

# Induction Motor Fault Detection Using MCSA & Machine Learning

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**Abstract**—This project presents the detection and classification of faults in an induction motor using Motor Current Signature Analysis (MCSA) and machine learning techniques. Stator current signals are acquired and processed to extract fault-related features in the frequency domain. These features are used to train a machine learning model capable of distinguishing healthy and faulty operating conditions. Experimental results show that the proposed approach provides accurate, non-invasive, and reliable fault detection suitable for condition monitoring of induction motors.

**Keywords**—induction motor, fault detection, motor current signature analysis, machine learning, condition monitoring.

## I. INTRODUCTION

Induction motors are extensively used in industrial applications due to their robustness and low cost, making their reliable operation critically important. Undetected faults can lead to efficiency loss, unexpected downtime, and severe equipment damage. This project focuses on induction motor fault detection using Motor Current Signature Analysis (MCSA), a non-invasive diagnostic technique. By combining MCSA with machine learning algorithms, the system enables early, accurate, and automated identification of motor faults for effective condition monitoring.

## II. PROBLEM STATEMENT

Traditional induction motor fault detection methods are often invasive, costly, and unable to provide early diagnosis. There is a need for a reliable, non-invasive, and automated technique that can accurately detect and classify motor faults using readily available electrical signals.

## III. COMPONENTS AND MATERIALS

The key components used in the implementation include:

- Induction Motor: The test motor used to generate current signals under healthy and faulty operating conditions for analysis.
- Current Sensor (CT / Hall-Effect Sensor): Measures the stator current of the induction motor non-invasively for signal acquisition.
- Data Acquisition System (DAQ): Converts the analog current signal into digital form for further processing and analysis.
- Signal Processing Software (MATLAB): Used to perform filtering, FFT, and feature extraction required for MCSA.

- Machine Learning Algorithm: Classifies motor conditions by learning patterns from extracted current signal features.
- Laptop: Executes signal processing and machine learning tasks and stores experimental data.
- Power Supply: Provides the required electrical input to operate the induction motor safely during experiments.

## IV. WORKING MECHANISM

The proposed system monitors the induction motor by analysing its stator current to detect faults using Motor Current Signature Analysis (MCSA) and machine learning. It detects the following faults: broken rotor bar, bearing inner race fault and bearing outer race fault. Our sampling rate was 10000 Hz. The motor current is continuously measured, processed in the frequency domain, and evaluated by a trained model to determine the motor's condition.

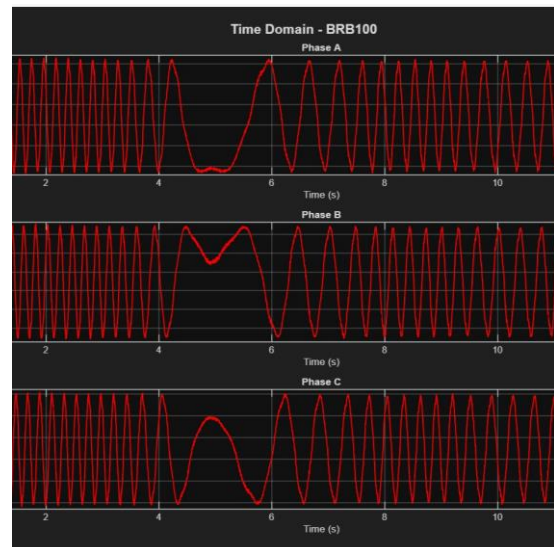


Fig.1. Time domain analysis.

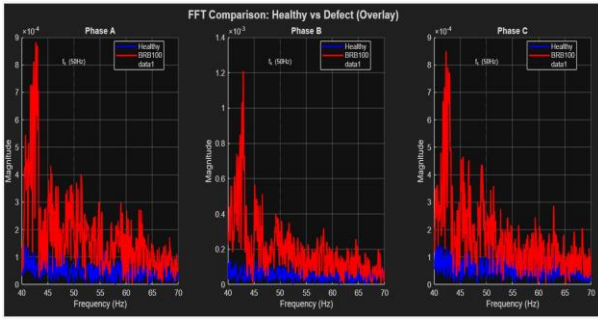


Fig.2. FFT analysis

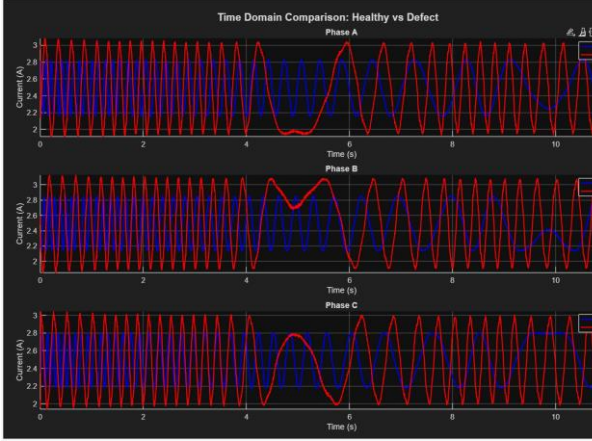


Fig.3. Time domain analysis: healthy vs defective

#### A. Current Signal Acquisition

The stator current of the induction motor is measured using a current sensor, providing a non-invasive and real-time representation of motor behaviour under different operating conditions. The acquired current reflects variations caused by electrical and mechanical faults without requiring physical access to internal motor components.

#### B. Signal Conditioning and Processing

The acquired current signal is filtered and converted into the frequency domain using FFT, where fault-related frequency components and harmonics are extracted as features. Noise reduction and normalization are applied to improve signal quality and enhance fault-related information.

#### C. Feature Extraction and Selection

Key spectral features such as sideband frequencies and amplitude variations are identified, as these features indicate specific faults in the induction motor. Relevant features are selected to reduce computational complexity and improve classification performance.

#### D. Machine Learning-Based Fault Classification

The extracted features are fed into a machine learning model, which classifies the motor as healthy or faulty by recognizing learned patterns. Multiple classifiers are trained and tested to compare performance under identical feature sets.

#### E. Fault Detection and Decision Output

The final classification result is displayed or logged, enabling early fault detection and supporting condition monitoring and maintenance decisions. This helps reduce unplanned downtime and improves motor reliability.

## V. RESULTS AND DISCUSSION

The proposed induction motor fault detection system was evaluated using seven machine learning classifiers. Among them, Random Forest and KNN achieved the highest classification accuracy, indicating their strong capability in handling nonlinear patterns in MCSA features. Naive Bayes, Decision Tree, Linear Discriminant, AdaBoost, and Quadratic Discriminant showed comparatively lower performance. The results demonstrate that ensemble and instance-based learning methods are more effective for accurate induction motor fault diagnosis using current signature analysis.

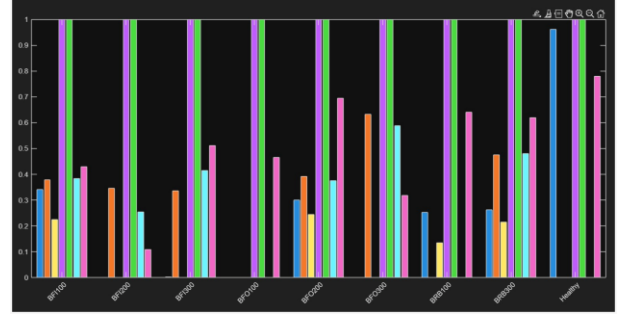


Fig.4. Different models with accuracy

TRAINING MODEL	ACCURACY
Naive Bayes	0.2951
Decision Tree	0.3359
Linear Discriminant	0.1515
KNN	0.9995
Random Forest	0.9995
AdaBoost	0.3324
Quadratic Discriminant	0.5390

Table.1. Accuracy comparison of different machine learning models

True Class	BF1100	BF1200	BF1300	BFO100	BFO200	BFO300	BRB100	BRB300	Healthy
BF1100	10774	796	1325	5984	1117		807	489	211
BF1200	8701	1279	1976	4908	877		658	342	63
BF1300	2878	1882	7656	3288	560	3	435	284	43
BFO100	3755	378	1483	11069	887		799	433	714
BFO200	767	128	116	366	16314	705	258	867	
BFO300	142	158	149	174	6635	2009	158	476	
BRB100	175	7	16	180	172		14917	5088	90
BRB300	51	42	18	160	244	4	6800	12716	
Healthy	1352		184	1903	669		1128	376	11934
Predicted Class	BF1100	BF1200	BF1300	BFO100	BFO200	BFO300	BRB100	BRB300	Healthy

Fig.5. Confusion matrix analysis

## REFERENCES

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- [4] Dataset from Mehran University of Engineering and Technology