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Acoustic Based Induction Motor Fault Detection System Using Adaptive Filtering Algorithm and Fusion Based Feature Extraction Method

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Abstract

The proposed machine fault diagnostic system utilizes acoustic signal processing and machine learning for early fault detection and localization in induction motors. The growth of the fault in an induction motor tends to be quick and can result in a significant failure that can lead to economic loss and huge maintenance expenses. Therefore, developing accurate and sensitive induction motor fault diagnostic procedures for the maintenance system is crucial. The main purpose of this paper was to propose an optimized noise reduction technique for an induction motor fault diagnosis system and two novel acoustic feature vectors that can be used in machine learning algorithms. The contribution of this paper is to implement the effectiveness of the fusion features of acoustic signals by concatenating them from different domains. The acoustic dataset for an induction motor is collected in a motor workshop, and the NLMS algorithm is used for background noise cancellation due to its quick adaptation, stability, and efficient error minimization. Data are segmented and normalized during pre-processing, and the induction motor fault diagnosis system is implemented using MATLAB. Zero Crossing Rate (ZCR), Spectral Entropy (SE), and Energy Entropy (EE) feature vectors are combined, and the F1 feature vector is built. Correlation calculations are employed to assess the motor's condition status, and if a fault is detected, the system proceeds with feature extraction for fault localization. In the feature extraction stage for induction motor (IM) fault localization, Gammatone Cepstral Coefficients (GTCC) and Mel Frequency Cepstral Coefficient (MFCC) features are combined to construct the second feature vector (F2). This feature vector is used as training feature data in machine learning algorithms. If the input test signal is strongly correlated with the faulty signals, the type of faults is classified using a Support Vector Machine (SVM) classifier.

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According to the experimental results, the proposed system achieved an average accuracy of 99% in fault detection, 97.5% in fault localization, and an error rate of 2.5%.

Keywords: Acoustic Signal Processing; Correlation Algorithm; Energy Entropy; Fault Detection and Localization; Mel-Frequency Cepstral Coefficient; Normalized Least Mean Square Algorithm; Spectral Entropy; Support Vector Machine; Zero Crossing Rate.

1. Introduction

The development of technology has enhanced convenience and ease of living, making it crucial to understand the potential defects in induction motors for effective industry repair and maintenance. A promising method for detecting and localizing faults in induction motors is through acoustic-based techniques, which analyze the sound signals generated by the motors. These signals can reveal the motor's operating conditions and help identify various faults, such as Inner Race Fault, Outer Race Fault, Ball Fault, Rotor Fault, and etc. This research aims to enhance the performance of acoustic-based fault detection and localization systems using machine learning by introducing two fusion-based feature vectors. It focuses on analyzing the acoustic signals from induction motors and developing a machine learning model for accurate fault detection and localization. The study will also assess the system's accuracy and reliability. The results will contribute to more effective and efficient induction motor fault detection systems, potentially reducing maintenance costs and informing future acoustic-based fault diagnosis system designs.

2. Literature Review and Related Work

In order provide insight into the many strategies used and the developments in the detection and diagnosis of induction motor (IM) problems, this section presents a review of the literature. The use of acoustic emission for condition monitoring and fault diagnosis of induction motors, highlighting its accuracy, efficiency, and potential advantages and limitations in detecting various faults in industrial machinery are presented in [1]. Effectively eliminating both white noise and nonlinear interference from vibration signals [2] using the combined adaptive filter method, using self-adaptive noise cancellation and kernel least mean square algorithms, to enhance fault features in planetary gearboxes. [3] proposes a novel noise reduction method by combining the least mean square (LMS) adaptive filter and spectral subtraction algorithms to enhance speech signals by reducing noise and improving signal-to-noise ratio (SNR), demonstrating superior performance compared to existing methods. Reference [4] combining a normalized least mean square (NLMS) filter with Hilbert envelope analysis to detect broken rotor bars in squirrel-cage induction motors, demonstrating improved accuracy over traditional Fast Fourier Transform (FFT) methods under various loading conditions. [5] proposes a multimodal feature fusion-based deep learning method for real-time and accurate online fault diagnosis of rotating machinery by extracting and combining features from the time domain, frequency domain, and curvature data to improve diagnostic efficiency. [6] introduces an improved fault diagnosis method for electromechanical systems using a zero-crossing algorithm, optimizing its parameters to enhance fault recognition accuracy and robustness, validated through simulations and experiments. [7] presents a multi-step progressive fault diagnosis method for rolling element bearings using energy entropy theory and a hybrid ensemble auto-encoder, which integrates statistical analysis with deep learning to improve feature learning, feature reduction, and fault classification, demonstrating superior efficiency and accuracy in practical applications. [8] proposes a novel fault damage degree identification method using high-order differential mathematical morphology gradient spectrum entropy (HMGSEDI) to accurately quantify the fault severity in rolling bearings, validated through experiments showing improved identification accuracy and robustness compared to traditional methods. [9] discusses various entropy-based methodologies used for detecting motor faults by analyzing signal complexities and integrating these methods with artificial intelligence for accurate classification. [10] compares the effects of Mel-Frequency Cepstral Coefficients (MFCC) and Gammatone Cepstral Coefficients (GTCC) on identifying the ideal recording time for body sound location identification, finding that MFCC features generally provide better performance than GTCC features. [11] proposes a method for automatic gearbox fault diagnosis using Mel-Frequency Cepstral Coefficients (MFCCs) and Support Vector Machine (SVM) to enhance machine condition monitoring by detecting and classifying mechanical faults with high accuracy based on acceleration signals from rotating machinery. Support Vector Machines (SVMs) are used [12] for induction motor fault detection because they can effectively classify different fault conditions by finding an optimal hyperplane that separates data points representing different classes, and by using kernel functions like Radial Basis Function (RBF) to handle non-linear data and improve the accuracy of fault classification.

3. Research Methodology

This paper aims to establish a fault detection and localization system for induction motors using Zero Crossing Rate (ZCR), Spectral Entropy (SE), Energy Entropy (EE), Gamma Tone Cepstral Coefficients (GTCC), Mel-Frequency Cepstral Coefficient (MFCC) and Support Vector Machine (SVM). ZCR, SE, and EE are employed to extract feature vectors for fault detection in induction motors. The efficiency and applicability of machine fault detection and classification are enhanced through the utilization of correlation classifier. The rotating machine fault diagnosis system involves two primary processes: fault detection and fault localization. The design of the proposed machine fault diagnosis system is illustrated in Figure 1 through a descriptive flowchart.

The correlation algorithm is used to carry out fault detection. The degree of similarity between training and test features is determined using the correlation algorithm. There are 300 recordings in the training features. The statistical features are extracted from the induction motor sound signals. The statistical features include mean, median, maximum, minimum, variance, standard deviation, skewness and kurtosis.

In the detection section, an incoming test data of audio file is first entered as one row in the testing feature section. Correlation between test data and successive rows of training features is calculated, producing three hundred different correlation values. A row with a high correlation value is chosen, its index is displayed, and classified into class zero (indices 1 to 60) or class one (indices 61 to 300).

In the test localization feature extraction section, MFCC and GTCC features are combined to construct the F2 feature vector. This feature vector is used as training features data in machine learning algorithms. Faults are classified and located using a Support Vector Machine if the input test signal strongly correlates with the faulty signal.

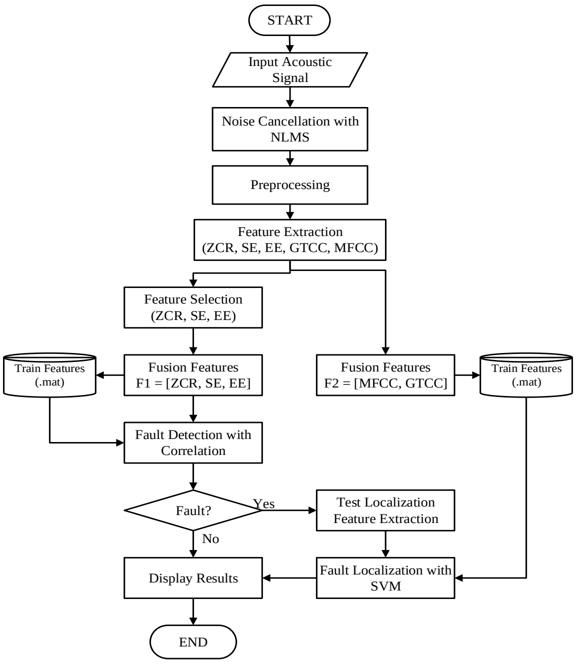

Figure 1: Proposed system design of fault detection and classification system for induction motor

3.1. Acoustic Data Collection

The datasets are constructed with acoustic signals that were collected at specific current levels with a microphone close to an induction motor. A completely transparent analog amplifier is utilized to amplify the signals, which have been collected under typical environmental conditions. The acoustic recordings have a resolution of 16 bits, monophonic, and (200.5Hz – 1.9kHz) frequency range. The sampling frequency of 44.1 kHz is commonly used in audio applications, including those related to motor control, due to the Nyquist theorem. This theorem states that the sampling frequency must be at least twice the maximum frequency of the signal being sampled to accurately reconstruct the original signal. The choice of a 16-bit analog-to-digital conversion (ADC) provides enough resolution to capture the dynamic range and nuances of the signals involved in motor control applications. The recorded acoustic signals are segmented into two-second (2sec x 44.1 kHz) duration because the necessary fault features are contained within that brief time frame.

Figure 2: One phase capacitor start induction motor

The dataset comprises of 400 recordings, encompassing normal and four faulty conditions (Inner Race Fault, Outer Race Fault, Ball Fault, and Rotor Fault). The experimental induction motor setup is shown in Table 1.

Table 1: Specification of induction motor

SERIAL	INDUCTION MOTOR
Motor Type	One Phase, Capacitor Start Motor
Model	YCL-100L-4,
Power	2 HP, 220 V
Specification Values	50Hz, 13 A, 1440 R.P.M.

3.2. Noise Reduction

In terms of noise reduction with adaptive filtering algorithm, Normalized Least Mean Squares (NLMS) algorithm is a popular technique used in signal processing and adaptive filtering. NLMS is an adaptive filter algorithm that aims to minimize the mean square error between the desired signal and the output of the filter. It's widely used for various applications including noise cancellation, echo cancellation, equalization, and system identification.

3.2.1. Adaptive Normalized Least Mean Square

The Normalized Least Mean Square (NLMS) algorithm is an enhancement of the Least Mean Squares (LMS) algorithm, one of the most widely used methods for adaptive filtering due to its simplicity and effectiveness. The core idea of LMS is to iteratively adjust the filter coefficients to minimize the mean square error between the desired signal and the filter output. LMS algorithms have a step size that determines the amount of correction applied as the filter adapts from one iteration to the next. A step size that is too small increases the time for the filter to converge on a set of coefficients. A step size that is too large might cause the adapting filter to diverge and never reach convergence. In this case, the resulting filter might not be stable. The NLMS algorithm modifies this approach by normalizing the step size used in the coefficient update equation, which significantly improves convergence speed and stability. The procedure of the NLMS algorithm is the same as the LMS algorithm except for the estimation of the time-varying step-size μ(k).

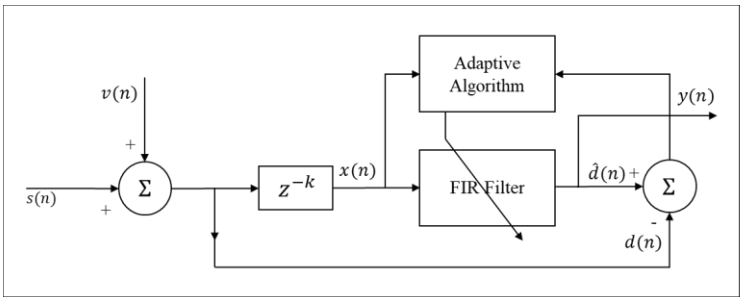

Figure 3: Adaptive NLMS algorithm

Figure 3 depicts the filter structure of an NLMS algorithm using the self-adjustable step-size μ(k) in the NLMS algorithm given in Equation 1.

$$\mu(k) = \frac{\mu}{\varepsilon + \|\vec{\varphi}(k)\|^2} \qquad (1)$$

Where, $\vec{\varphi}(k)$ represents the data vector. ε is a very small positive number that prevents the denominator from equaling zero when $\|\vec{\varphi}(k)\|^2$ approaches zero.

The step-size $\mu(k)$ is time-varying because the step-size changes with the time index k. Substituting $\mu(k)$ into the parametric vector $\vec{w}(k)$ equation yields the following Equation 2.

$$\vec{w}(k+1) = \vec{w}(k) + \mu(k)e(k)\vec{\varphi}(k) \qquad (2)$$

Where, $\vec{\varphi}(k)$ represents the data vector, $e(k)$ is the error signal, and $\mu(k)$ is the step size.

Figure 4 demonstrates the resultant output after filtering the healthy signal. As shown in Figure 4, the signal is smoother than the raw signal by using the NLMS filter. This leads to the performance of system. Table 2 shows the performance of the proposed system using NLMS filter.

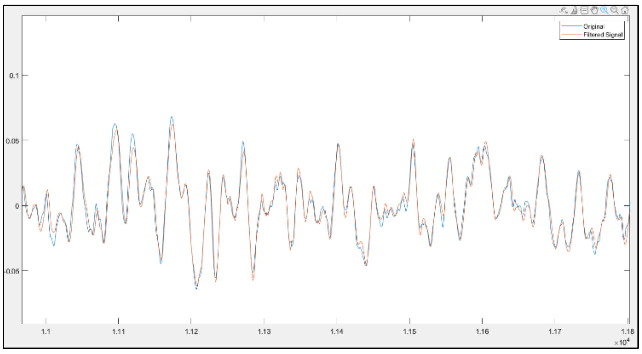

Figure 4: Original signals and filtering signal of healthy state using NLMS algorithm

Table 2: Performance of proposed system using NLMS

	Accuracy	Precision	Recall	F1-Score
NLMS	97.5	97.73	97.5	97.53

3.2.2. Mean Square Error (MSE)

Mean Square Error (MSE) is crucial for evaluating and improving model performance in statistical modeling and machine learning, particularly in induction motor fault detection systems, where it ensures the reliability and efficiency of critical machinery. MSE aids in anomaly detection and fault classification by identifying significant deviations between actual and predicted motor performance, enhancing model accuracy, and evaluating model performance by averaging the squared errors between predicted and actual values, particularly for assessing induction motor behavior and efficiency. A lower values of MSE indicates that the model's predictions are close to the actual motor conditions. If the MSE exceeds a predefined threshold, it indicates a potential fault. Mathematically the MSE equation is represented as:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2 \qquad (3)$$

Where n is the number of data points, y_i is the actual value for the i-th data point, and $\hat{y}_i$is the predicted value for the i-th data point.

3.2.3. Signal-to-Noise Ratio (SNR)

Signal-to-Noise Ratio (SNR) in induction motor fault detection and classification systems is a measure used to quantify the level of the desired signal relative to the background noise. Higher SNR indicates a clearer and more detectable fault signal, making it easier to accurately identify and classify such as ball fault, inner race fault, outer race fault, rotor fault, bearing faults, stator faults, and etc. in the induction motor. Low SNR can obscure the signal, making it difficult to distinguish between normal operating conditions and faults. Using adaptive noise cancellation techniques and real-time signal processing algorithms helps maintain a high SNR even in changing operational environments. Mathematically the SNR equation is represented as:

$$SNR_{dB} = 10log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \qquad (4)$$

where P_{signal} is the power of the signal and P_{noise} is the power of the noise.

Table 3 presents experimental results of the average Signal to Noise Ratio (SNR) and average Means Square Error (MSE) for different types of faults in induction motor.

Table 3: Different values of SNR and MSE of induction motor signals

No.	Type of Signals	Averaged SNR	Averaged MSE
1.	Normal Signal	-6.4636	0.0158
2.	Ball Fault Signal	-7.9908	0.0104
3.	Inner Race Fault Signal	-6.3257	0.0178
4.	Outer Race Fault Signal	-8.1923	0.0182
5.	Rotor Fault Signal	-6.3390	0.0157

3.3. Preprocessing

Data normalization adjusts the amplitude of a signal to a desired level without altering the signal-to-noise ratio or relative dynamics, with one method involving setting the signal's peak magnitude to a specified level. It is also known as Max-Min normalization. For every feature, the minimum value of that feature gets transformed into a -1, the maximum value is transformed into a 1, and every other value gets transformed into a decimal between -1 and 1. Mathematically the normalization equation is represented as

$$x_{norm} = (x - x_{min})/(x_{max} - x_{min}) \qquad (5)$$

where, x_{norm} is the normalized value of x. The normalized recorded signals are described in Figure 5.

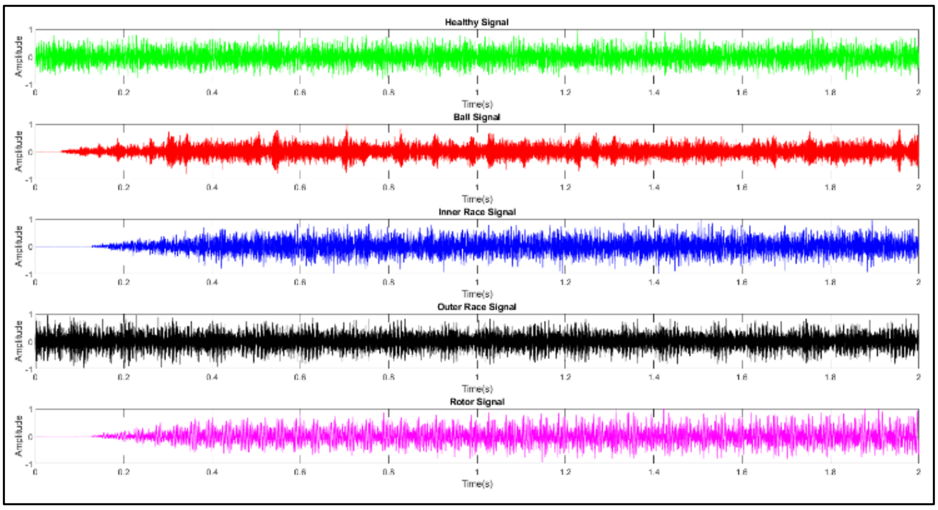

Figure 5: Normalized acoustic signals

During the pre-processing stage of acoustic feature extraction, the non-stationary characteristics of acoustic signals are addressed by segmenting them into frames, overlapping to retain information, and minimizing discontinuities through windowing techniques, such as the Hanning function, to maintain a continuous waveform for further experimentation. Equation 6 defines the mathematical expression of a Hanning window function.

$$w(n) = 0.5\ (1 - cos(2\pi \frac{n}{N-1})) \qquad (6)$$

Where, N is the total number of samples (the window length), and n is the sample index ranging from 0 to N-1. The statistical properties of an acoustic signal are time-dependent due to its non-stationary nature. To analyze the signal effectively, it is necessary to extract spectral features and other characteristic properties from small signal blocks. The number of samples can be determined from time in seconds as follows.

$$F_{length\ in\ sample} = sr \times F_{length\ in\ second} \qquad (7)$$

where, $F_{length\ in\ sample}$ is the frame length in sample, sr is the sampling rate and $F_{length\ in\ second}$ is the frame length in seconds.

The Equation 8 provided facilitates the computation of the expected number of frames.

$$\#\ F = \frac{N_s - M}{N_f - M} \qquad (8)$$

where, #F is the total number of frames, N_s is the signal length in the sample, N_f is the frame length in the sample, and M is the frame overlap.

Windowing reduces the amplitude of discontinuities at the borders of finite sequences. The Hanning window function is employed in the study for its effectiveness in reducing spectral leakage and providing good frequency resolution. The first frame of the recorded data after windowing is shown in Figure 6.

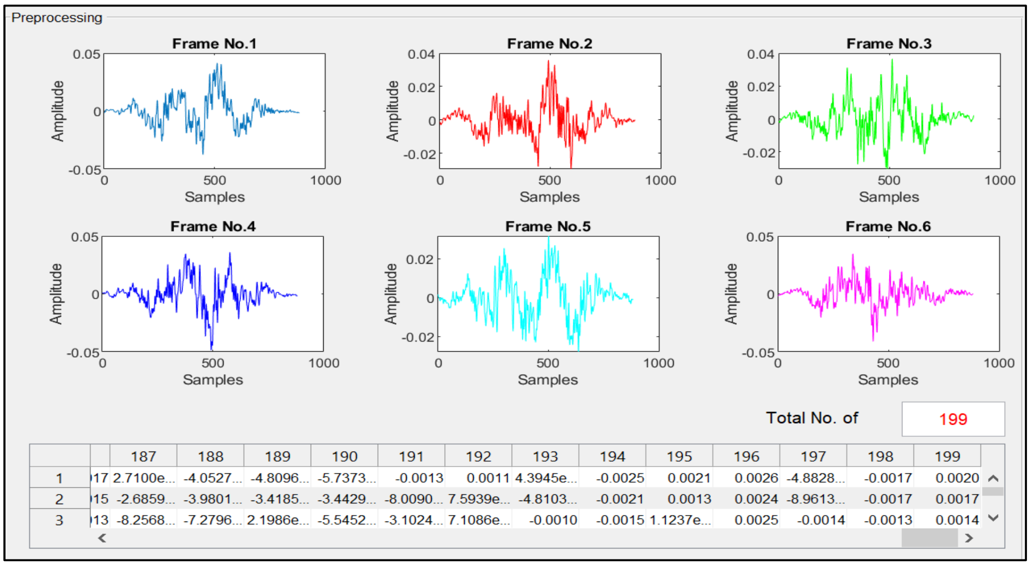

Figure 6: First frame of the induction motor's acoustic signals after windowing

3.4. Feature Extraction for IM Fault Detection and Localization

A fault detection and classification system for induction motors is proposed, leveraging fusion features like Zero Crossing Rate (ZCR), Spectral Entropy (SE), Energy Entropy (EE), Gamma Tone Cepstral Coefficient (GTCC), and Mel-Frequency Cepstral Coefficient (MFCC), alongside Machine Learning techniques including Support Vector Machine (SVM). The system aims to enhance fault detection and localization utilizing the proposed fusion features.

3.5. Proposed Detection Features Extraction

In the feature extraction stage, Zero Crossing Rate (ZCR), Spectral Entropy (SE), and Energy Entropy (EE) feature vectors are chosen. Then, feature selection is performed using the statistical approaches. The statistical features of Zero Crossing Rate (ZCR), Spectral Entropy (SE), and Energy Entropy (EE) feature vectors features are combined and fusion feature vector F1 is created as training features. Induction motor fault detection involves extracting specific features in the sound emitted by induction motor to identify and diagnose potential issues or malfunctions. Correlation calculations are employed to assess the motor's condition status, and if a fault is detected, the system proceeds with feature extraction for fault localization. The extracted feature vector for the induction motor fault detection task is illustrated in Figure 7.

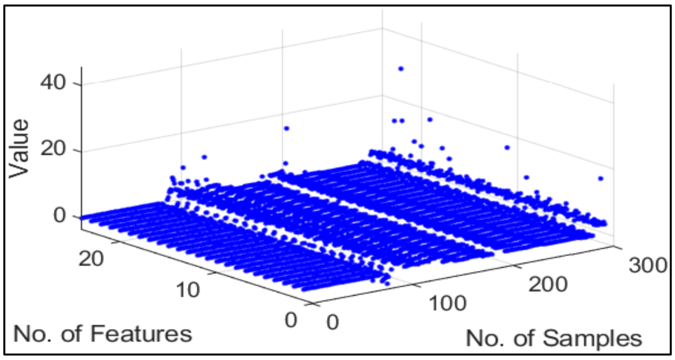

Figure 7: The extracted feature vector for the induction motor fault detection

3.5.1. Zero Crossing Rate (ZCR)

Zero Crossing Rate (ZCR) is a fundamental feature in signal processing and audio analysis, measuring how often an audio signal's waveform crosses the zero amplitude line. It indicates signal transitions from positive to negative or vice versa. A higher ZCR generally indicates a higher frequency of signal changes, which can be associated with higher pitch sounds in audio signals. ZCR is valuable for tasks like speech recognition and music genre classification. It's calculated by counting sign changes in the signal within a specified window. The formula for ZCR within the window is typically expressed as:

$$ZCR = \frac{1}{N-1}\sum_{n=1}^{N-1} |sign(x[n]) - sign(x[n-1])| \qquad (9)$$

Where N is the length of the window, x[n] is the value of the signal at sample index n, $sign(x[n])$ is the sign function.

3.5.2. Spectral Entropy

The spectral entropy of a signal is a measure of its spectral power distribution. The concept is based on the Shannon entropy, or information entropy, in information theory. Shannon's Entropy is the measure of set of relational parameters that vary linearly with the logarithm of the number of possibilities [5]. Spectral entropy provides a measure of the complexity or randomness of a signal's frequency content. It is also a measure of data spread and is most commonly used to assess the dynamical order of a system. The main advantage of Shannon's Entropy is that, it is better adapted to normal distributions. However, few drawbacks of this entropy are: the possibility of losing more information due to aggregation, the possibility of over-estimation of entropy level if too many zones are used, and this method fails to explain temporal relationships between different values extracted from a time series signal. Shannon's Entropy is obtained by multiplying the power in each frequency by the logarithm of the same power, and the product is multiplied by −1. The Shannon's Entropy is given by the Equation 10.

$$SEN = \sum_f p_f \log \frac{1}{p_f} \qquad (10)$$

Where, SEN is a Shannon's entropy and p_f is the power in each frequency.

3.5.3. Energy Entropy

Energy Entropy (EE) is a feature commonly used in signal processing and analysis, particularly in the field of fault detection in machinery like induction motors. In the context of feature extraction for fault detection, EE is a measure of the randomness present in the energy distribution of a signal. It quantifies the complexity of the energy distribution across different frequency components within the signal. EE is calculated by first dividing the signal into smaller segments (often using techniques like windowing), then computing the energy spectrum of each segment. Higher values of EE indicate greater complexity or irregularity in the signal's energy distribution, which can be indicative of faults or anomalies in mechanical systems of induction motors. The entropy of the energy distribution is calculated using methods Shannon entropy.

$$E(f) = \int_{-\infty}^{\infty} |x(t)|^2 e^{-2\pi i f t} dt \tag{11}$$

$$P(f) = \frac{E(f)}{\sum_f E(f)} \tag{12}$$

$$EE = -\sum_f P(f)\, log_2(P(f)) \tag{13}$$

Where *E(f)* is the energy spectrum of the signal using the Fourier Transform, *x(t)* is the signal, $|x(t)|^2$ represents the squared magnitude of the signal, the integral computes the energy across all time, *P(f)* is the normalized energy spectrum, $\sum_f E(f)$ is the total energy across all frequencies, and *EE* is the Energy Entropy of the normalized energy spectrum.

3.6. Feature Extraction for Fault Localization

Feature extraction for fault localization involves selecting and transforming raw data into informative features to identify fault locations in a system. The effectiveness relies on feature quality, relevance, and modeling accuracy. Through this process, fault localization techniques help in maintenance and troubleshooting. The diagnosing of induction motor conditions requires a database of signals and features from diverse domains.

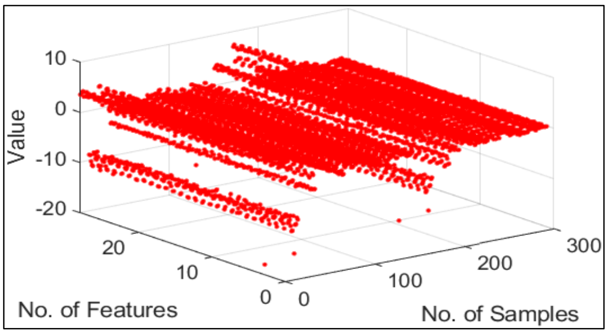

Figure 8: The extracted feature vector for the induction motor fault localization

3.6.1. Mel-Frequency Cepstral Coefficient

MFCC are fundamental in audio processing, capturing crucial spectral features used in tasks like speech recognition, speaker identification, and music genre classification. Their compact representation of the signal's spectral envelope makes them robust to variations in audio conditions. Widely employed in speech and audio processing, MFCCs play a pivotal role in tasks such as speech recognition and speaker identification.

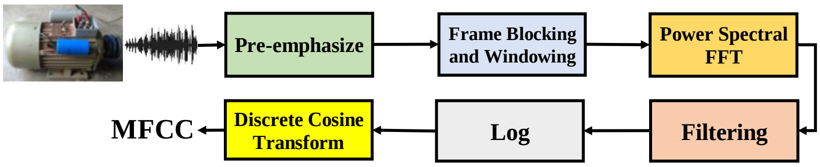

Figure 9: Block diagram of MFCC feature extraction method

In Figure 9, the process involves preprocessing the input signal with a pre-emphasis filter to enhance high frequencies. The signal is then divided into short time frames using framing, each frame is windowed with functions like the Hamming window. Subsequently, the Fast Fourier Transform (FFT) is applied to obtain the frequency representation. Following this, a mapping from linear to Mel frequency scale is defined, and filter bank coefficients are computed. Finally, Mel-Frequency Cepstral Coefficients (MFCCs) are derived using discrete cosine transformation. This comprehensive approach captures essential spectral features crucial for various audio processing applications.

$$MFCC_i=\sqrt{\frac{2}{N}}\ \sum_{j=1}^{N} m_j \cos\left(\frac{\pi i}{N}(j-0.5)\right) \qquad (14)$$

where, N represent the number of bandpass filters, and m_j denotes the log band pass filter output amplitudes.

3.6.2. Gamma Tone Cepstral Coefficient (GTCC)

The Gamma Tone Cepstral Coefficients (GTCC) are a feature extraction method used in audio signal processing and speech recognition. It derived from modeling the human auditory system to capture auditory perception characteristics. GTCC involves, gamma tone filterbank: mimics the human cochlea's frequency analysis using gamma tone filters, filtering: audio signals are filtered through these gamma tone filters, covering various frequency bands, Cepstral Analysis: cepstral analysis emphasizes important frequency domain features by computing the cepstrum of the filtered signals, Coefficient Calculation: cepstral coefficients are derived from the filtered signals, capturing audio characteristics compactly. GTCCs are valuable for tasks like speech recognition, speaker identification, and audio classification, where understanding auditory perception is essential. The mathematical computation of Gamma Tone Cepstral Coefficients (GTCC) comprises several stages, including filtering the input signal through a gamma tone filterbank and conducting cepstral analysis.

$$yk(t) = x(t) * hk(t) \qquad (15)$$

Where *yk(t)* is the gamma tone filterbank output of the k-th filter, *x(t)* is the input signal, and *hk(t)* is the impulse response of each gamma tone filter.

$$ck(t) = F^{-1}\{log(|F\{y_k(t)\}|^2)\} \qquad (16)$$

Where *ck(t)* is the cepstrum of each filtered signal, *F* denotes the Fourier transform, and |.| is the magnitude of the complex number.

$$GTCCm = \sum_{k=1}^{N} C_k(t)cos\left[\frac{\pi m(k-0.5)}{N}\right] \qquad (17)$$

Finally, the *GTCCs* are obtained by taking the Discrete Cosine Transform (DCT) of the cepstral coefficients. Where N is the number of cepstral coefficients, m is the index of the *GTCC*, and $C_k(t)$ are the cepstral coefficients.

3.7. Detection and Localization Algorithms

Detection and localization algorithms are pivotal for induction motor fault diagnosis systems, facilitating early fault detection, reduced downtime, lower maintenance costs, improved operational efficiency, enhanced safety, and predictive maintenance strategies, ensuring optimal motor performance and reliability.

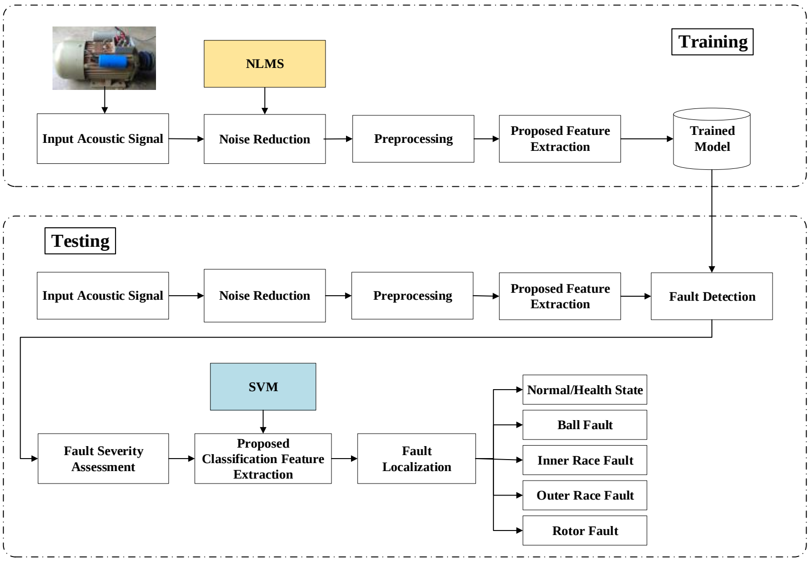

Figure 10: Induction motor fault detection and localization system design

Creating a comprehensive sample signal database containing induction motor fault waveforms and features is vital for effective condition detection. The subsequent discussion focuses on the theory behind Correlation and Support Vector Machine (SVM) algorithms, which are utilized for this purpose.

3.7.1. Correlation

In an induction motor fault detection system, correlation involves comparing a measured signal with a reference signal to identify faults. The reference signal represents normal motor behavior, while the measured signal is monitored in real-time and may show deviations due to faults. The correlation coefficient, ranging from -1 to 1, measures the similarity between these signals: a high coefficient indicates strong similarity, while a low coefficient suggests anomalies. For the healthy stage, the induction motor's average correlation value is 1. By analyzing changes in the correlation coefficient over time, the system can detect motor faults. This method, often combined with other techniques, effectively identifies deviations associated with faults. The mathematical formula for calculating the correlation coefficient between two signals x(t) and y(t) can be expressed using Pearson's correlation coefficient *r*.

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}} \qquad (18)$$

Where n is the number of data points in the signals, x_i and y_i are individual data points of x(t) and y(t), $\bar{x}$ and $\bar{y}$ are the mean values of x(t) and y(t). In Table 4 presents experimental results of maximum correlation score for different types of faults in induction motor fault detection.

Table 4: Feature extraction for fault detection of induction motor

No.	Type of Faults	Maximum Correlation Score	Index
1.	Normal Signal	1	1
2.	Ball Fault	0.99922	69
3.	Inner Race Fault	0.99609	300
4.	Outer Race Fault	0.99891	226
5.	Rotor Fault	0.9981	272

3.7.2. Support Vector Machine (SVM)

Support Vector Machines are used for induction motor fault detection due to their ability to handle high-dimensional and non-linear data, robust classification performance, and excellent generalization capabilities. These characteristics make SVMs particularly effective in identifying and classifying different types of motor faults, leading to more reliable and efficient maintenance and monitoring systems. The goal is to find a hyperplane in an n-dimensional space that optimizes the distance between data points and possible classes. Kernel functions, such as Radial Basis Function (RBF), Sigmoid, Gaussian, Linear, and Polynomial, are used to calculate the distance between data points. Adjusting the hyperparameters of these functions can lead to overfitting or underfitting, affecting the separation of classes. For multiclass classification, the problem is divided into several binary classification problems, using the same method for each. The Radial Basis Function (RBF) is specifically employed to determine the relationship between two variables.

$$K(x_1,x_2) = exp(-\frac{\|x_1-x_2\|^2}{2\sigma^2}) \qquad (19)$$

where, $\|x_1 - x_2\|$ is the Euclidean distance between two points x_1 *and* x_2, and σ is the variance.

4. Experimental Result

The acoustic dataset is first collected on the induction motor type of one-phase capacitor starts motor in the motor workshop environment. The normalized least mean square (NLMS) algorithm is used in background noise cancellation of induction motor because it adapts quickly to changing noise environments, ensures stability by normalizing the input signal, and efficiently minimizes the mean square error between the desired and actual signals. The dataset consists of 400 recordings, which include 1 to 80 normal sounds and 81 to 400 of four different faults (Inner Race Fault, Outer Race Fault, Ball Fault, and Rotor Fault). Each of the four different faults has 80 samples. The average length of each recorded data is 2 seconds.

There are 300 sound files of induction motor in the training features. The 240 features that are taken from the training features section include Inner Race Fault of 60, Outer Race Fault of 60, Ball Fault of 60, and Rotor Fault of 60. Data Splitting for the induction motor fault detection task is presented in Table 5. During pre-processing, collected data are normalized to a desired amplitude level. Then, the input acoustic signals are framed into short segments. The proposed feature extraction approach employs a frame step of 0.01 seconds, a 50% overlap area, and a frame duration of 0.02 seconds. With a sampling rate of 44.1 kHz, 199 frames are obtained for the framed signal, which has a dimension of the framed signal (199 x 400), and subsequently, the framed signal is multiplied by the Hanning window function are described in Figure 6. MATLAB has been selected and used to implement the fault diagnosis system. The results were obtained using a PC with an intel core i5 8th generation CPU @ 1.60GHz, and 8 GB of RAM.

Zero Crossing Rate (ZCR), Spectral Entropy (SE), and Energy Entropy (EE) feature vectors are concatenated, and the F1 feature vector is built and presented in Figure 1. Motor sound fault detection involves analyzing specific features in the sound emitted by induction motor to identify and diagnose potential issues.

Table 5: Data splitting for induction motor fault detection

Data	Health	Fault
Train	60	240
Test	20	80
Total	80	320

In the test detection, the correlation algorithm is used to carry out the induction motor fault detection. An incoming test data of the audio sound file is first entered as one row in the testing feature section. Correlation between test data and successive rows of training features is calculated, producing three hundred different correlation values. In the detection section, a row with a high correlation value is chosen, its index displayed, and classified into class zero (indices 1 to 60) or class one (indices 61 to 300). Class zero is healthy (or) normal state of induction motor and class one is different types of faults (Inner Race Fault, Outer Race Fault, Ball Fault, and Rotor Fault). Correlation calculations are employed to assess the motor's condition status, and if a fault is detected, the system proceeds with feature extraction for fault localization. The extracted feature vector for the induction motor fault detection task is illustrated in Figure 11.

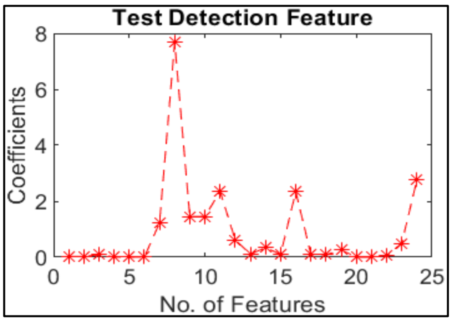

Figure 11: The extracted feature vector for the induction motor fault detection

In the test localization feature extraction section, MFCC (14 order) and GTCC features are fusion to construct the F2 feature are presented in Figure 1. This feature vector is used as training features data in machine learning algorithms. The extracted feature vector for the induction motor fault classification task is illustrated in Figure 12.

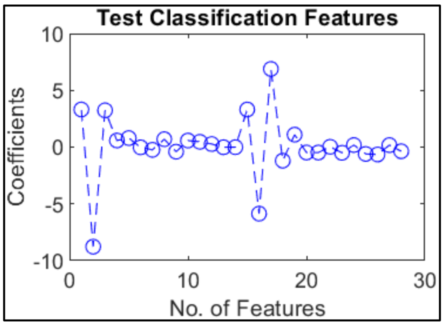

Figure 12: The extracted feature vector for the induction motor fault classification

According to the experimental results, the dataset is divided into training and testing segments. If the induction motor's test signal is identified as being in a fault state during the testing phase, the localization section provides information about the particular fault type. The defect diagnosis system has been implemented using MATLAB. Figure 13 depicts the architecture and structure of the machine learning-based acoustic-based induction motor defect detection and classification system.

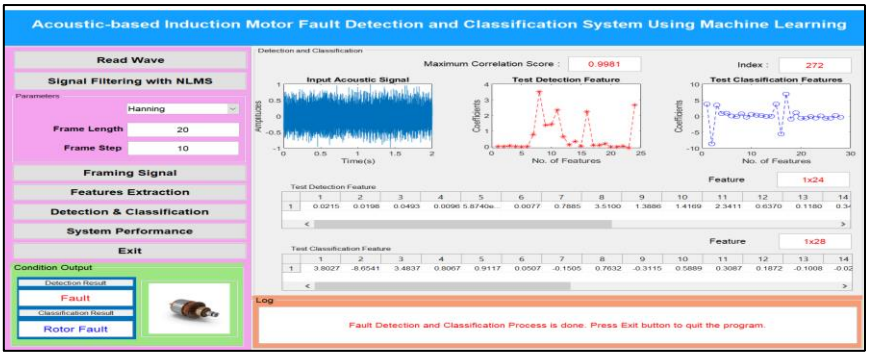

Figure 13: Design and implementation of fault detection and classification stage of the proposed system

For performance evaluation of the induction motor fault detection system, before starting the experiment, the dataset was split into 75% training data and 25% testing data. Thus, 300 recordings, which include 60 healthy recordings and 240 different faulty recordings, are used as training data. And 100 recordings, which include 20 healthy signals and 80 different faulty signals, are used as testing data are presented in Table 5.

The performance evaluation of the proposed system is evaluated comparatively according to accuracy, precision, recall, and F1-score values calculated as given in Equations 20-23.

$$Accuracy\ (\%) = \frac{\sum TP + \sum TN}{\sum TP+FP+FN+TN} \times 100 \qquad (20)$$

$$Precision\ (\%) = \frac{\sum TP}{\sum TP + \sum FP} \times 100 \qquad (21)$$

$$Recall = \frac{\sum TP}{\sum TP + \sum FN} \times 100 \qquad (22)$$

$$F1 - score = 2 \times \frac{Precision\ x\ Recall}{Precision + Recall} \qquad (23)$$

The proposed detection system's confusion matrix is shown in Figure 14, where 20 health state are accurately identified during the prediction process. One state is not recognized as fault, but the other 79 are accurately identified as fault states.

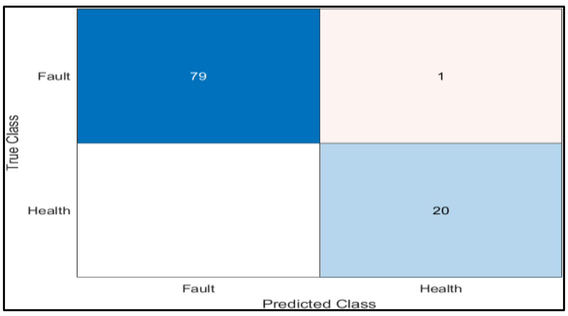

Figure 14: Confusion matrix of induction motor fault detection system

Figure 15 shows the evaluation results for the induction motor fault detection system. Experimentally, the system achieved an average accuracy of 99%, precision of 95.2381%, recall of 100%, and F1_score of 97.561%. The system's error rate is 1%.

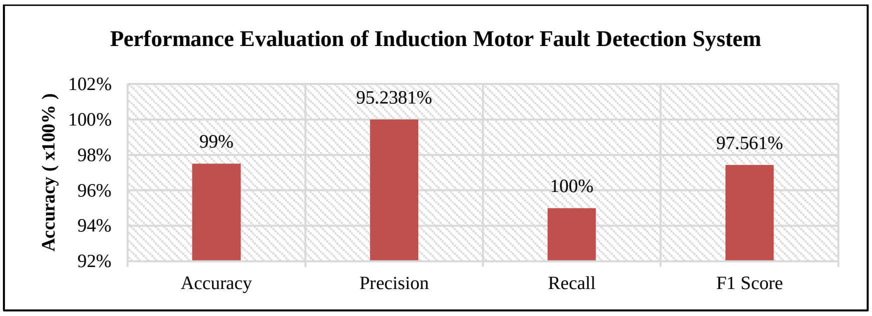

Figure 15: Performance evaluation of the induction motor fault detection system

The dataset for the proposed localization model includes 320 recordings of different faulty motor sounds (Inner Race Fault, Outer Race Fault, Ball Fault, and Rotor Fault), split into 75% training (240 recordings) and 25% testing (80 recordings). Data Splitting for the induction motor fault localization task is presented in Table 6. The localization system, tested with Support Vector Machine (SVM) algorithms, has its confusion matrix shown in Figure 16. The model accurately classifies faulty signals using the SVM classifier, but one Outer Race fault and one Rotor fault are misclassified as Inner Race faults.

Table 6: Data splitting for induction motor fault localization

Fault Types	Train Data (75%)	Test Data (25%)	Dataset for the proposed localization model
Inner Race Fault	240	80	320
Outer Race Fault			
Ball Fault			
Rotor Fault			

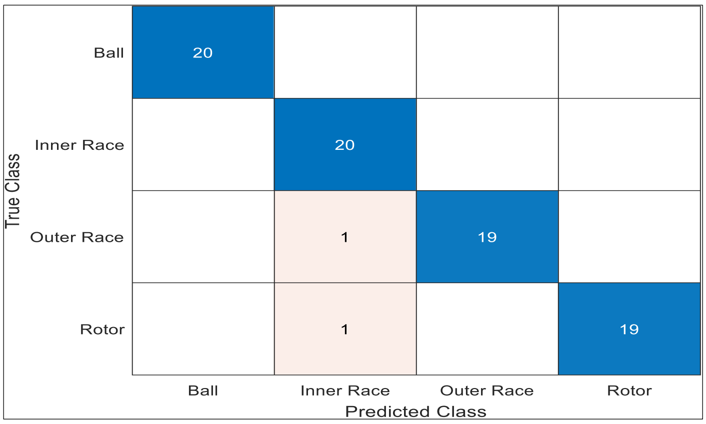

Figure 16: Confusion matrix of induction motor fault localization system

The performance evaluation of the proposed localization system provides a comprehensive performance analysis, demonstrating the system's overall effectiveness. According to experimental result, the system achieves an average accuracy of 97.5%, with precision, recall, and F1 scores of 97.73%, 97.5%, and 97.53%, respectively as shown in Figure 17. The system's error rate is 2.5%.

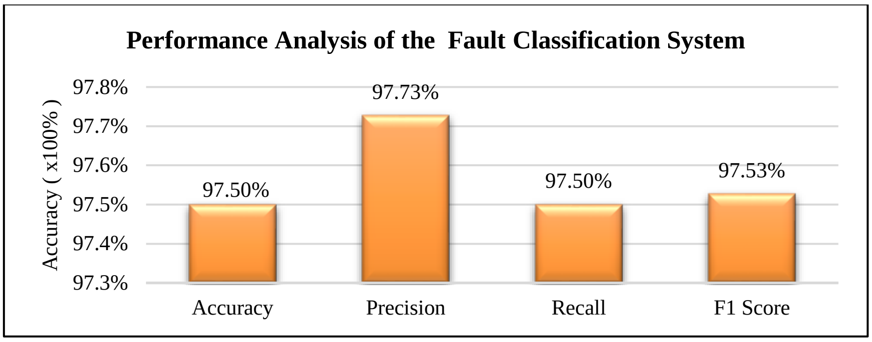

Figure 17: Performance evaluation of the induction motor fault localization system

5. Conclusion

The paper proposes the use of an adaptive filtering algorithm for induction motor fault diagnosis system and a fusion-based feature extraction method using machine learning algorithms to improve the accuracy and efficiency of fault detection and localization systems. The induction motor fault detection and localization system have many challenges because acoustic signals contain many noises, such as motor vibration, wind effects, environmental noise, and vehicle noise. The NLMS filtering technique is adopted to address the above issues. This research paper demonstrates that combining multiple features from both time and frequency domains effectively captures different aspects of the data, improving the overall system accuracy. Additionally, it emphasizes the importance of selecting features using statistical methods and optimizing parameters to ensure system accuracy. And the proposed fusion-based method overcomes the challenging problem and gets better and more reliable accuracy for fault diagnosis systems. The study found that the proposed feature vectors achieve a better result with a correlation algorithm for fault detection and an SVM classifier for fault localization. According to the experimental results, the proposed system achieved an average accuracy of 99% in fault detection, 97.5% in fault localization, and an error rate of 2.5%. Therefore, the proposed system can be used in an early fault diagnosis system for induction motor and rotating machines.

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