Identification of the Health of a Mechanical Device using Machine Learning

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Abstract

Acoustic signal classification is a problem that manifests itself in multiple situations such as voice recognition, sonar classification etc. The problem we aim to solve in this paper is the Health Identification of a mechanical system. We have used Machine Learning and Acoustic Signal Processing to solve this problem. We have captured the audio signal produced by the device, extracted a robust feature set and performed ML-based analysis to detect whether the device is in perfect working condition or suffering a defect. In this paper, we have explained the feature extraction and classification methods that we have adopted to solve the problem. The solution proposed in this paper is an efficient method to identify the fault in the system which does not include any expensive or time-consuming processes. Thus, it would help the manufacturing company to cut down its costs in the quality control department. We have performed comprehensive analysis of multiple ML algorithms. Every algorithm has been discussed in this paper.

Keywords—acoustic signal, feature extraction, machine learning, classification, MFCCs (Mel frequency cepstral coefficients), support vector machine

I. INTRODUCTION

Acoustic signals are sound waves that propagate as disturbances in the ambient pressure level.[1] Audio signals have two main parameters; Amplitude and frequency, which characterize the signal. Other characteristics of the audio signal such as timbre, loudness, intensity etc can be exploited to understand the characteristics of the signal on a more physical level. Machine Learning is an application that provides a system the ability to learn and improve from experience without being explicitly programmed.[2] Machine learning has practically infinite number of applications, such as sales prediction, weather forecast, house pricing etc, but in this project we aim to perform audio signal classification using machine learning.

Machine Learning has been widely used in the field of acoustics. Sound source classification is a major application of machine learning in the field of acoustics. It has also been used in fault detection in mechanical systems. Many NN(neural networks) and CNN(convolutional neural networks) architectures have been used for sound source detection. With continuous development in the field of artificial intelligence, traditional methods which were used initially for audio signal processing is now being replaced by more efficient, more robust and more automated approaches involving multiple ML and DL algorithms. Keeping up with the recent advancements, we have taken an ML approach to a problem involving fault detection in a mechanical system.

We aim to detect gear-based defects in the mechanical system by capturing and processing the audio signal produced, and then applying machine learning algorithms to classify the sample as ‘healthy’ or ‘defective’.

During the manufacturing of any gear-based mechanical system, out of 1000 pieces, a small but significant number of pieces end up having gear-based defects which currently cannot be detected without performing expensive and intensive experiments. Therefore, these samples enter the market, thus hurting the brand-customer relationship. Therefore, there is a need of an ML-based approach to solve this problem using the acoustics produced by the system which would largely benefit the manufacturers by cutting down their losses.

Therefore, the main objective of this paper is to provide an ML approach to classify between a healthy sample and a defective sample of the mechanical system.

II. LITERATURE SURVEY

In [3], research has been done on the application of Support Vector Machines in a system involving fault diagnosis. Here, kernels have been used in the model. This paper has conclusively depicted the robustness of SVMs in high dimensional feature spaces.

In [4], the K-nearest neighbors algorithm has been explored and compared with the SVM to diagnose respiratory pathologies using pulmonary acoustic signals.

In [6], multiple feature extraction techniques have been studied in the audio domain. Features in the time, frequency and the time-frequency domains have been explored. Multiple features like, spectral centroid, RMS power, spectrogram etc have been studied in this paper.

In [8], Mel Frequency Cepstral Coefficients have been deeply explored as a robust feature set for audio signal classification. In this paper, 13 MFCCs have been used for classification.

III. SYSTEM METHODOLOGY

The methodology consists of three broad steps. These include data compilation, feature extraction and classification. These 3 steps are discussed below.

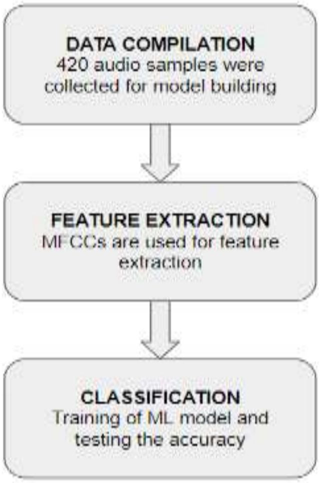

Fig. 1. Proposed System's Flow Chart.

A. *Data Compilation*

For any classification problem to be tackled in an efficient way, collection of a large, clean and noiseless data-set is vital. After sufficient pre-processing which included processes like denoising, normalization, amplification etc, we compiled a data-set of 420 samples. Out of these, 150 samples corresponded to healthy systems while 270 samples corresponded to defective systems.

B. *Feature Extraction*

To solve the classification problem, we have made use of MFCCs(Mel Frequency Cepstral Coefficients) in the feature extraction phase. We have constructed a feature set of 20 features. The advantage of MFCCs over other possible features is that they are highly uncorrelated. This sharply enhances the performance of any Machine Learning algorithm as there is no redundancy among the features.

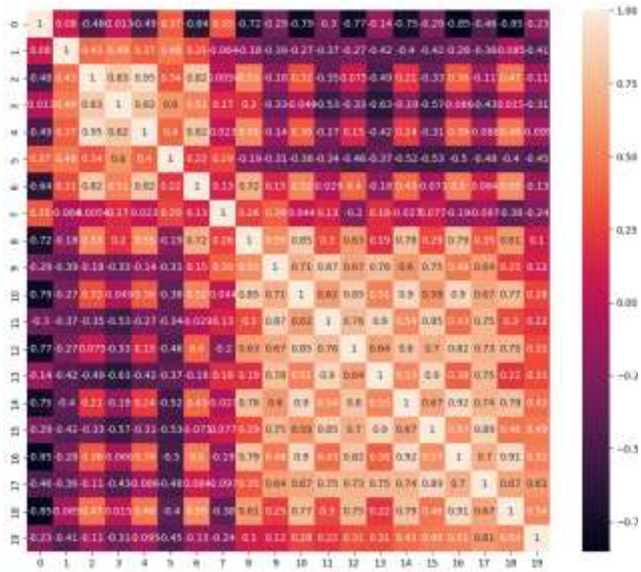

Fig. 2. Correlation Matrix for the feature set.

C. *Classification*

After performing the feature extraction on the data set, the next step is to perform the splitting of the data into two parts for training the model and testing the trained model for accuracy. The training data is about 75% of the total data set and testing data is 25% of the total data set. The classification algorithms used are Logistic Regression, Support Vector Machine (SVM), Extra Tree Classifier.

Classification Algorithms:

1. *Support Vector Machine:*

Support Vector Machine (SVM) is a supervised machine learning algorithm mostly used for classification. The objective of SVM algorithm is to find a hyperplane in an N-dimensional space that distinctly classifies the data points. The dimension of the hyperplane depends upon the number of features. In our case, the dimension of our feature set is 20, therefore the hyperplane will be 20-dimensional. SVMs are extremely effective in high dimensional spaces which makes it the perfect algorithm to solve our problem which is in the 20-D space. SVMs are one of the most used algorithms for classification. This is due to their robustness with respect to accuracy which is achieved because of the margin that accounts for any possible error in training and testing. We used a regularization parameter of C=10 to avoid overfitting. The accuracy of the trained SVM model is 97.14% and it's precision and recall values are 98.5% and 97.05% respectively and the F1-Score is 97.77% and Area under ROC (Receiver operating characteristic) is 97.17%.

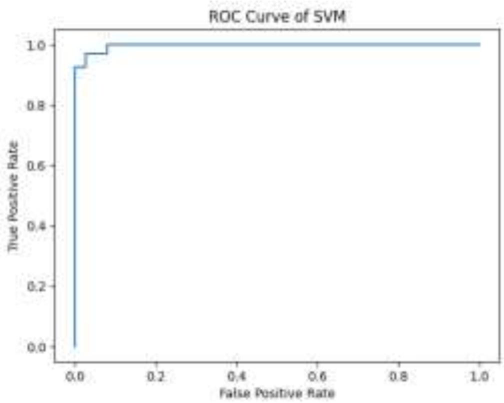

Fig. 3. ROC Curve of SVM

2. *Logistic Regression:*

The First algorithm that we have used for the classification purpose is logistic regression. We applied a regularization parameter C=10 in order to avoid overfitting. We increased the maximum iterations to 10000 to make sure that the algorithm converges. The accuracy of the trained logistic regression model is 87.61% which is less than the SVM model, the precision and recall values are 88.73 % and 92.64% respectively and the F1-Score is 90.64% and Area under ROC (Receiver operating characteristic) is 85.51%.

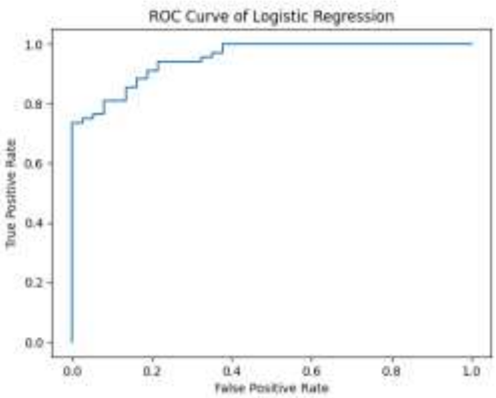

Fig. 4. ROC Curve of Logistic Regression

3. Extra Tree Classifier:

Extra Tree classifier is an ensemble algorithm. This classification method is based on dividing the data sets into multiple data sets and applying the decision tree algorithm to every data set. At first the set of decision trees are formed using the training data and the test nodes are provided with k set of features to each decision tree, the splitting of the k features is based on mathematical formula, which is the Gini index in this case. The accuracy of the Extra Tree classifier is 98.09% which is better than both Logistic regression and SVM models and its precision and recall values are 97.14% and 100% respectively and the F1-Score is 98.55% and Area under ROC (Receiver operating characteristic) is 97.29%.

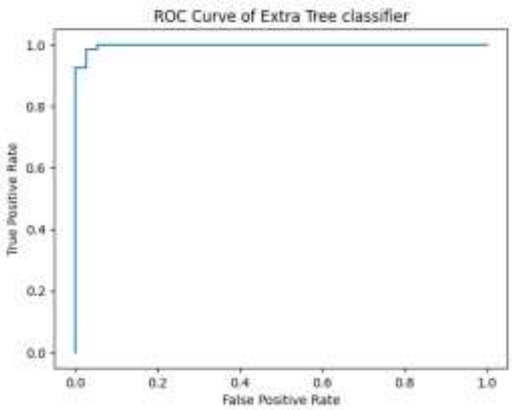

Fig. 5. ROC Curve of Extra Tree Classifier

IV. Results

In this section, the results on the test set have been depicted. We have used accuracy score, recall, precision and the F1 score as the performance metrics to evaluate the model. Extra trees classifier has worked the best in our case.

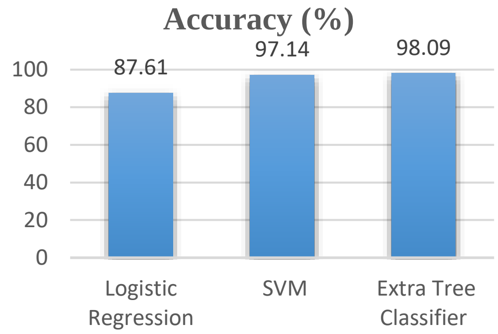

Fig. 6. Comparing the Accuracies of ML Algorithms

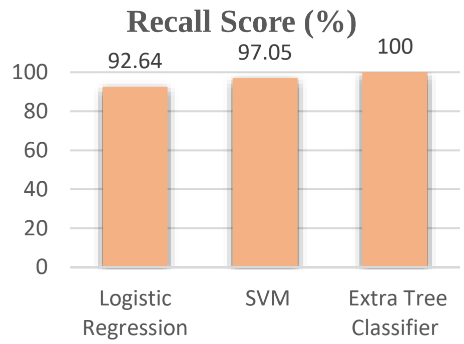

Fig. 7. Comparing the Recall scores of ML Algorithms

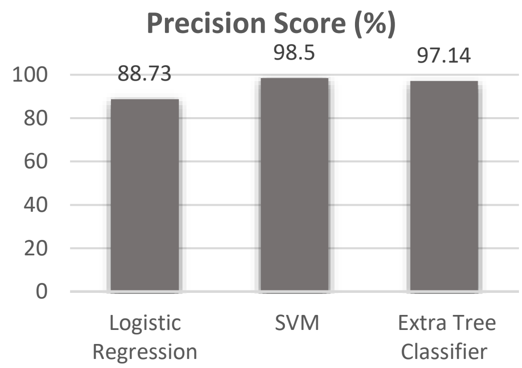

Fig. 7. Comparing the Precision scores of ML Algorithms

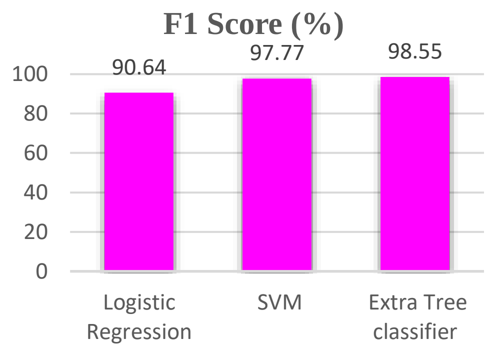

Fig. 8. Comparing the F1 scores of ML Algorithms

V. CONCLUSION AND FUTURE SCOPE

In this paper, we have successfully collected a clean and sufficiently large data-set, engineered a set of uncorrelated features and developed a robust model to perform classification. We have solved the problem of identification of the health of a mechanical system without disrupting it at the system level. The models developed has performed reasonably well on the train and the test set with accuracies greater than 90%.

This problem can be extended further. A larger data-set could be compiled by multiple data-augmentation techniques and deep learning methods can be explored for fault diagnosis of any mechanical system which produces an acoustic signal.

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