Report:

Intelligent Condition Based Monitoring Using Acoustic Signals for Air Compressors

1. INTRODUCTION

Industrial assets such as reciprocating air-compressors are subject to progressive wear in valves, bearings, piston rings and ancillary components; undetected, these defects can trigger unscheduled shutdowns, safety incidents and high maintenance bills. Condition-Based Maintenance (CBM) offers a cost-effective alternative to time- or run-to-failure strategies by detecting and isolating faults while the machine is still operating, allowing repairs to be scheduled at the most economical moment. Acoustic sensing has emerged as an attractive CBM modality because airborne sound is comparatively insensitive to structural resonances, less contaminated by background vibration and highly responsive to incipient defects in moving parts.

The paper "Intelligent Condition-Based Monitoring Using Acoustic Signals for Air Compressors" proposes a complete data-mining workflow—spanning data acquisition, sensor-position optimisation, signal conditioning, feature engineering, feature selection and multi-class classification—that converts raw microphone recordings into reliable health decisions for a single-stage reciprocating compressor configured with eight operating states (one healthy, seven faulty). Novel contributions include an Empirical Mode Decomposition (EMD)–based Sensitive Position Analysis (SPA) that pinpoints the single most informative microphone location, an outlier-robust normalisation scheme and an extensive, multi-domain feature set that feeds a Support Vector Machine (SVM) classifier to achieve near-perfect fault recognition.

2. SYSTEM OVERVIEW

2.1 Data Acquisition

Unidirectional condenser microphones are placed ≈1.5 cm from the compressor casing and connected to an NI-9234 dynamic signal module (50 kHz max, 24-bit) via an NI-9172 USB chassis; each recording spans 5 s (250 000 samples).
Twenty-four candidate mounting points—distributed around the piston crown, non-return-valve (NRV) side, opposite NRV side and opposite fly-wheel side—are evaluated to locate the most “sensitive” position for fault discrimination.

2.2 Sensitive Position Analysis (SPA)

Raw traces from every candidate point are decomposed into Intrinsic Mode Functions using EMD; IMFs with high correlation to the original waveform are retained and re-summed to suppress noise.
The envelope of the reconstructed signal is computed via the Hilbert transform, and two statistical figures (absolute mean, RMS) are averaged across 15 trials per position. Positions are ranked by the combined score, giving a consistent global optimum (Position 8 in the case study).

2.3 Signal Pre-processing (applied to all subsequent recordings from the chosen position)

- **Filtering:** a 400 Hz high-pass FIR “fan-filter” removes blower noise; an 18-order Butterworth low-pass at 12 kHz suppresses high-frequency artefacts.

- **Clipping:** the 5-s trace is windowed into nine 1-s segments with 50% overlap; the segment of minimum standard deviation is retained to avoid transient disturbances.
- **Smoothing:** a 5-point moving-average attenuates impulsive outliers.
- **Normalisation:** a modified max–min scheme discards the outer 0.025% of histogram counts before scaling to [–1, 1], eliminating the leverage of extreme outliers while preserving amplitude relationships.

2.4 Feature Extraction

286 baseline features span time domain (8), FFT-based frequency domain (8), Morlet Wavelet Transform (7), discrete wavelet transform using db4 (9) and 7-level wavelet-packet energy signatures (254).
An extended library adds 343 descriptors from ten further transforms (DCT, autocorrelation, short-time Fourier, S-transform, updated Morlet, Wigner–Ville, pseudo-WVD, Choi-Williams, Born-Jordan, etc.), bringing the total to 629.

2.5 Feature Selection

Six algorithms—PCA, MIFS, mRMR, NMIFS, MIFS-U and Bhattacharyya Distance—rank or transform the candidate set to curb the curse of dimensionality; mRMR and NMIFS deliver the best accuracy with as few as 25 features.

2.6 Classification

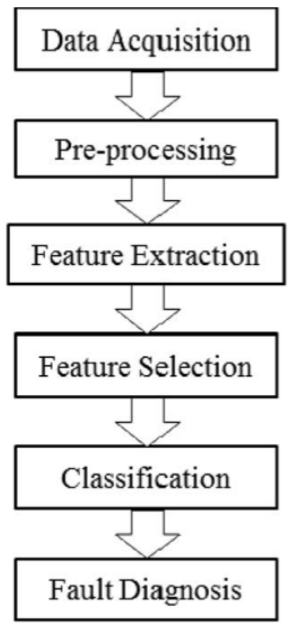
A v-SVM with radial-basis-function kernel performs state identification; multi-class support is realized through One-Against-One, One-Against-All or Decision-Directed Acyclic Graph decompositions, with negligible accuracy differences but lower computational cost for OAO/DDAG.

2.7 Case-Study Performance

Using only the single microphone at Position 8, 1 800 recordings (225 per state) are split into training/testing folds. With 50–75 selected features, the system exceeds 99% correct identification across healthy and seven

seeded fault conditions (LIV, LOV, NRV, piston-ring, fly-wheel, rider-belt and bearing faults).
Together, these stages constitute an integrated, real-time-capable CBM platform that converts raw airborne sound into actionable diagnostics for reciprocating air-compressor assets.

3. METHODOLOGY



(System block diagram)

This section introduces a comprehensive methodology used for developing an intelligent condition-based monitoring plan for reciprocating air compressors from acoustic signals. The process follows a modular pipeline: from sensor deployment until end fault classification. Each stage is explained as follows.

3.1 EMD-based Sensitive Position Analysis

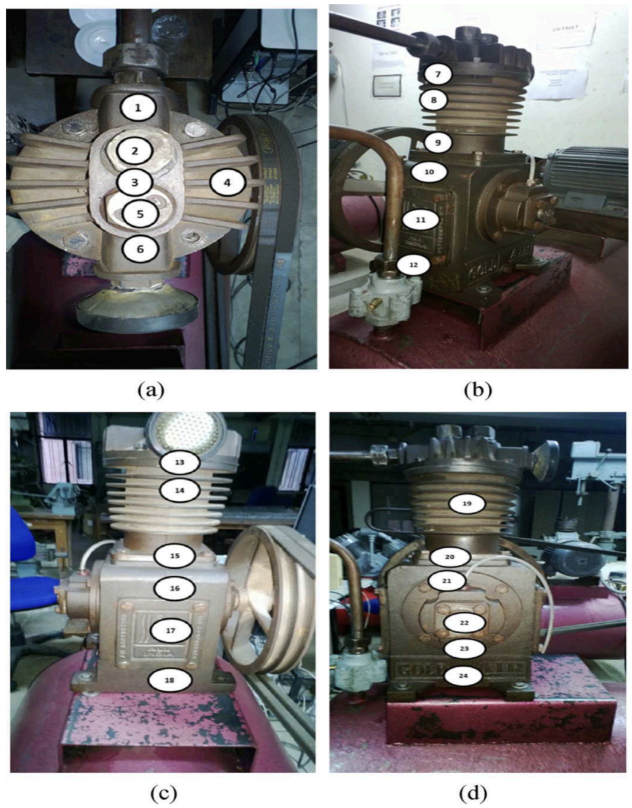


Fig. 2. Positions taken for SPA on each side of the air compressor : (a) Top of Piston, (b) NRV side, (c) Opposite NRV side, and (d) Opposite Fly wheel side.

SPA Diagram (Sensor Positioning)

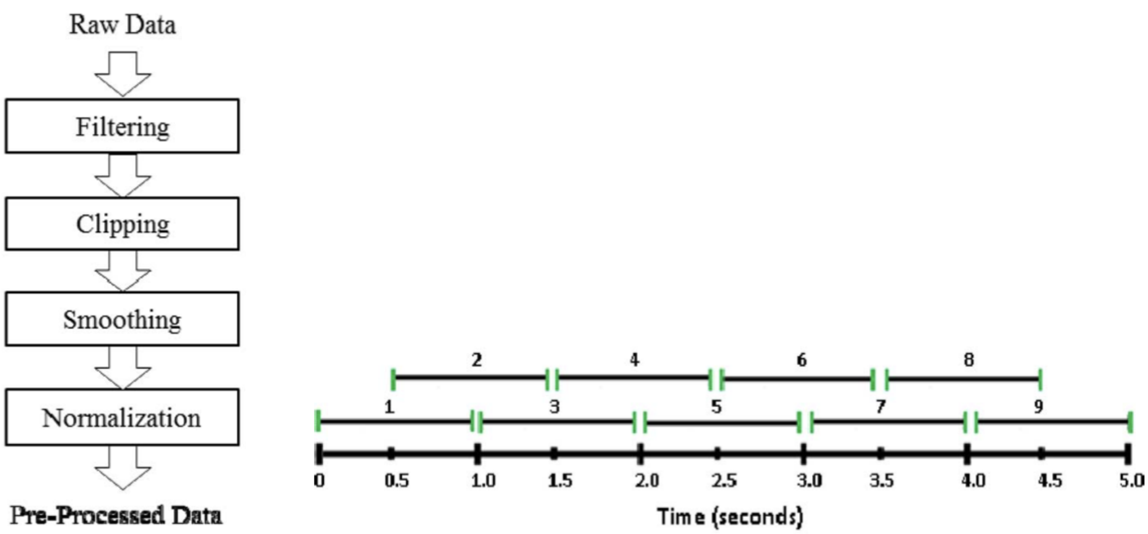
Since different components of a compressor generate distinctive acoustic signals depending on how far from internal faults a component is positioned, finding an optimal position for a microphone is critical. Doing this is termed **Sensitive Position Analysis (SPA).**

Empirical Mode Decomposition (EMD) for SPA

- Data from 24 machine positions were collected.
- EMD decomposes raw signals into a set of finite **Intrinsic Mode Functions (IMFs)** that represent various frequency bands.
- Selection criteria for relevant IMFs are correlation thresholds.
- These IMFs are aggregated together in order to restore a cleaner signal.
- **Hilbert Transform** is utilized in obtaining the signal envelope.

- Two statistical measures — **Absolute mean and Root Mean Square (RMS)** — are computed on the envelope for ranking sensor positions.
- **Result:** It was found that position 8 was very sensitive for every state of the machine and was chosen for final data recording.

3.2 Preprocessing



Preprocessing flow

The acoustic signals from the real environment are typically contaminated with fan noises, vibrations, and background machines. To enhance data quality and prepare for subsequent analysis, we apply the following steps:

A. Filtering

- A **high-pass FIR filte**r (at cut-off = 400 Hz) suppresses fan low-frequency noise.
- **Low-pass Butterworth filter** (cut-off = 12 kHz, 18th order) eliminates high-frequency artifacts.

B. Clipping

- Each recording of 5 seconds (250,000 samples) is divided into 9 overlapping 1-second windows.
- It selects the portion with **least standard deviation** for stability.

C. Smoothing

- **Moving Average Filter** serves to suppress outliers without modifying principal signal patterns.
- It is performed best with a kernel width of 5.

D. Normalization

- It uses a modified max-min normalization.
- In order to reduce outlier effect, top and bottom **0.025%** observations are excluded. Values scaled to a [–1, 1] range.

Output: Normalized, clipped, and cleaned acoustic signal ready for feature extraction.

3.3 Feature Extraction

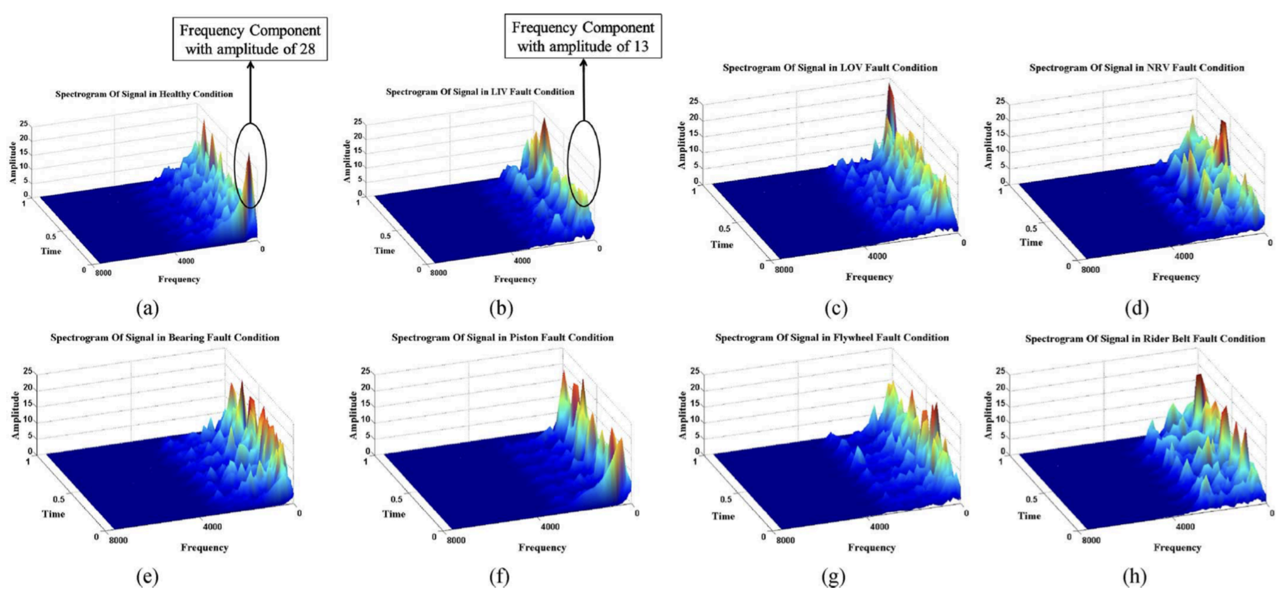


Fig. 6. Spectrogram plot of pre-processed recordings when machine is in different states : (a) Healthy Condition, (b) LIV fault condition, (c) LOV fault condition, (d) NRV fault condition, (e) Bearing fault condition, (f) Piston fault condition, (g) Rider belt fault condition, (h) Flywheel fault condition.

Feature Domains Overview

Features are extracted to summarize major patterns that appear in the acoustic signal. The extraction covers three domains:

A. Time Domain Features
Statistical measures computed from the signal itself:
- Absolute mean, RMS, variance
- Skewness, kurtosis
- Crest factor (peak/RMS
- Shape factor (RMS/mean)

B. Frequency Domain Features
Using **Fast Fourier Transform (FFT):**
- The spectrum is divided into 8 equal energy-bins.
- Energy ratios from every bin create 8 frequency domain features.

C. Wavelet Domain Features
To obtain time-varying frequency features:
1. **Morlet Wavelet Transform (MWT):**
- Convolve signal with a Morlet wavelet.
- Extract 7 Features: entropy, peaks, kurtosis, zero-crossings etc.
2. **Discrete Wavelet Transform (DWT):**
- Decompose the signal into 6 levels using **Daubechies-4** wavelets.
- Compute variance, autocorrelation variance, and smoothed means.
3. **Wavelet Packet Transform (WPT):**
- Decompose the signal entirely into a binary tree until level 7.
- Extract energy from each node → 254 features

Total features (Phase I): 286
Extended feature set (Phase II): +343 (e.g., DCT, STFT, WVD, BJD) → **629 features**

3.4 Feature Selection

To reduce dimensionality and improve classifier performance, six feature selection techniques are used:

- **PCA (Principal Component Analysis):** Transforms features into uncorrelated components which represent maximum variance.
- **MIFS / NMIFS / MIFS-U:** Selects features taking **Mutual Information** between features and class labels and reducing redundancy into account.
- **Minimum Redundancy Maximum Relevance (mRMR):** Balances information gain and independence.
- **Bhattacharyya Distance (BD):** Measures statistical separability between classes.

Best-performing methods: mRMR and **NMIFS**, especially with 10–50 selected features.

3.5 Classification

The final classification of compressor states is carried out based on **Support Vector Machines (SVMs)** with the **RBF kernel**.

Binary classification on SVM

- It maximizes margin between classes.
- Allows non-linear separability using kernel trick.
- These parameters (C, γ) are adjusted using grid search and cross-validation.

Multiclass Strategies

To classify between 8 states (1 healthy + 7 faulty), SVM is extended:

1. **One-vs-One (OAO)**

- Train SVM for each pair of classes (28 models)

- Final prediction by majority voting

2. **One-vs-All (OAA):**
- One model for every class versus every other class (8 models)
- Prediction with highest confidence value

3. **Decision Directed Acyclic Graph (DDAG)**
- Efficient traversal of a learned DAG of binary SVMs

Result: OAO was superior both in speed and accuracy when feature sets were selected by mRMR.

4. EXPERIMENTAL SETUP

This section outlines the practical implementation of the proposed acoustic-based condition monitoring system on a reciprocating air compressor. The setup involved deliberate simulation of faults, strategic sensor placement, data acquisition using high-resolution instrumentation, and rigorous data collection under controlled conditions. The objective was to build a reliable and representative dataset covering various real-world fault scenarios for use in the machine learning pipeline.

4.1 Compressor Specifications

The experiments were conducted on a **single-stage reciprocating air compressor** installed in the electrical machines lab at the Indian Institute of Technology (IIT) Kanpur. The detailed specifications of the compressor are:

- **Motor**: 3-phase induction motor

- **Power Rating**: 5 HP
- **Voltage**: 415 V
- **Current**: 5 A
- **Frequency**: 50 Hz
- **Speed**: 1440 RPM
- **Operating Pressure**: 0–500 psi (0–35 kg/cm²)
- **Pressure Switch**: Type PR-15, Range: 100–213 psi

This setup was chosen because reciprocating air compressors are commonly used in industries and are prone to mechanical faults that alter their acoustic signatures.

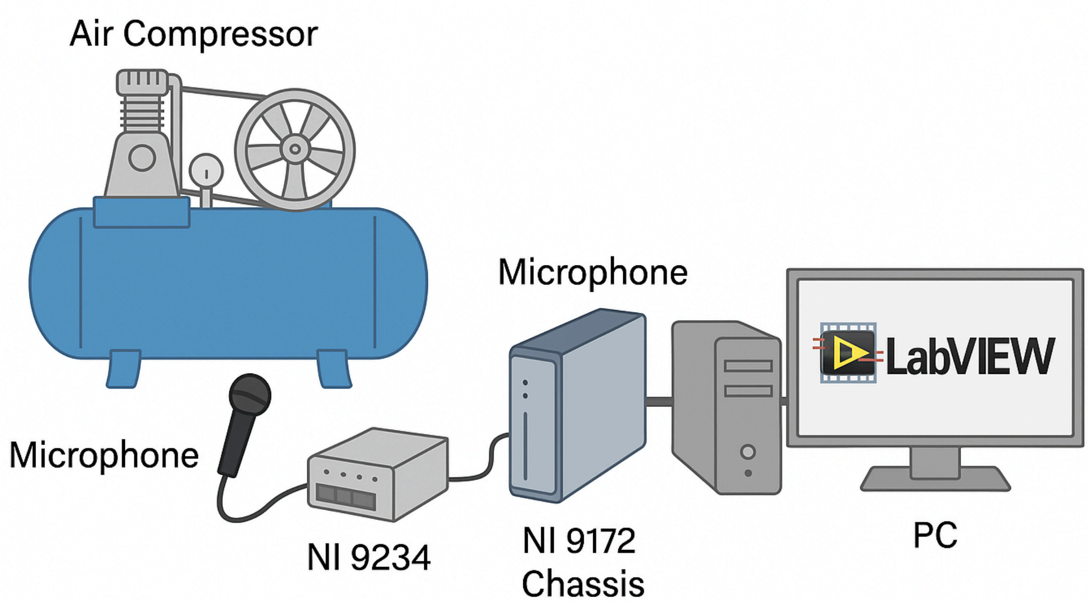
4.2 Simulated Compressor States

To develop a robust fault classification model, the air compressor was run under **eight different operating conditions**, representing both healthy and faulty states:

1. **Healthy Condition (HC)**: No seeded fault; normal working condition.
2. **Leakage in Inlet Valve (LIV)**: Air leakage caused due to improper sealing of the inlet valve.
3. **Leakage in Outlet Valve (LOV)**: A similar air leak but at the discharge point.
4. **Non-return Valve Fault (NRV)**: Air leaks back into the system due to faulty non-return valves.
5. **Piston Ring Fault (PRF)**: Due to wear or loosening, air escapes between the piston and cylinder.
6. **Flywheel Fault (FWF)**: Imbalance or deformation in the flywheel mechanism.
7. **Rider Belt Fault (RBF)**: The belt connecting the motor and flywheel slips or misaligns.
8. **Bearing Fault (BF)**: Mechanical degradation or cracks in the ball bearings, causing irregular sound patterns.

These faults were **manually induced** to mimic actual industrial failure scenarios as closely as possible. Care was taken to isolate each fault independently to ensure the accuracy of the label and to prevent noise from compounding effects.

4.3Microphone & Data Acquisition System



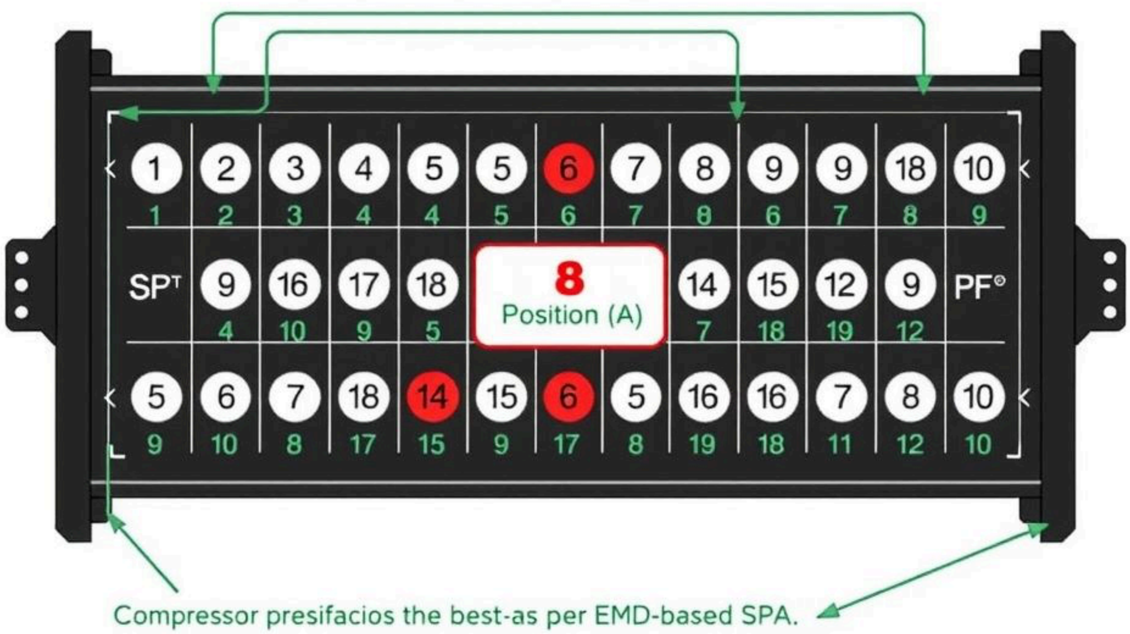
The acoustic signals were recorded using **unidirectional condenser microphones** to minimize ambient noise and improve sensitivity to direct sound waves emitted from the compressor. The sensors were connected to a **National Instruments (NI) data acquisition system**, configured as follows:

- **NI 9234 Module**: High-precision analog-to-digital converter supporting 24-bit resolution

- **NI 9172 USB Chassis**: Interface module between sensors and computer
- **LabVIEW Software**: Used for real-time signal recording, calibration, and signal monitoring

  Each audio sample was recorded for **5 seconds** at a **sampling rate of 50 kHz**, yielding a total of **250,000 data points per recording**. The signals were stored in .dat format for ease of processing using MATLAB and Python.

4.4 Sensor Position Selection



To identify the most informative microphone location on the compressor, **24 unique sensor positions** were tested, as defined in a circular pattern around the compressor body. For each position, recordings were taken for all 8 states and analyzed using **Empirical Mode Decomposition (EMD)** followed by **Hilbert Transform**, a technique referred to in the paper as **Sensitive Position Analysis (SPA)**.

The position with the highest **average signal energy** and **lowest mode overlap across states** was considered the most discriminative. Based on this analysis, **Position 8** was identified as the most suitable for all subsequent data collection. This optimized placement ensures consistent and high-quality signal capture for training the classification model.

4.5 Data Collection Summary

- **Total Microphone Positions Tested**: 24
- **Final Position Used**: Position 8
- **Total Operating States**: 8 (1 healthy + 7 faulty)
- **Recordings per State**: 225
- **Total Recordings Collected**: 225 × 8 = **1800 recordings**

All recordings were taken from the **same optimal sensor position (Position 8)** to maintain consistency in the dataset and eliminate positional variability. This dataset forms the basis for the signal processing, feature extraction, and classification modules implemented later in the system.

5. RESULTS & DISCUSSION

- With recordings from a single microphone, the model separated the healthy compressor from seven seeded faults with 95–97% accuracy across eight states.
- Feature selection, not the classifier, drove that result. Minimum-redundancy–maximum-relevance (mRMR) and Normalised MI (NMIFS) reached peak accuracy with 5–10 carefully chosen

features; an OAO-SVM with just five features (two FFT, three wavelet-packet) still delivered ≈96%.

- Accuracy climbed steeply for the first 25–50 features and then plateaued; adding more than ~75 features provided no benefit and could even hurt because of over-fitting.
- Classic PCA needed dozens of components to match mRMR/NMIFS and tailed off after ≈50, while simple MIFS improved only when almost every feature was kept; Bhattacharyya distance converged slowly and stopped improving beyond 50–75 features.
- Using only half of the available training data (2-fold CV) yielded virtually the same accuracy as larger folds, indicating good generalisation and reduced data requirements.
- The choice of SVM decomposition (OAO, OAA, DDAG) altered run-time more than accuracy: all three produced similar results, but OAO/DDAG were faster because OAA trains on all samples for every binary sub-problem.
- Computation time depended on the transform. FFT and DCT were fast, WPT and STFT moderate, and Wigner-Ville the slowest; expanding the feature set from 286 to 629 pushed per-record processing from 0.9 s to 206 s—orders of magnitude for little extra information.
- Examining the mRMR/NMIFS selections shows most discriminative cues reside in FFT and WPT features, with useful additions from WVD and STFT; time-domain statistics were seldom chosen.

6. CONCLUSION

This study demonstrates that a single acoustic sensor, coupled with judicious feature selection, can diagnose eight compressor states with industrial-grade reliability. Minimum-redundancy maximum-relevance (mRMR) consistently delivered the highest accuracy with the smallest input—5–10 features already captured most of the discriminative power, and ~25 features pushed overall accuracy to ≈99% while holding computation to seconds per record. The classifier generalised well: halving the training set barely affected performance, and swapping multiclass SVM schemes altered runtime more than accuracy.

Looking forward, three extensions would make the approach deployment-ready:

- Simultaneous multi-fault recognition—current models assume one fault at a time; overlapping-fault scenarios will need either ensemble reasoning or multi-label classifiers.
- Adaptive or online learning to track ageing machines and maintain accuracy as acoustic signatures drift over months or years.
- True real-time execution, achieved by further pruning feature extraction or moving heavy transforms (e.g., WVD) to hardware accelerators or streaming signal-processing pipelines.

By addressing these points, the acoustic-based condition monitoring framework can evolve from an accurate laboratory prototype into a practical, always-on predictive-maintenance tool for production compressors.