Intelligent Condition Based Monitoring Using Acoustic Signals for Air Compressors

A Data-Driven Fault Diagnosis Approach

Problem Motivation

Machine Failures:

- Lead to **production downtime**, **financial loss**, and **safety risks**
- Common in **reciprocating air compressors** due to wear & tear (e.g. valves, bearings)

Limitations of Traditional Methods:

- **Vibration sensors** are accurate but **expensive**
- Difficult installation & maintenance

Why Acoustic Signals?

- **Low-cost** and **non-invasive**
- Easier to deploy and maintain
- Sensitive to early fault-induced disturbances
- Less affected by structural resonance & background noise

Goal:

Leverage **acoustic signals + machine learning** to

- Detect faults early
- Enable condition-based maintenance (CBM)
- Prevent breakdowns before they occur

System Architecture

Input:

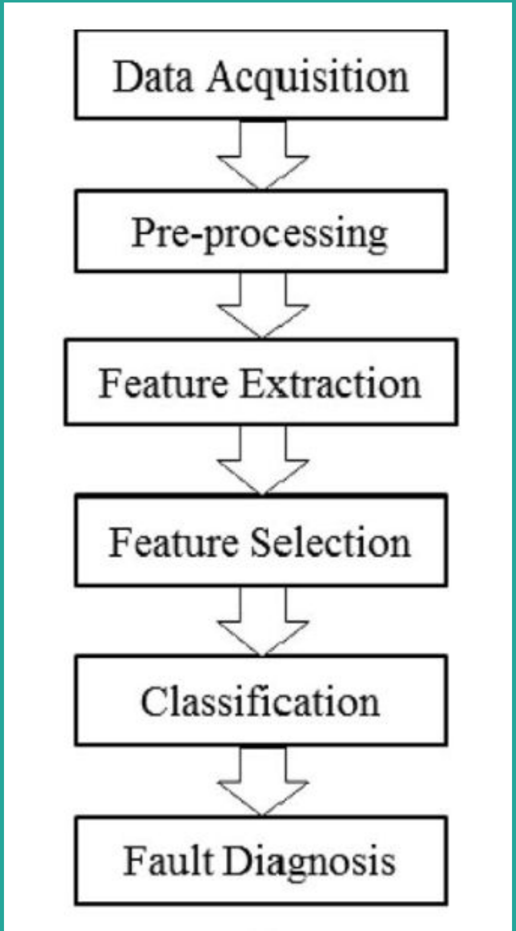
Acoustic Signal from air compressor
→ Captured using unidirectional microphones (low noise)

Preprocessing:

- Noise Filtering (High-pass, Low-pass filters)
- Clipping & Smoothing
- **Normalization** using modified min-max method

Feature Extraction:

- Time Domain (RMS, Skewness, Kurtosis)
- Frequency Domain (FFT – energy bins)
- Time-Frequency Domain (Wavelet Transforms: DWT, WPT, MWT)



Feature Selection:

- Techniques: PCA, mRMR, NMIFS
- Removes redundancy & improves classifier performance

Classification:

- Multiclass SVM (OAO/OAA/DDAG)
- Predicts fault state (Healthy, LIV, LOV, etc.)

Output:

Early and accurate fault identification

Enables predictive maintenance and reduces downtime

Data Acquisition

- Hardware Setup
- Sensor Placement Strategy

Hardware Setup

1. **Unidirectional microphones**:
   Capture focused acoustic signals with minimal background noise

2. **NI 9234 DAQ + NI 9172 USB Interface:**
   High-fidelity data acquisition system

3. **Sampling Rate:**
   50,000 samples/sec

4. **Recording Duration:**
   5 seconds per trial
   250,000 data points per recording

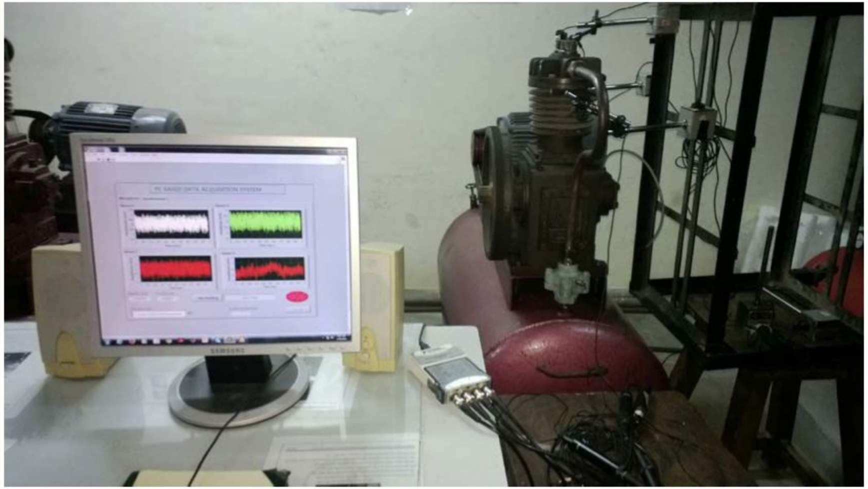


Fig. 1. Data Acquisition Setup.

Sensor Placement Strategy

1. Microphone placed at **24 distinct locations** around the air compressor

2. **Sensitive Position Analysis (SPA)** used to evaluate signal quality:
   Based on **RMS** and **Absolute Mean** of signal envelope

3. **Optimal Position Identified**:
   Position 8 chosen for all final recordings

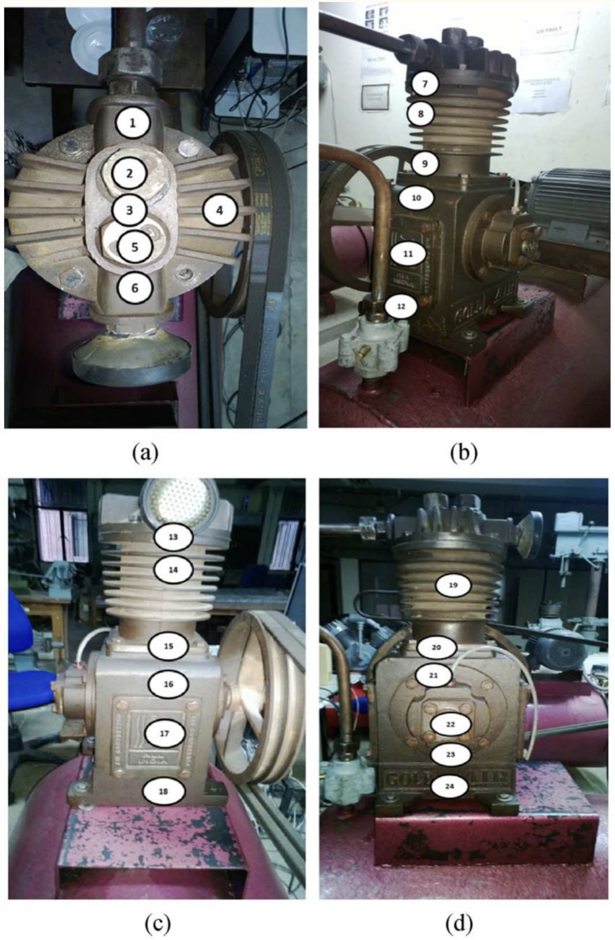


Fig. 2. Positions taken for SPA on each side of the air compressor : (a) Top of Piston, (b) NRV side, (c) Opposite NRV side, and (d) Opposite Fly wheel side.

Preprocessing Steps

1. Filtering
2. Clipping
3. Smoothing
4. Normalization

Filtering

1. **High-pass filter @ 400Hz:**
   Removes low-frequency fan and ambient noise
2. **Low-pass Butterworth filter @ 12kHz:**
   Eliminates irrelevant high-frequency spikes

Result: *Focused signal range with useful frequency content*

Clipping

1. 5-second recording split into **9 overlapping 1-second segments**
2. Segment with **lowest standard deviation** selected

Purpose: *Capture stable, disturbance-free portion of the signal*

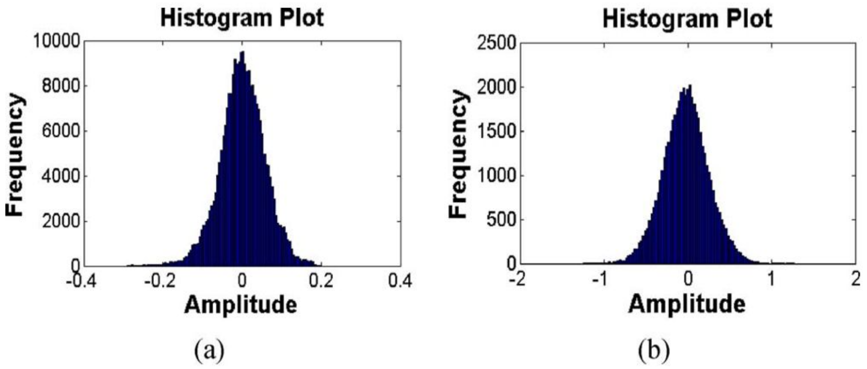


Fig. 4. Histogram plots of sampled signal values of recording a) before pre-processing, b) after pre-processing.

Smoothing

Moving Average Filter (kernel=5) applied

Effect: *Suppresses outliers without losing signal integrity*

Normalization

1. **Modified Max-Min Scaling** (-1 to 1 range)
2. Ignores top and bottom **0.025% outliers**

Ensures consistency and comparability across recordings

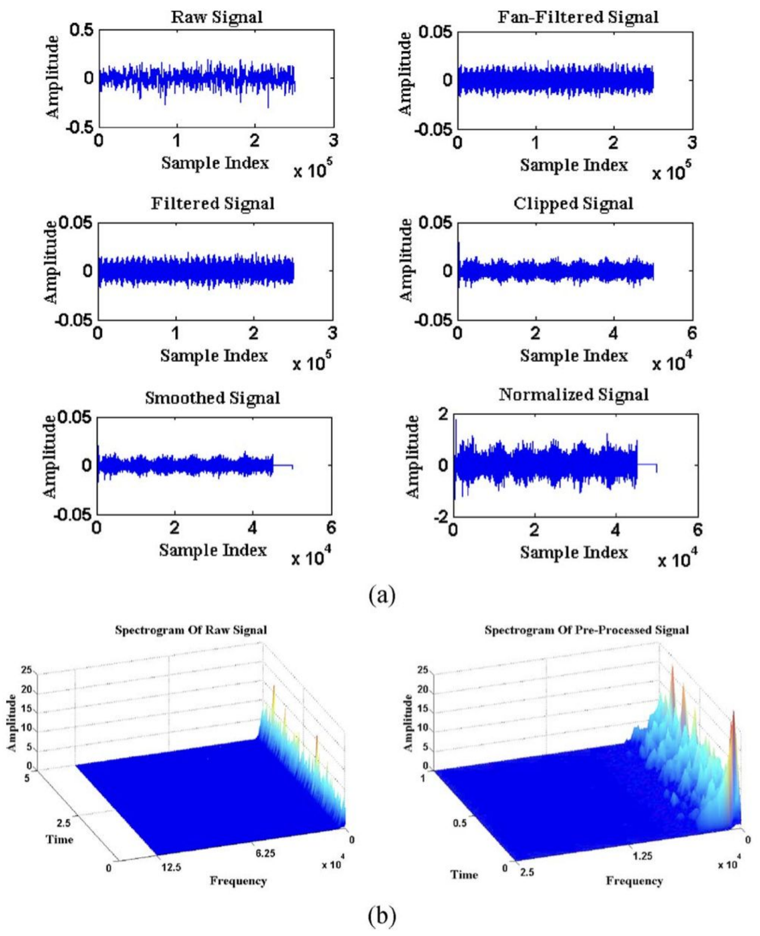


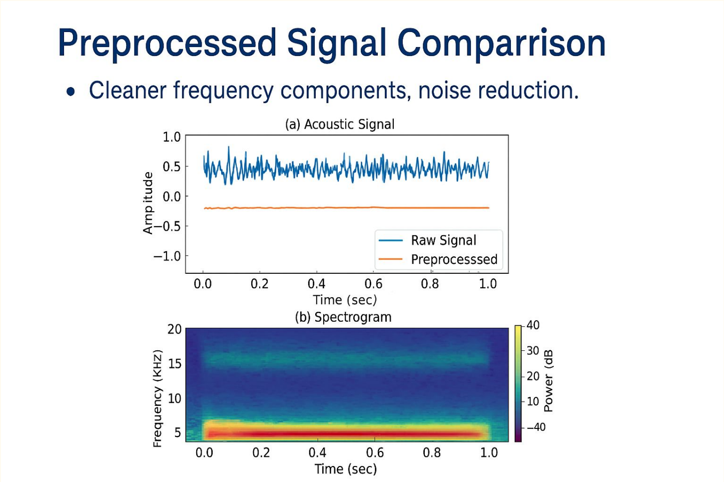
Fig. 5. (a) Plots of signal at every step of Pre-processing. (b) Spectrogram plots of signal before and after pre-processing.

Preprocessed Signal Comparison

Objective:
To improve signal clarity and extract meaningful acoustic patterns for fault diagnosis.

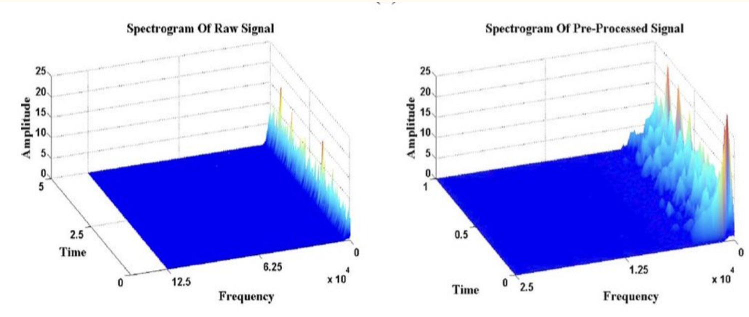
Before vs After Preprocessing

1. **Raw Signal:**
   Noisy, unstable, distorted by fan and environmental noise
2. **Preprocessed Signal:** Cleaned, stable and smoother
   Improved signal-to-noise



Spectrogram Comparison

1. **Raw spectrogram:**
   Broad, noisy frequency bands
2. **Preprocessed Signal:**
   Sharp frequency lines, reduced background noise



Spectrogram plots of signal before and after pre-processing

Key Impact

1. Enhanced fault features
2. Reliable input for feature extraction and classification

Feature Extraction Domains

- Time Domain Features
- Frequency Domain Features
- Wavelet Domain Features

Time Domain Features

1. **RMS (Root Mean Square)**
2. **Skewness, Kurtosis**
3. **Mean, Variance, Peak Values**

Captures signal shape and amplitude characteristics

Frequency Domain Features

1. **FFT: Energy in 8 spectral bins**
2. **Spectral Centroid, Band Energy**

Captures how energy is distributed across frequencies

Wavelet Domain Features

1. **MWT**: Morlet Wavelet Transform
2. **DWT**: Discrete Wavelet Transform (Daubechies-4)
3. **WPT**: Wavelet Packet Transform (level 7)

Captures time-localized frequency patterns

Feature Summary

1. **Phase I**: 286 features (Time + FFT + Wavelets)
2. **Phase II**: Extended to **629 features** with DCT, STFT, WVD, BJD

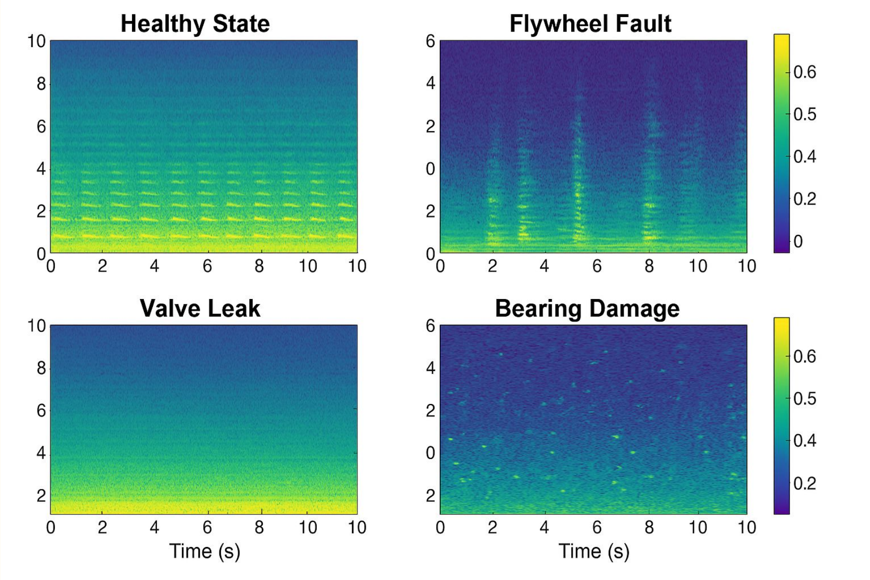
Feature Extraction Domains

Domain	Method	Example Features
Time	Statistical Measures	RMS, Mean, Variance, Skewness, Kurtosis
Frequency	FFT	Energy in Spectral Bins, Spectral Centroid
Wavelet	MWT, DWT, WPT	Entropy, Peaks, Zero-Crossings, Node Energy

Spectrograms by Fault Type

Key Observation

1. Different **compressor faults** produce **unique acoustic patterns**
2. These can be **visually identified** in time–frequency spectrograms



Examples

1. **Healthy State**: Clear, consistent harmonic bands
2. **Flywheel Fault**: Irregular high-frequency bursts
3. **Valve Leak**: Dense low-mid frequency noise
4. **Bearing Damage**: Random scattered energy across spectrum

Why it Matters?

1. Spectrograms allow **early fault detection**
2. Confirms the effectiveness of **acoustic-based monitoring**

Feature Selection Techniques

- Why Feature Selection?
- Techniques Used
- Key Result

Why Feature Selection

1. Reduce computational load
2. Improve classifier accuracy
3. Remove redundant or irrelevant features

Feature Extraction Domains

Method	Type	Description
PCA	Projection-based	Converts features into uncorrelated axes
mRMR	Mutual Information-based	Selects features with high relevance + low redundancy
MIFS/NMIFS	Mutual Information variants	Refine mutual info with normalization or weighting
BD	Distance-based	Measures class separability (Bhattacharyya Distance)

Key Result

Best Accuracy achieved with :

- **mRMR** and **NMIFS**
- Using only **10 to 50 features**

SVM Classification Results

SVM Classification Results

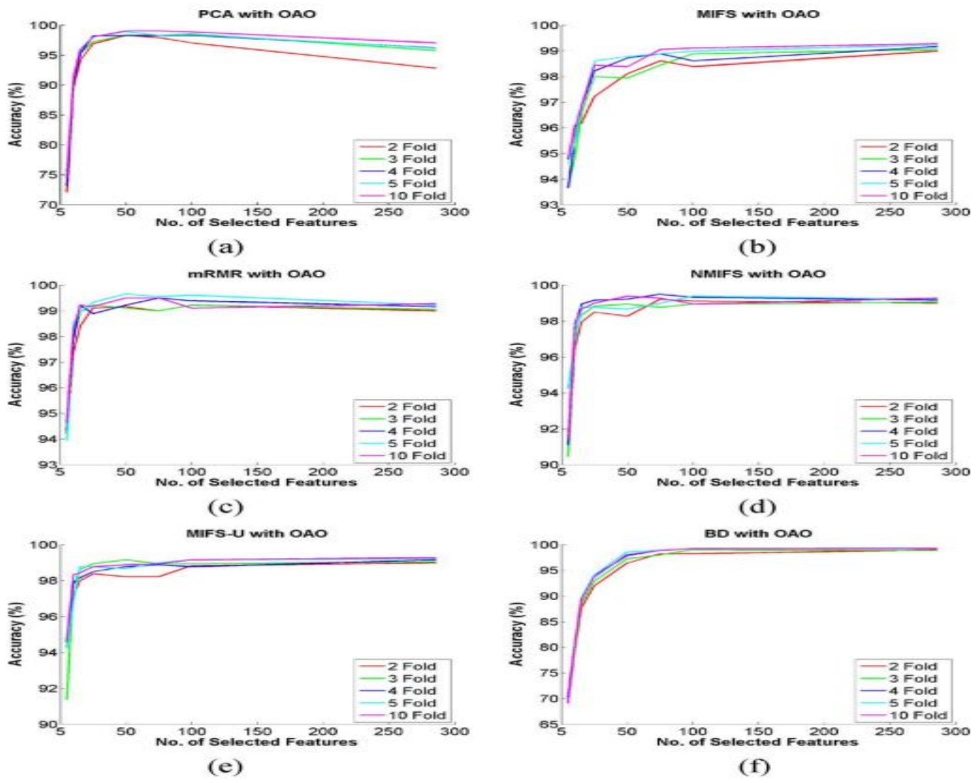


Fig. 7. Graphs of OAO based classifier accuracies of (a) PCA, (b) MIFS, (c) mRMR, (d) NMIFS, (e) MIFS–U, and (f) BD.

Strategy : One-vs-One (OAO)

Computational Complexity : k(k-1)/2 models

Best Accuracy : 99.44%

Efficiency : Most Efficient

One-vs-One (OAO): Train 28 binary classifiers (for 8 classes) → Majority voting.

Key Performance Achievements

Best Classification Accuracy: 99.44% achieved using RBF kernel SVM with One-vs-One (OAO) multiclass decomposition strategy

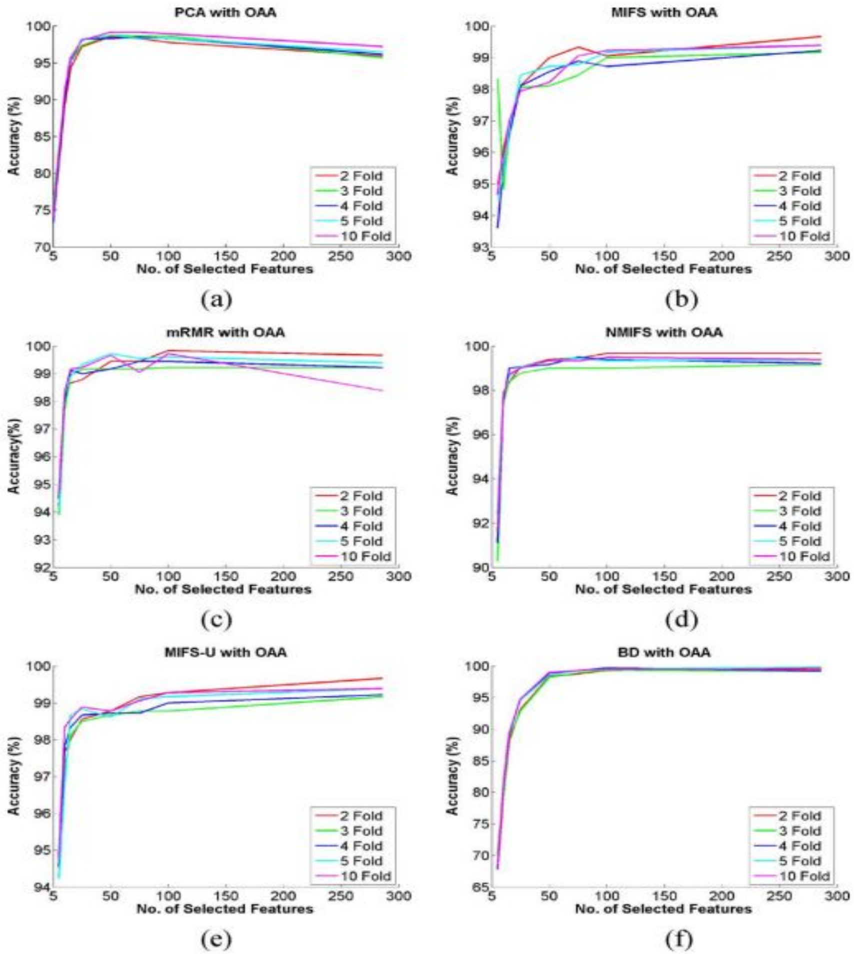


Fig. 8. Graphs of OAA based classifier accuracies of (a) PCA, (b) MIFS, (c) mRMR, (d) NMIFS, (e) MIFS–U, and (f) BD.

Strategy : One-vs-All (OAA)

Computational Complexity : k models

Best Accuracy : 99.30%

Efficiency : High Memory Usage

One-vs-All (OAA): 8 classifiers (1 per class) →

Computationally expensive

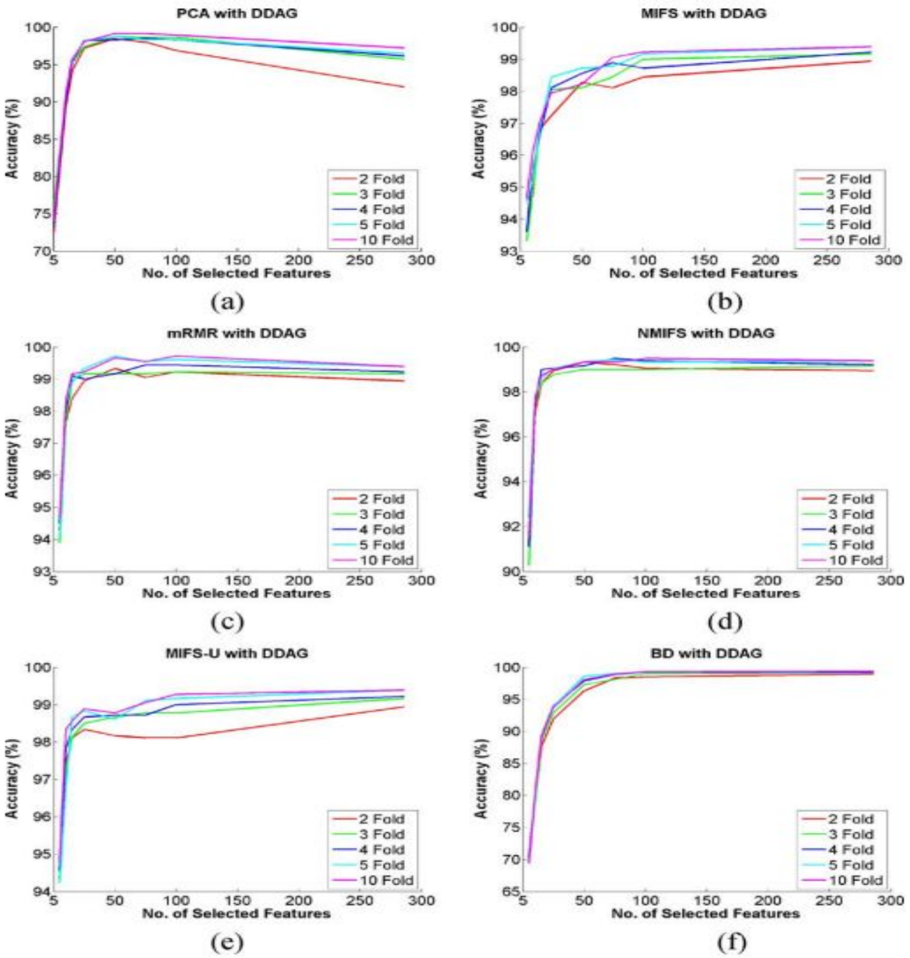


Fig. 9. Graphs of DDAG based classifier accuracies of (a) PCA, (b) MIFS, (c) mRMR, (d) NMIFS, (e) MIFS –U, and (f) BD.

Strategy : DDAG

Computational Complexity : (k-1) models/Test

Best Accuracy : 99.35%

Efficiency : Fast Testing

DDAG: Decision tree of binary classifiers → Fastest inference (only 7 evaluations).

Efficiency & Details

Training Data Efficiency

Critical Finding: Only 50% training data (113 recordings per state) provides performance equivalent to using larger training sets1. This demonstrates exceptional data efficiency, making the system practical for industrial deployment where collecting extensive training data can be costly.

Optimization Details

- Kernel: RBF kernel consistently outperformed linear and polynomial kernels.
- Parameter Optimization: Grid search across 225 combinations of C and γ parameters
- Feature Selection: mRMR (minimum Redundancy Maximum Relevance) technique proved most effective
- Cross-validation: 2-fold cross-validation performed as well as higher fold configurations

Final Insights

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1. EMD-based Sensitive Position Analysis (SPA) Improvements

Traditional vs. EMD-based Approach

Traditional SPA Limitations:

- Relied on technician intuition and experience
- Used basic statistical parameters (peak, standard deviation, RMS)
- Susceptible to noise interference
- Inconsistent results in high-noise environments

EMD-based SPA Advantages:

- Noise Resilience: Isolates signal from noise using Intrinsic Mode Functions (IMFs)
- Automated Process: Reduces dependence on human expertise
- Reliability: More consistent results across different noise conditions
- Consistency: Position 8 ranked highest across all 8 machine states

Sensor Placement Results

Position	Absolute Mean	RMS Value	Combined Rank	Final Ranking
08	0.0421	0.0528	2	1
15	0.0394	0.0501	4	2
22	0.0389	0.0489	6	3
11	0.0385	0.0478	8	4
04	0.0378	0.0465	10	5

2. Feature Importance Analysis

Most Critical Features (mRMR Selection Results)

Transformer type	Total Features	Selected@25 Features	Selected@50 Features
Wavelet Packet (WPT)	254	15	28
Frequency Domain (FFT)	8	5	8
Morlet Wavelet	7	2	4
Discrete Wavelet	9	2	5
Time Domain	8	1	3

Key Finding: Just 2 frequency domain features and 3 WPT features achieved over 94% classification accuracy.

Recommended Feature Set

For optimal balance of performance and computational efficiency:

- FFT (Fast Fourier Transform)
- WPT (Wavelet Packet Transform)
- DCT (Discrete Cosine Transform)
- STFT (Short Time Fourier Transform)
- WVD (Wigner Ville Distribution)

3. Computational Load Reduction

Processing Time Comparison

- Basic Feature Set (286 features): 0.9 seconds per recording
- Extended Feature Set (629 features): 206 seconds per recording
- Optimized Set (5 transforms): 9-10 seconds per recording
- Memory Efficiency: 95% reduction in features while maintaining 99%+ accuracy[1]

4. Classification Robustness

Exceptional Robustness Demonstrated:

- Minimal Features: 96.61% accuracy achieved with just 5 features
- Single Sensor: Complete diagnosis using one optimally placed sensor
- Fault Coverage: All 7 fault types successfully classified
- Stability: Less than 1% variation across different cross-validation configurations
- Generalization: Consistent performance across different training/testing splits

Future Work

Future Work

- *Multi-fault classification*
  Extend the current single-fault model to detect and isolate simultaneous faults (e.g., combined valve and bearing defects), requiring development of hierarchical or probabilistic multiclass-multi-label strategies.
- *Real-time acoustic monitoring*
  Integrate continuous data ingestion and onboard pre-processing pipelines that feed streaming acoustic signals into the trained SVM, enabling immediate on-machine diagnostics.
- *Adaptive/online learning*
  Implement incremental feature-selection mechanisms and online SVM updating to accommodate evolving acoustic signatures over time, reducing the need for frequent retraining.
- *Embedded deployment*
  Port the lightweight feature-extraction and classification modules onto microcontrollers or edge-AI accelerators, enabling in-situ fault detection on resource-constrained hardware platforms without cloud connectivity.

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THANK YOU