machine specific reach the next step after this.

Modern methods for analyzing vibrations include wavelet transform, orbit, demodulation, order, cepstrum, envelope, and demodulation analyses. It takes a very competent technician with an in-depth familiarity with the equipment in question as well as a solid grasp of the methods used to find faults utilizing these methods. Automating fault detection using pattern recognition algorithms may help address this limitation.The signal pattern or associated defect may be recognized via the classification process utilizing a machine learning algorithm. The use of machine learning may lead to the development of an automated system for defect diagnostics. There are three stages to the process of defect detection utilizing machine learning methods. Classification, feature selection/reduction, and feature extraction are the three of them. Extracting statistical, histogram, wavelet, and other characteristics from acoustic and vibration data is what feature extraction is all about. The two main categories of data reduction strategies are feature reduction and feature selection. Techniques for reducing features include projecting the current features into a higher dimensional space. Without modifying any of the preexisting characteristics, the feature selection approach chooses a subset to use. Decision trees are feature selection tools, whereas independent component analysis and principal component analysis are feature reduction tools. In the third stage of a machine learning process, there are two steps. The initial step is to train the classification algorithms using features extracted from the training data of different types of fault signals. The second step involves using certain test data characteristics to evaluate the trained algorithm.

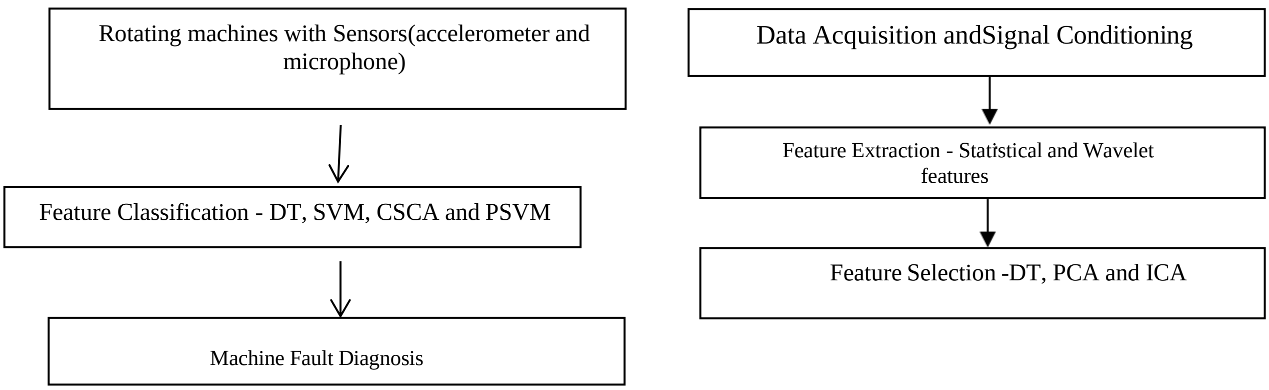
During the categorization process, the defective part is located. There has been a lot of study on whether or not machine learning systems can undertake fault diagnosis. A limited number of fault classes were studied in most studies, and they only looked at one or two components. The amount of components and the number of defects they have determine the number of fault classes. It is critical to verify that machine learning approaches can accurately classify multi-component faults. Additionally, it is crucial to determine how the capacity of machine learning techniques for defect identification in rotating machines is affected by the quantity of components or problem classes. The classification method becomes more challenging as the number of fault classes rises due to the increased likelihood of signal pattern similarities. Using machine learning approaches for problem detection, only few researchers have published on sound signal analysis. Therefore, in this area, in-depth research is necessary. For medium and small businesses, sound signal based fault diagnostics is a great solution since it may be affordable. In order to decrease calculation time by removing unnecessary or duplicated data, dimensionality reduction approaches have gained prominence in the last ten years. Therefore, finding the optimal feature selection method for rotating machine multi-component failure detection is essential. While clonal selection classification algorithms based on artificial immune systems (CSCAs) have seen extensive use in medical diagnostics, their application to the identification of machinery faults has received comparatively little attention. This study aims to test how well CSCA can detect problems with spinning machines. It finds the optimal feature-classifier combination for defect detection in multi-component rotating machines. In several fields, including power generation, transportation, aerospace, and industry, automated fault detection of multi-component rotating equipment is crucial. This is why it is being used for the study project. Using vibration and sound inputs, the goal of this study is to determine the optimal feature-classifier combination for diagnosing multi-component faults in rotating machinery. This research uses a machine learning problem model to determine the optimal feature-classifier combination for automated fault detection in rotating machines. The goal of every step of the machine learning method was to find the optimal feature-classifier combination for rotating machine fault diagnostics.

• The first of the two parts of the problem-solving process involves thinking about a rotating machine with three parts—the shaft, the rotor, and the bearings—and twelve possible failure circumstances.
In the second stage of the research, a four-component rotating machine with 24 possible shaft, rotor, bearing, and gear faults is taken into account.
In the second part of the research, we'll see how well machine learning methods work for defect identification when broken down by component count or problem kind.

• In both stages, when the machine rotated at speeds of 500 rpm, 700 rpm, 900 rpm, and 1100 rpm, an accelerometer recorded vibration data and a microphone recorded sound data for each class. Statistical features, discrete wavelet energy, and energy to entropy ratio characteristics are used to extract fault information from the recorded data. Automated fault diagnosis based on sound is thoroughly investigated in this paper. We compared the vibration signal's behavior to that of the sound signal and spoke at length about the statistical and wavelet characteristics' behavior. Decision tree (DT), principal component analysis (PCA), and independent component analysis (ICA) were some of the dimensionality reduction methods used to choose the most important statistical characteristics. In order to speed up computations, dimensionality reduction methods remove unnecessary or superfluous data. Using decision tree classification, we were able to determine which of three feature reduction strategies was most effective for the rotating machine issue.

Decision trees, support vector machines (SVMs), clonal selection classification algorithms, and proximal support vector machines (PSVMs) were fed the significant statistical data and wavelet features. The outcome provides the optimal feature-classifier pairing for defect detection in rotating machinery.

Figure 1. Flowchart for fault diagnostic procedure



The study's fault information extraction method relied on statistical characteristics and wavelet features applied to vibration and sound inputs. Decision trees, principal component analysis, and independent component analysis were used to decrease the feature count in this study. By doing so, we may cut down on calculation time and eliminate unnecessary data. The next step was to use the same decision tree, SVM, clonal selection classification method, and proximal SVM to identify problems with the rotating machine.

Sound and Vibration Signals Based Fault Diagnosis Using Statistical Features

The spinning machine is able to provide a wealth of information on the various problem states via vibration and sound signals. By examining the collected data on vibration and sound, statistical parameters may be derived for various failure scenarios. The time domain signals provide information about the various flaws as a result of modifying these parameters. These metrics are the statistical features used to identify defects. In this study, eleven statistical variables were used. Numbers like as median, sample variance, range, minimum, kurtosis, standard deviation, and standard error are all part of this. We can extract the eleven most discriminating characteristics using dimensionality reduction techniques. This research made use of a number of dimensionality reduction techniques, such as decision trees, PCA, and ICM. The several classifiers were given these reduced attributes in order to categorize different failure situations. This study makes use of decision trees, support vector machines (SVMs), clonal selection techniques, and proximal support vector machines as classifiers. The study presents its findings for two sets of data, one covering twelve different fault conditions involving the rotating machine's shaft, rotor, and bearings (a three-component system), and the other covering twenty-four different fault conditions involving the gears (a four-component system). The feature reduction techniques and classifiers mentioned earlier are used in conjunction with statistical features extracted from vibration and sound signals.

Incorporating superfluous or redundant data into the statistical features extracted from the vibration and sound inputs could have a detrimental impact on the classifier's performance and computation time. Consequently, getting the data input ready is very important for overcoming these problems. Dimensionality reduction techniques are used to lessen the number of statistical features. Feature reduction and feature selection are the two primary classes of data reduction procedures. One approach to feature reduction is to first generate a higher-dimensional space from the existing features, and then to reduce them. Through the use of feature selection, a subset may be chosen without altering any of the current features. A decision tree was used as a feature selection method, and dimensionality reduction techniques such as principal component analysis (PCA) and independent component analysis (ICA) were employed in this study. We compared the feature-count-efficiency of DT, PCA, and ICA to find the appropriate method and set of important statistical characteristics for future classification studies.

Modern production environments rely on well-oiled industrial gear to keep output constant and costly downtime to a minimum. The intricate architecture of these machines makes it challenging to detect and repair issues promptly because of all the pieces and subsystems that make them up. Traditional methods of fault analysis rely on human inspection or use basic rule-based systems; both approaches are labor-intensive, subjective, and prone to errors. Therefore, there is a strong need for state-of-the-art technology that may significantly improve the efficiency and reliability of industrial processes by changing the way problems are detected and diagnosed.To meet this need, we provide a novel machine learning-based automated method for diagnosing failures in industrial equipment with many components. Our solution aims to transform fault detection and diagnosis by using state-of-the-art data analytics and artificial intelligence to efficiently analyze large volumes of sensor data, spot anomalies, and pinpoint potential faults in several components at once. This article provides a detailed description of our proposed system, including its key characteristics and methodologies, and how it might enhance the operational efficiency of industrial machines by addressing the issues with traditional fault diagnostic methods. Among other things, we cover how to apply various ML algorithms for classification and defect detection jobs, why data pretreatment techniques are important for handling noisy sensor data and extracting important characteristics, and how to implement them. We highlight the requirement of developing an easy-to-use interface for visualizing and interpreting data and using model explainability approaches to further enhance trust and understanding of the automated diagnostic process. Our goal in developing this technology is to provide manufacturers an extendable and dependable solution for troubleshooting industrial machines. Early detection and preventive maintenance, made possible by our technology, may improve the efficiency and reliability of industrial processes by decreasing maintenance expenses and downtime. Rotating machinery and precise motion systems are examples of production-related industrial equipment that might benefit from defect diagnosis based on machine learning.

Applications of machine learning methods, such as precision compensation and defect recognition, might improve the accuracy and reliability of precision motion systems. Applying machine learning methods to rotating machinery might improve the detection and prediction of errors in moving elements, such as gears and bearings. Machine learning-based fault diagnostics could be useful for a variety of industrial equipment, including electrical systems, induction motors, and transformers. These sensors may potentially identify and anticipate faults using thermal imaging analysis, standard signal analysis techniques, and machine learning algorithms. The act of predicting when a machine will require repairs using analytics and past data is known as predictive maintenance, and one use of machine learning in this area is fault analysis. As a result, plant or production line disruptions may be planned for in advance, leading to less downtime and increased productivity.Making use of machine learning to analyze vibration and sound inputs, this study aims to create a system for identifying multi-component problems in rotating equipment. Extracting features, selecting features, and classifying features are the three main components of machine learning methods. We were able to deduce specifics about the various rotating machine failure kinds from the signals. From audio and vibration data, three types of features may be extracted: statistical, discrete wavelet energy, and discrete wavelet energy to entropy. Using the decision tree method, principal component analysis, and independent component analysis, the second stage of the machine learning technique selected the most essential qualities from the recovered features. Using the feature classification approach, features were categorized in order to locate the flaws. Problems with rotating machine fault detection were modeled as machine learning issues in order to determine the best feature-classifier combination for automated fault diagnosis. The objective of each stage of the machine learning approach was to determine the best feature-classifier combination for rotating machine fault diagnoses. Phase one of the two-part inquiry into the matter included testing a rotating machine under twelve distinct failure scenarios including shafts, rotors, and bearings. Afterwards, we examined the machine in motion under 24 distinct fault scenarios involving the shaft, rotor, bearings, and gears. The purpose of these two parts of the study was to compare the performance of machine learning approaches to fault detection based on the quantity of components or types of faults.

Decision tree classification efficiency informed the choice of the best feature selection approach among three alternatives for choosing the wavelet and optimal amount of features.
From a total of twelve and twenty-four fault scenarios, eleven statistical features were derived from vibration and sound data. Out of the three feature selection algorithms, the decision tree technique showed the best performance in dimensionality reduction. There are five defining features for twelve different types of faults, including those involving vibration and audible indications. Despite the increased number of components, the four statistical features were adequate for 24 vibration signal defect conditions. No matter which of the three feature selection procedures used eleven statistical criteria, the mean classification efficiency for all 24 classes of sound signal defects remained below 50%. Therefore, all eleven statistical variables were used for the purpose of future classification study.In this study, the wavelet energy-to-entropy ratio and the wavelet energy are two independent wavelet properties. Discrete wavelet characteristics were obtained by processing the sound and vibration inputs using 59 wavelets. The decision tree approach evaluated the mean classification efficiency of these two discrete wavelet features to find the most successful one. As compared to the wavelet energy to entropy ratio features, the wavelet energy features perform better in both the 12 and 24 fault scenarios of vibration and sound signals. Out of the 59 wavelet energy characteristics, the one with the best classification efficiency was selected. To classify, we used the selected wavelet together with its most notable features.This section will go over the results of the four algorithms that were used to categorize the twelve and twenty-four fault states according to crucial statistical features of the audio and vibration data:

Table 1 Mean classification efficiency of the classifier using statistical features andwavelet features

Classifier	Mean Classification Efficiency %							
	Vibration signals				Sound signals			
	12 classes		24 classes		12 classes		24 classes	
	Statistical Features	Wavelet Features	Statistical Features	Wavelet Features	Statistical Features	Wavelet Features	Statistical Features	Wavelet Features
DT	99.01	97.59	82.28	79.50	75.06	98.52	40.96	89.42
SVM	98.99	97.22	87.11	82.92	82.83	97.63	49.35	92.87
CSCA	87.22	96.42	77.95	81.32	87.83	98.32	48.25	72.35

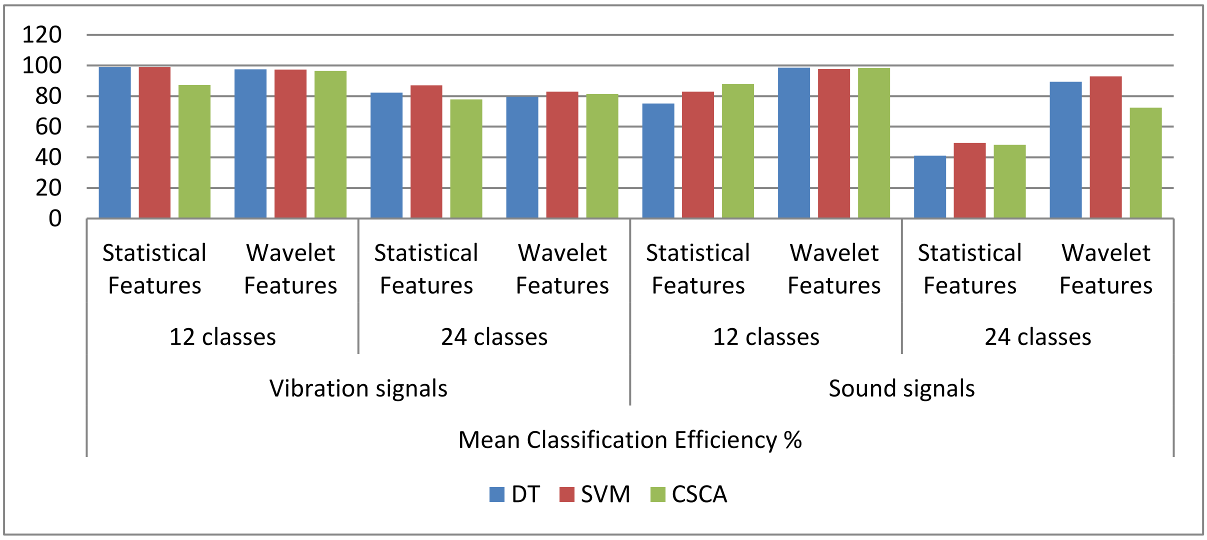


Figure 2.Mean classification efficiency of the classifier using statistical features and wavelet features

Conclusion

The creation of a machine learning-based automated system for multi-component fault analysis of industrial machines represents a significant step forward in optimizing manufacturing operations. By embracing advanced technologies and methodologies, our system has the potential to revolutionize fault detection and diagnosis processes, ultimately leading to improved productivity, reduced downtime, and enhanced competitiveness in the global manufacturing landscape. Additionally, the incorporation of a user-friendly interface for visualization and interpretation of results, along with techniques for model explain ability, enhances the usability and trustworthiness of the automated diagnostic process.

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