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AI-Based Universal Mechanical Noise Classifier for Fault Diagnosis

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***Abstract*—Mechanical systems such as motors, pumps, gearboxes, and compressors generate characteristic noise patterns during operation. Deviations in these acoustic signatures often indicate faults such as bearing wear, misalignment, or imbalance. Traditional fault diagnosis techniques rely on vibration sensors and expert analysis, which are costly, equipment-specific, and not scalable.**

This project proposes an AI-based universal mechanical noise classifier that uses acoustic signals captured via microphones to automatically identify fault conditions. Audio signals are preprocessed, transformed into spectral features, and classified using machine learning/deep learning models. The system provides an affordable, scalable, and non-intrusive solution for early fault detection across multiple mechanical systems.

***Index Terms*—Acoustic Fault Diagnosis, Machine Learning, Predictive Maintenance, MFCC Feature Extraction, Mechanical Condition Monitoring**

I. INTRODUCTION

Industrial automation has significantly increased reliance on mechanical equipment such as motors, compressors, pumps, and gearboxes. unexpected failure of such systems leads to productivity loss, maintenance cost escalation, and safety hazards. predictive maintenance aims to detect faults before catastrophic failure occurs. traditional techniques such as vibration analysis require specialized sensors and skilled technicians. recent advancements in machine learning and signal processing enable acoustic monitoring as an alternative approach. acoustic signals provide rich information about machine condition and can be captured using low-cost microphones.

A. Scope

The system focuses on detecting mechanical faults using acoustic signals and machine learning classification models.

B. Literature Survey

Numerous studies have explored vibration-based fault diagnosis as a standard approach for machinery health monitoring. Randall (2011) demonstrated the effectiveness of vibration analysis in bearing fault detection. However, installation complexity and cost remain limitations. Recent research highlights acoustic monitoring as a promising alternative. Machine learning algorithms such as Support Vector Machines, Random Forest, and Convolutional Neural Networks have been applied to audio classification tasks. Studies show that MFCC and spectrogram features effectively capture frequency characteristics of mechanical noise.

C. Problem Statement

Traditional mechanical fault diagnosis systems suffer from high hardware cost, limited scalability, and dependence on expert interpretation. Additionally, periodic inspection may fail to detect early-stage faults. Therefore, a universal, low- cost, AI-driven acoustic monitoring solution is required.

D. Objectives

Develop an acoustic-based mechanical fault detection framework,Extract spectral features from machine noise,Train machine learning models for classification,Implement real- time prediction capability,Provide visualization and monitoring interface

E. Organization of Paper

This paper is organized as follows. Section II discusses system analysis. Section III describes system design. Section IV implementation. Section V presents experimental results. Section VI Applications. Section VII concludes the paper.

II. SYSTEM ANALYSIS

A. Existing System
Existing approaches include vibration analysis, thermal monitoring, oil analysis, and manual inspection. While effective, these techniques require specialized hardware and domain expertise.

B. Drawbacks of Existing System
Expensive sensors and installation,Machine-specific solutions,Complex setup,Limited automation

C. Proposed System
The proposed system uses acoustic signals captured via microphones and processes them using machine learning algorithms for automated fault classification.

III. SYSTEM DESIGN

A. System Architecture
The architecture consists of audio acquisition, preprocessing, feature extraction, model training, classification, and visualization modules.

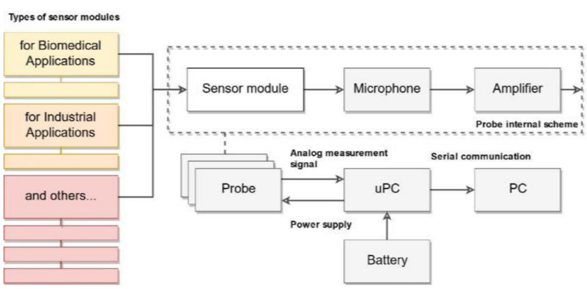

Figure 1: Type of Sensor modules

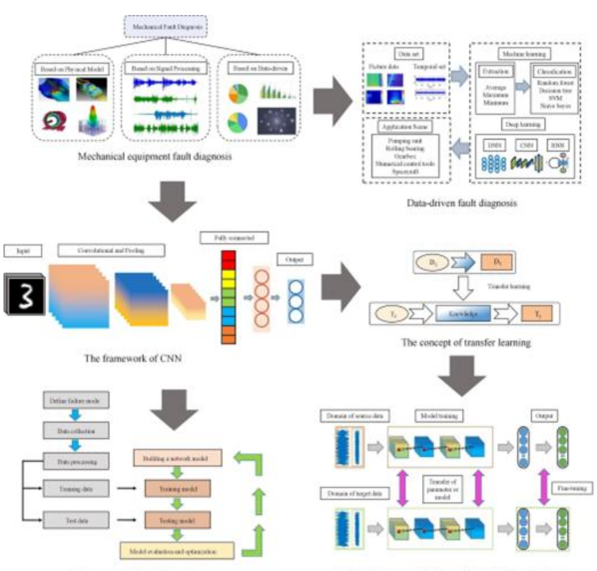

Figure 2 : The process of fault diagnosis

B. Methodology
Data Acquisition: Audio signals are recorded from mechanical systems under normal and faulty conditions. Preprocessing: Noise filtering and normalization improve signal quality. Feature Extraction: MFCC and spectrogram features are extracted. Model Training: Random Forest classifier is trained on extracted features.

C. System Design
Includes use case diagram, flowchart, and data flow diagram.

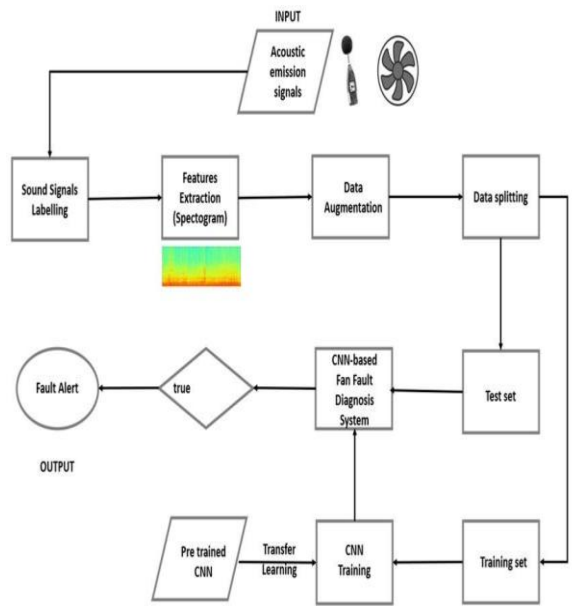

Figure 3 : Input

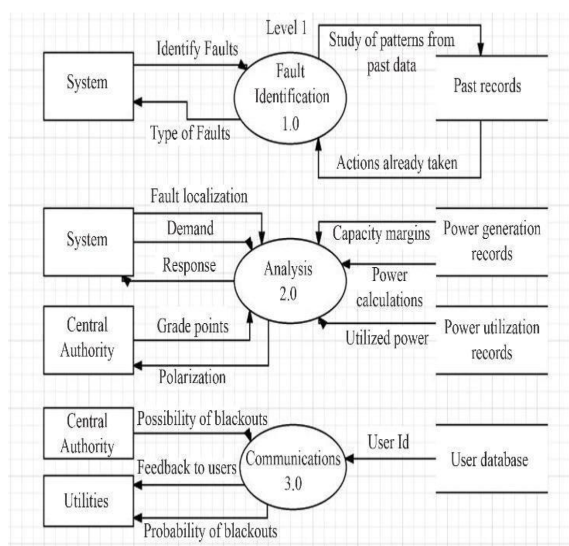

Figure 4 : Level 1

D. Module Description

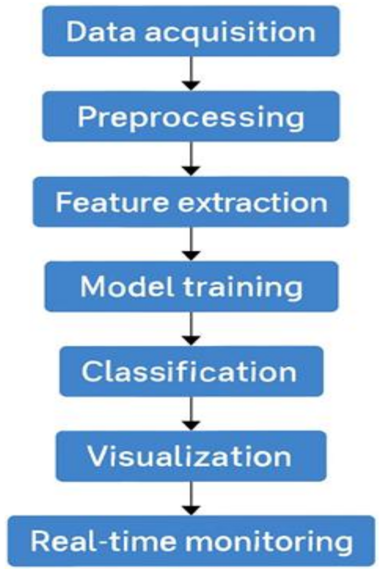

Figure 5 : Module Description

IV. IMPLEMENTATION

A. Software Requirements

Python:

Python provides an integrated development environment for implementing acoustic signal processing, feature extraction, machine learning, and real-time prediction, making it an effective platform for building intelligent mechanical fault detection systems.Librosa, NumPy,Scikit-learn,Matplotlib Python is used as the core development platform for the AI- based acoustic fault detection system due to its strong support for audio processing, machine learning, and rapid implementation. In this project, Python enables recording and handling mechanical noise signals, preprocessing audio data, and extracting meaningful spectral features such as MFCC using libraries like Librosa and SciPy. Machine learning algorithms, particularly the Random Forest classifier implemented through Scikit-learn, are employed to train models that distinguish between normal and faulty machine conditions. Additionally, NumPy and Pandas support efficient numerical computations and dataset management, while Matplotlib is used for visualizing spectrograms and performance metrics. Python also facilitates real-time prediction by integrating microphone input with trained models, making it a practical and scalable tool for developing an automated acoustic fault diagnosis system.

B. Hardware Requirements

The hardware requirements for this project include a microphone and a PC or laptop to support acoustic data acquisition and system processing. The microphone is used to capture mechanical noise generated by machines under normal and faulty operating conditions, serving as the primary sensing component for the system. A standard USB microphone or built-in laptop microphone is sufficient for recording audio samples during dataset preparation and real- time monitoring. The PC or laptop functions as the processing unit, providing computational resources for audio preprocessing, feature extraction, machine learning model training, and prediction. A system with at least 4 GB RAM and a modern processor is adequate for running Python-based audio processing libraries and machine learning algorithms, making the hardware setup cost-effective and easy to deploy for academic and small-scale industrial environments.

C. Implementation

Implementation includes dataset preparation, feature extraction, model training, and prediction modules.

The implementation of this project involves integrating acoustic signal processing with machine learning to detect mechanical faults automatically.

1. Dataset Preparation

The dataset contains audio recordings of mechanical systems operating under normal and faulty conditions.

Steps involved:Recording mechanical noise using a microphone. Collecting publicly available audio datasets (optional).Labeling audio samples into categories such as normal and faulty. Organizing files into structured directories. Splitting dataset into training and testing sets **Purpose:** To create a balanced dataset that captures variations in acoustic behavior of machines.

2. Feature Extraction

Raw audio signals are high-dimensional and unsuitable for direct model training. Therefore,

meaningful spectral features are extracted.
Techniques used: (Mel Frequency Cepstral Coefficients). Spectrogram analysis. Frequency-domain feature computation.
Process: Load audio signal. Apply preprocessing and normalization. Extract MFCC features. Convert features into numerical vectors.
Purpose: To capture frequency and temporal characteristics of mechanical noise that indicate faults.

3. Model Training
Machine learning algorithms are trained using extracted features to classify machine conditions.
Steps involved: Prepare feature matrix and label vector. Train classifier (Random Forest / SVM).Evaluate performance using accuracy and confusion matrix.Save trained model for future inference
Purpose:To learn patterns distinguishing normal and faulty acoustic signals.

4. Prediction Module
The prediction module performs real-time or offline fault classification.
Process: Capture or load new audio sample. Extract MFCC features. Load trained model. Predict machine condition. Display classification result and confidence score **Purpose:** To enable automated fault detection during system operation.

D. ALGORITHM
The proposed system employs MFCC feature extraction for acoustic signal representation and a Random Forest classifier for mechanical fault classification.

1. MFCC Feature Extraction Algorithm
MFCC (Mel Frequency Cepstral Coefficients) captures perceptually relevant frequency characteristics of mechanical noise.
Steps : Audio Acquisition Capture or load the mechanical noise signal. Pre-emphasis Apply filtering to amplify high- frequency components. Framing
Divide the signal into short overlapping frames.
Windowing Apply a window function (e.g., Hamming) to reduce spectral leakage. Fast Fourier Transform (FFT) Convert time-domain signal into frequency domain. Mel Filter Bank Processing Map frequency spectrum to Mel scale to mimic human auditory perception. Logarithmic Compression Apply logarithm to Mel spectrum to stabilize variance. Discrete Cosine Transform (DCT)Generate MFCC coefficients representing compact feature vectors.
Output: MFCC feature vector for each audio sample.

2. Random Forest Classification Algorithm
Random Forest is an ensemble learning method that combines multiple decision trees to improve classification accuracy and robustness.
Steps :Prepare feature matrix using MFCC vectors and corresponding labels. Generate multiple decision trees using random subsets of training data. Each tree independently predicts class labels. Combine predictions using majority voting. Output final classification (Normal or Faulty).
Advantages: Handles noisy data effectively. Reduces overfitting. Provides feature importance estimation

V. RESULT ANALYSIS

Evaluation metrics include accuracy, precision, recall, and confusion matrix.

A. Accuracy
Accuracy represents the overall correctness of the model.
Accuracy=TP+TN/TP+TN+FP+FN
Interpretation:
Indicates the percentage of correctly classified normal and faulty samples. Higher accuracy reflects better model performance.

B. Precision
Precision measures the reliability of fault predictions.
Precision=TP/TP+FP
Interpretation:
Represents how many predicted faults are actually faults. High precision indicates fewer false alarms.

C. Recall (Sensitivity)
Recall evaluates the model’s ability to detect actual faults.
Recall=TP/TP+FN

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Interpretation:
Measures how effectively the system identifies faulty conditions. High recall is critical for predictive maintenance.

D. Confusion Matrix
The confusion matrix provides a detailed breakdown of classification results.

	Predicted Normal	Predicted Faulty
Actual Normal	TN	FP
Actual Faulty	FN	TP

Interpretation:
- TN → Correct normal predictions
- TP → Correct fault detections
- FP → False alarms
- FN → Missed faults

Advantages
- Low cost
- Non-intrusive
- Scalable
- Real-time monitoring

VI. APPLICATIONS

Industrial monitoring, automotive diagnostics, predictive maintenance.

A. Industrial Monitoring
The proposed system can be deployed in industrial environments to continuously monitor machinery such as motors, pumps, compressors, and gearboxes. By analyzing acoustic signals, the system detects abnormal operating conditions and enables early fault identification. This helps reduce unexpected downtime, improves operational efficiency, and lowers maintenance costs.

B. Automotive Diagnostics
In automotive systems, acoustic analysis can identify faults in engines, transmissions, bearings, and exhaust components. The system assists in detecting abnormal noise patterns associated with mechanical defects, supporting preventive maintenance and improving vehicle reliability and safety.

C. Predictive Maintenance
The AI-based acoustic monitoring framework supports predictive maintenance strategies by detecting early-stage faults before catastrophic failure occurs. Continuous condition monitoring allows maintenance activities to be scheduled proactively, minimizing equipment failure risk, optimizing maintenance planning, and extending machine lifespan.

VII. CONCLUSION

The project demonstrates the feasibility of acoustic monitoring for mechanical fault diagnosis using machine learning techniques.
The rapid growth of industrial automation has increased dependence on mechanical equipment such as motors, pumps, compressors, and gear systems. Ensuring reliable operation of these systems is critical for maintaining productivity, safety, and cost efficiency. Traditional fault diagnosis techniques primarily rely on vibration analysis, thermal inspection, and manual monitoring, which often require specialized hardware and expert interpretation. These limitations highlight the need for alternative, scalable, and cost-effective monitoring solutions.
This project presented an AI-based acoustic fault detection system that utilizes mechanical noise as a diagnostic indicator for identifying abnormal machine conditions. The proposed system integrates signal processing and machine learning techniques to analyze acoustic signals and classify machine states into normal and faulty categories. By leveraging MFCC feature extraction and Random Forest classification, the system effectively captures discriminative frequency characteristics of mechanical noise and learns patterns associated with fault conditions.
The implementation involved dataset preparation, preprocessing, feature extraction, model training, and prediction modules. Acoustic signals were collected under varying operational conditions and organized into labeled datasets. MFCC features were extracted to represent the spectral characteristics of mechanical noise in a compact and informative manner. A Random Forest classifier was trained on these features, providing robust performance due to

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its ensemble learning capability and resistance to overfitting. The prediction module enabled both offline and real-time fault classification, demonstrating the practicality of the proposed approach.

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