The 14th ISAV2024
International Conference on Acoustics and Vibration
11-12 Dec 2024 Karaj - Iran
Iranian Society of Acoustics and Vibration
Kharazmi University

Audio-Based Fault Diagnosis of Ventilation Fans Using Machine Learning Algorithms

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Abstract

A practical approach for fault diagnosis of ventilation fans is introduced in this paper, where audio signals captured through a laboratory microphone are used to enhance efficiency and minimize costs in industrial and personal settings. Ventilation fans are deemed important in industries, labs, and personal use. Machine learning classification algorithms are employed to process audio signals, and the need for specialized devices or expensive sensors is eliminated, making the methodology accessible through a common microphone. Data were systematically collected from ventilation fans in three distinct operational states, and features were extracted from the audio signals for analysis. Classification models, including k-Nearest Neighbors (KNN), logistic regression, and decision trees, were utilized. A practical and accessible methodology for identifying machine faults using laboratory microphone-captured audio signals is offered in this study and results were acceptable, training accuracy were at least 97% and test accuracy were 96% that show good accuracy in diagnosis. The efficacy of Machine Learning algorithms in industrial and personal applications is underscored by the findings, and valuable insights are provided for optimizing machine performance while minimizing costs.

Keywords: Fault Diagnosis; Machine Learning; Audio Signals; Ventilation Fan.

1. Introduction

Rapid advancements in technology and industry, coupled with growing demands for products, necessitate fast adaptation within manufacturing sectors. Fault detection, rooted in machine learning, is regarded as a crucial component of predictive and condition-based maintenance. Several advantages, including enhanced operational efficiency, cost savings, and early fault diagnosis, are provided by predictive maintenance. Potential safety hazards and risks associated with equipment failures are identified, allowing preventive measures to be implemented proactively. A safer working environment for employees is created, and the likelihood of accidents or injuries is reduced. Motivated by these benefits, processes are accelerated, accuracy is augmented, and costs are minimized. Ventilation fans are considered important in industry and personal use. Common faults of fans and other industrial devices, including imbalance, misalignment, and bearing failure, are addressed. While features such as vibration, voltage, and temperature are mainly used in extant research for fault detection, the practicality and simplicity of implementation are often overlooked. An approach using audio signals captured by a microphone is pioneered in this study, facilitating accessibility and usability for individuals across diverse settings. In recent years, maintenance practices across various industries have been revolutionized by the integration of Artificial Intelligence (AI) and Machine Learning (ML) algorithms. Operational efficiency is enhanced, speed and accuracy are improved, and costs are reduced through the elimination of expert workers in maintenance tasks. Various Machine Learning (ML) and deep learning (DL) models have demonstrated efficacy in fault detection, such as Support Vector Machines (SVM), Random Forest, k-Nearest Neighbors (k-NN), and Convolutional Neural Networks (CNN). In this investigation, four key algorithms, K-Nearest Neighbors (KNN), Decision Trees, and Logistic Regression, are employed to prognosticate the likelihood of faults. Subsequent sections describe the data collection methodology, preprocessing techniques, and the proposed methodology. Findings are presented to showcase the effectiveness of the approach in fault detection and classification.

2. Fault Diagnosis of Ventilation Fans Through laboratory microphone captured Audio

In industry, efficiency improvement while minimizing costs is prioritized. Fault diagnosis using audio signals captured by a standard laboratory microphone is focused on in this research. The signals are processed and analyzed with Machine Learning (ML) algorithms to classify the machine's operational status. Costly sensors are eliminated in this approach, making it practical and accessible to a wider audience.

2.1. Data Collection

Three distinct statuses for experimentation were systematically generated in this phase of the research, encompassing: 1) a healthy ventilation fan, 2) an unbalanced fan of type 1, and 3) an unbalanced fan of type 2. To induce these statuses, a nominal 5 grams mass was introduced onto the fan blade, as illustrated in Figures 1 and 2. A microphone was subsequently positioned at a stable distance of 10 centimeters from the ventilation fan, and recording was initiated for each status. Each status was recorded for approximately 11 minutes, accumulating to a total recording time of 33 minutes. Following this recording phase, the audio file was systematically segmented into 2000 discrete segments, each lasting approximately 1 second. The segmentation process served as the foundation for the compilation of the raw datasets, and images of the experiment are presented.

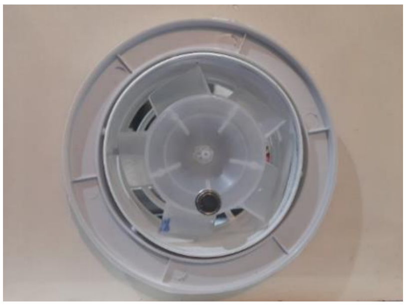

Figure 1 an unbalanced fan type1

Figure 2 an unbalanced fan type2

Figure 3 Healthy fan

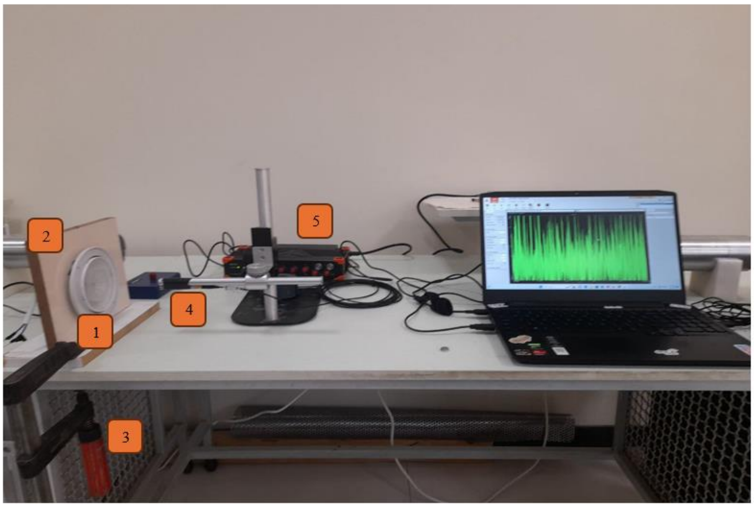

Figure 4. 1: ventilation fan, 2: fan station, 3: fixture, 4: laboratory microphone, 5:data logger

2.2. Feature Extraction

The feature extraction process employed for analyzing audio data collected from ventilation fans in three distinct operational states is defined in this section. The chosen features for this investigation were Spectral Rolloff, Spectral Contrast, Spectral Bandwidth, Spectral Centroid, Bandwidth Ratio, Zero-Crossing Rate, Root Mean Square (RMS), Mean Wavelength, and Maximum Frequency. Valuable insights into the characteristics of the audio signals were offered by each feature, facilitating the differentiation between different states of the ventilation fans.

2.1 Standardization

In mechanical engineering, especially in fan performance analysis, Machine Learning (ML) algorithms are regarded as crucial for predictive modeling and optimization. Effective preprocessing, particularly standardization, is considered essential for accurate ML performance. Features like Spectral Rolloff, Contrast, Bandwidth, Centroid, and RMS, with varying scales, are included in the dataset. Since scale differences are known to affect ML algorithms, standardization is performed to ensure that all features share a mean of 0 and a standard deviation of 1, thereby improving learning and model convergence.

3. Methods

3.1 K-Nearest Neighbors (KNN) Algorithm:

The K-Nearest Neighbors (KNN) algorithm is a widely utilized method for classification tasks in Machine Learning. It operates by classifying new data points based on the majority class label among their K-Nearest Neighbors in the training dataset.

3.1.1 Methodology:

Training Phase: During training, the KNN algorithm memorizes the entire training dataset without any explicit model training.
Prediction Phase: Classification When presented with a new data point, the algorithm computes the distances between it and all other points in the training dataset, typically using Euclidean distance. Based on these distances, it selects the k nearest neighbors.
For instance, if k = 3, the algorithm identifies the 3 closest neighbors to the new data point.
Decision: For classification, the algorithm assigns the most frequent class label among the K nearest neighbors to the new data point.

3.2 Logistic Regression with One-vs-All Method

Logistic regression is a fundamental and widely used statistical method for binary classification tasks. However, it can also be extended to handle multi-class classification problems through the one-vs-all (OvA) method, also known as one-vs-rest (OvR) method. In this method, a separate binary logistic regression model is trained for each class, where each model predicts whether a data point belongs to that class or not.

3.2.1 Methodology:

Binary Classification Models: For a multi-class classification problem with k classes, k separate binary logistic regression models are trained using the OvA method.
Training Phase: For each binary logistic regression model, the training dataset is modified such that data points belonging to the target class are labelled as positive (1), and all other data points are labelled as negative (0).
Prediction Phase: Given a new data point, all k binary logistic regression models are used to predict the probability that the data point belongs to each class. The class with the highest predicted probability is then assigned as the final predicted class for the data point.

3.3 Decision Tree

A Decision Tree is a supervised Machine Learning algorithm used for both classification and regression tasks. It creates a model that predicts the value of a target variable based on several input features by learning simple decision rules inferred from the data features. Decision Trees are popular due to their simplicity, interpretability, and ability to handle both numerical and categorical data.

3.3.1 Structure:

A Decision Tree consists of a root node, internal nodes, and leaf nodes:
Root Node: Represents the entire dataset and is split into two or more child nodes based on the most significant feature.
Internal Nodes: Represent features and are split into child nodes based on a decision rule (e.g., if-else conditions).

Leaf Nodes: Represent the final outcome (class label or regression value).

3.3.2 Construction:

Feature Selection: The algorithm selects the feature that best splits the dataset into homogeneous subsets. Common splitting criteria include Gini impurity, entropy, and information gain.
Splitting: The selected feature is used to split the dataset into two or more subsets based on certain conditions (e.g., if-else statements).
Recursion: Steps 1 and 2 are repeated recursively for each subset until a stopping criterion is met, such as reaching a maximum depth, minimum number of samples, or purity threshold.
Leaf Node Assignment: Once the tree is fully grown, each leaf node is assigned a class label or regression value based on the majority class or average value of the samples in that node.

4. Results

In this scientific study, the performance of various classification models is meticulously evaluated by employing key metrics such as training accuracy, testing accuracy, testing recall, testing precision, and the confusion matrix. Comprehensive insight into the efficacy of each model in classifying instances within the dataset is collectively provided by these metrics. The accuracy of a model, a fundamental measure of its overall correctness, is computed as the ratio of correctly classified instances to the total number of instances. This metric is regarded as pivotal in determining the ability of the model to make accurate predictions across all classes.

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Precision, another crucial metric, is used to gauge the proportion of true positive predictions relative to all positive predictions made by the model. The model's capability to avoid misclassifying negative instances as positive is assessed by this measure, which highlights the precision of positive predictions.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall, also referred to as sensitivity, is employed to assess the model's capacity to correctly identify positive instances from the entire pool of actual positive instances. This metric is considered invaluable for evaluating the ability of the model to capture all relevant instances within a particular class.

$$Recall = \frac{TN}{TN + FN} \tag{3}$$

The confusion matrix is regarded as key to evaluating classification models, as it details true positives, true negatives, false positives, and false negatives. These metrics are highlighted in the analysis to assess each model's strengths and weaknesses, offering a clear framework for comparing their effectiveness.

4.1 KNN Model

Figure 27 depicts the KNN model's confusion matrix. The accompanying confusion matrix illustrates the distribution of true positive, true negative, false positive, and false negative predictions, providing a detailed overview of the model's classification performance. Our analysis reveals impressive metrics for the KNN model. The training data accuracy stands at 97%, indicating a high level of correctness in classifying instances during the model's training phase. Similarly, the accuracy of testing data is notably high at 98%, affirming the robustness of the model's predictive capabilities when applied to unseen data. Moreover, the model demonstrates exceptional recall and precision rates, both at 98%. This proves that the KNN model captures true positives, minimizes false negatives, and maintains precision in identifying positive classes, making it more reliable and efficient for dataset classification. In the following, model performance can be seen.

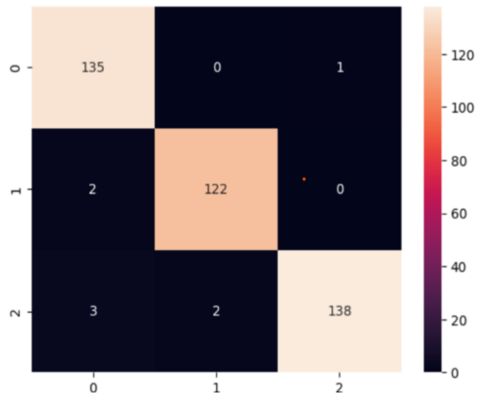

Fig 5: Assessing KNN Model Performance through Confusion Matrix Visualization

4.2 Logistics Regression

In the context of logistic regression, our analysis unveils compelling performance metrics indicative of the model's efficacy in classification tasks. With a training accuracy of 97%, the logistic regression model demonstrates a high degree of correctness in categorizing instances during the training phase, attesting to its capacity to learn from the provided data. Furthermore, the model exhibits a remarkable testing accuracy of 98%, underscoring its ability to generalize well to unseen data and maintain robust predictive performance beyond the training set. This high level of accuracy on the testing data reaffirms the model's reliability and applicability in real-world scenarios. Moreover, our evaluation reveals impressive recall and precision rates of 98%, emphasizing the model's proficiency in correctly identifying positive instances while minimizing false negatives, as well as its precision in accurately classifying positive instances among all instances classified as positive. These notable performance metrics underscore the effectiveness of logistic regression as a powerful classification algorithm, capable of delivering accurate and reliable predictions across various datasets. Such findings position logistic regression as a valuable tool in data analysis and decision-making processes within our research domain. In the following, model performance can be seen.

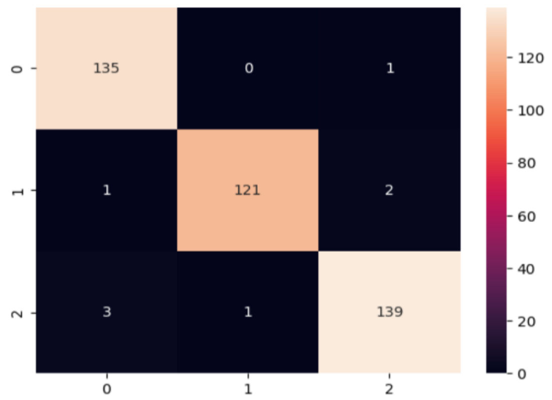

Fig 6: Assessing Logistic Regression Model Performance through Confusion Matrix Visualization

4.3 Decision Tree

The findings pertaining to the decision tree model are detailed in this section. Fig. 29 illustrates the confusion matrix. The model achieving a remarkable accuracy of 98% on the training data and 96% on the testing data. Furthermore, the model exhibits impressive recall and precision scores, both standing at 96%. This indicates the model's proficiency in accurately identifying positive instances from the entire pool of actual positive instances (recall), as well as its precision in correctly predicting positive instances out of all positive predictions made by the model (precision). These results collectively highlight the robust performance of the decision tree model, as evidenced by its high accuracy, recall, and precision scores across both training and testing datasets.

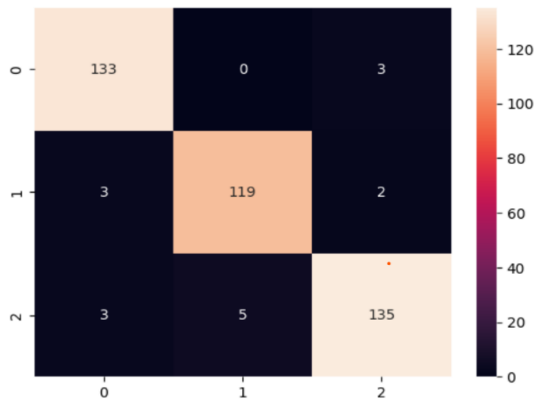

Fig 7: Assessing Decision Tree Model Performance through Confusion Matrix Visualization

Another objective of this study is to calculate the correlation between the State and other features. For this purpose, we use the correlation matrix. Table 1 shows the correlation between features. As evident from Table 1, the correlation between the State variable and various other attributes provides insights into the relationships between them. Analyzing the correlation matrix enables us to identify potential dependencies and interactions between the State variable and other features under consideration.

Table 1: correlation matrix

Column1	Spectral Rolloff	Spectral Contrast	Spectral Bandwidth	Spectral Centroid	Bandwidth Ratio	Zero-Crossing Rate	RMS	Mean Wave Length	Maximum Frequency	State
Spectral Rolloff	1	0.660352	0.874558	0.879503	-0.823411	0.646776	0.796158	0.112599	0.752797	0.70585
Spectral Contrast	0.660352	1	0.797909	0.7408	-0.611743	0.262424	0.809834	-0.002762	0.813892	0.843838
Spectral Bandwidth	0.874558	0.797909	1	0.99304	-0.905658	0.655991	0.943708	0.10183	0.892851	0.821392
Spectral Centroid	0.879503	0.7408	0.99304	1	-0.945133	0.727269	0.897481	0.138354	0.84485	0.87032
Bandwidth Ratio	-0.823411	-0.611743	-0.905658	-0.945133	1	-0.7939	-0.730677	-0.120589	-0.656219	-0.610761
Zero-Cross-ing Rate	0.646776	0.262424	0.655991	0.727269	-0.7939	1	0.469399	0.291666	0.424342	0.226867
RMS	0.796158	0.809834	0.943708	0.897481	-0.730677	0.469399	1	0.053269	0.942427	0.849304
Mean Wave Length	0.112599	-0.002762	0.10183	0.138354	-0.120589	0.291666	0.053269	1	0.044102	0.000759
Maximum Frequency	0.752797	0.813892	0.892851	0.84485	-0.656219	0.424342	0.942427	0.044102	1	0.799675
State	0.70585	0.843838	0.821392	0.87032	-0.610761	0.226867	0.849304	0.000759	0.799675	1

Table 2: Evaluation Metrics for our Models

Model / Metrics	K-NN	Logistics Regression	Decision Tree
Train Accuracy	97%	97%	98%
Test Accuracy	98%	98%	96%
Test Recall	98%	98%	96%
Test Precision	98%	98%	96%

5. Conclusion

In this study, an innovative approach for fault diagnosis of ventilation fans was introduced, where audio signals captured through a microphone were utilized. Machine Learning classification algorithms were leveraged to process these audio signals, and the need for specialized devices or expensive sensors was eliminated, thus making the approach accessible through common devices.

Data were systematically collected from ventilation fans operating in three distinct states: healthy, unbalanced type 1, and unbalanced type 2. Three key Machine Learning algorithms—K-Nearest Neighbors (KNN), Logistic Regression, and Decision Trees—were employed in the research. The performance of these models was evaluated using key metrics such as training accuracy, testing accuracy, recall, precision, and the confusion matrix. The results indicated the following:

1. **K-Nearest Neighbors (KNN)**: A training accuracy of 97% and a testing accuracy of 98% were achieved, with both recall and precision rates at 98%. KNN's robustness in capturing true positive instances while minimizing false negatives was demonstrated.

2. **Logistic Regression**: A training accuracy of 97% and a testing accuracy of 98% were recorded, with both recall and precision rates at 98%. The reliability and effectiveness of the model in accurately predicting positive instances were highlighted.

3. **Decision Tree**: A training accuracy of 98% and a testing accuracy of 96% were achieved, with recall and precision scores both at 96%. The model's proficiency in classifying instances accurately within both training and testing datasets was reflected.

The findings from the study underscore the efficacy of machine learning techniques in fault diagnosis for ventilation fans. By utilizing microphone-captured audio signals, a practical and cost-effective solution was provided, which can be easily implemented in both industrial and personal settings. This approach not only enhances the accessibility of fault detection methodologies but also paves the way for further advancements in the field of predictive maintenance. The study contributes to the broader field of mechanical engineering by offering an efficient and practical solution for fault diagnosis, potentially reducing maintenance costs and improving operational efficiency in various industrial applications.

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