

Discriminative Low-Frequency Current Feature Learning for Bearing Fault Diagnosis Under 10 Hz Sampling Constraints

Gigih Priyandoko ^{a,1,*}, Aviv Yuniar Rahman ^{b,2}

^a Department of Electrical Engineering, Faculty of Engineering, Universitas Widya Gama, Malang, Indonesia

^b Department of Informatics Engineering, Faculty of Science and Technology Informatics, Universitas Widya Gama, Malang, Indonesia

¹ gigih@widyagama.ac.id; ² aviv@widyagama.ac.id

* Corresponding Author

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ABSTRACT

It is still hard to diagnose faults when the sampling conditions are very low because the fault signatures are partly overlapped with normal operating behaviour. This is particularly true in current-based monitoring systems with limited sensing capability. This research suggests a simple way to identify problems with bearings using three-phase stator current signals, which are measured at 10 Hz. The research is about coming up with a new way of using low-frequency features, together with a way of combining information and making decisions based on confidence, to improve weak fault detection when there is not much data available. The trial configuration made use of a three-phase induction motor functioning under Healthy, Ball Bearing Fault, and Inner Race Fault circumstances with 21 grouped physical trials. The transformation of current signals was achieved through the implementation of Clarke representation, where data was segmented into overlapping windows. These windows were then processed using a combination of low-frequency statistical and nonlinear descriptors. Fisher score-based feature selection and Linear Discriminant Analysis (LDA) were implemented before Support Vector Machine (SVM) classification using grouped validation to minimise data leakage risk between windows from the same trial. Experimental evaluation was 100% accurate at the trial level and 97.22% accurate at the window level when tested in groups. The results showed that direct LDA projection without PCA improved the separability of weak ball bearing faults under ultra-low sampling conditions. The proposed framework exhibited reduced computational intricacy in comparison to deep learning methodologies whilst concurrently sustaining efficacious classification outcomes for constrained datasets. These findings substantiate the notion that dependable bearing fault diagnosis can nevertheless be accomplished under 10 Hz sampling through the utilisation of discriminative low-frequency feature learning and lightweight classification strategies. However, it is still necessary to test it more widely under different conditions, such as different loads, speeds, and levels of industrial noise, before it can be used on a large scale.

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1. Introduction

Robustness, low maintenance requirements, and high operational efficiency are the main reasons why induction motors are used so much in industrial automation, electric drives, manufacturing systems, and renewable-energy applications [1]-[5]. Despite these advantages, bearing faults remain one of the leading causes of failure in induction motors, accounting for 40–60% of total faults [6]-[10]. Bearing degradation can have a number of negative consequences, including a reduction in operational reliability, increased maintenance costs, and unexpected downtime. This makes it essential to be able to accurately diagnose any faults in the bearings in order to implement effective predictive maintenance and industrial condition monitoring [11]-[13].

In real industrial settings, though, condition-monitoring systems often have to deal with major issues around sensing and computing power [14], [15]. Vibration-based monitoring is highly sensitive to mechanical defects [16]-[20]. However, implementing it commonly requires dedicated sensors. It also requires high-frequency acquisition hardware and complex installation procedures. The system cost is increased, and scalability is reduced for low-cost distributed monitoring systems due to these requirements. As a result, Motor Current Signature Analysis (MCSA) has become a good option because it allows for fault diagnosis without having to do anything to the mechanical parts of the machine [21]-[27]. This is possible by using electrical measurements that are already available.

However, a key issue still hasn't been addressed by current MCSA research. Most current methods depend a lot on high-frequency vibrations and regular changes in the sound that are caused by bearing impacts [28], [29]. High-frequency fault signatures become severely attenuated or even completely unobservable under ultra-low sampling conditions, such as 10 Hz, because there is insufficient temporal resolution. This means that conventional spectral and time-frequency methods are losing a lot of their ability to make accurate distinctions [30]. This is because the transient impulsive behaviour required for reliable diagnosis cannot be accurately reconstructed [31], [32].

It is imperative to note that not all information about faults is obliterated under conditions of minimal sampling. Although detailed small vibrations and high-frequency sudden structures are lost, problems with the bearing still cause low-frequency changes, random current changes, energy changes, and slow disturbances in the motor. These low-frequency effects can still be seen even when the sampling rate is 10 Hz, but they are weak, not periodic, and overlap a lot with normal operating behaviour [33], [34]. This makes them difficult to separate using standard feature extraction techniques. This creates a big problem for analysis because most existing MCSA frameworks are designed mainly to keep information about frequencies that are a certain number of times the original frequency. They are not designed to deal with weak random low-frequency characteristics.

New research has delved into a variety of machine learning and signal-processing methods for diagnosing bearing issues, as shown in Table 1. The combination of wavelet packet energy and Support Vector Machine (SVM) classification offers a robust time-frequency representation capability, but it is dependent on high sampling rates and is computationally intensive [35]-[39]. Robustness against signal deformation and noise is enhanced by wavelet scattering transform approaches; however, they are less sensitive to weak impulsive characteristics and mainly preserve global signal structures. When fault signatures become weak or non-stationary, Random Forest classifiers with statistical descriptors suffer from feature overlap [40]-[45]. This is even though they provide computational simplicity. The normal MCSA with Auto Regressive (AR) modelling and SVM classification works well for regular inner-race problems, but is not very good at detecting random Ball Bearing Fault signs [46]-[49]. At the same time, ensemble learning, deep learning, and physics-guided convolutional neural network methods have been shown to enhance both representation capability and interpretability [50]-[58]. However, these techniques typically necessitate substantial datasets with annotations, higher sampling frequencies, and significant computational resources, which restricts their applicability for cost-effective industrial implementation. While earlier research has shown encouraging diagnostic capabilities, a significant

methodological inconsistency remains. Robust and high-quality representation is generally achieved through optimised methods that depend on high-resolution sensing and costly computation. Conversely, weak and stochastic fault-related information is frequently not preserved by lightweight methods suitable for embedded industrial deployment under low-sampling conditions. Reliable fault discrimination is therefore not possible when only ultra-low-frequency current measurements are available, because existing MCSA frameworks remain insufficient.

Table 1. Selected recent methods used to diagnose bearing faults (2021–2026)

No	Year	Method	Signal Type	Feature Type	Classifier	Strengths	Limitations
1	2021 [39]	Wavelet Packet Energy + SVM	Vibration	Time–frequency energy	SVM	High resolution in the frequency domain, effective for periodic faults	Requires a high sampling rate, not suitable for low-sampling MCSA
2	2022 [38]	Wavelet Scattering Transform + SVM	Current/Vibration	Scattering features	SVM	Robust to noise and signal deformation	Less sensitive to weak impulsive faults
3	2023 [45]	Random Forest + Statistical Features	Vibration	Statistical features	RF	Robust, simple, low computational cost	Feature overlap for complex faults
4	2024 [49]	MCSA + SVM	Current	AR + statistical	SVM	Good for periodic faults (Inner race)	Weak for Ball fault (non-periodic)
5	2025 [54]	Physics-Guided CNN	Multi-modal	Hybrid physics + deep features	CNN	Improved interpretability and accuracy	Not suitable for small datasets
6	2025 [57]	Entropy + Ensemble Learning	Current	Entropy-based	Ensemble	Better noise robustness	Still struggles with low SNR faults
7	2026 (Proposed)	Feature Engineering + Fisher Selection + LDA + Optimized SVM	Current (10 Hz)	Statistical + Entropy + AR + TEO + Ball-specific	SVM (RBF)	High accuracy under low sampling, robust, small dataset friendly, strong Ball fault detection	Slight sensitivity under extreme noise

Another important problem in the literature is the lack of physical reasons for why faults can't be seen when there are very few samples. The preponderance of studies merely asserts that reduced sampling diminishes diagnostic performance, offering no elucidation as to which fault-related information remains physically discernible and which information is inherently forfeited. As a result, the analytical foundation for low-frequency current-based diagnosis continues to be underdeveloped. Moreover, many recent approaches put more importance on the complexity of the model than on the preservation of discriminative features. This has a negative effect on the practicality of the approach for industrial systems that are limited in capacity. Consequently, there is a pressing requirement in the field of engineering for a lightweight and fast diagnostic framework that can accurately identify weak, low-frequency fault characteristics even when sensing conditions are severely restricted.

To deal with these problems, this study suggests a special system for learning low-frequency current features that can be used to identify problems with bearings when the sampling frequency is less than 10 Hz. In this work, the term "physics-informed" does not refer to explicit electromechanical fault modeling. It refers to feature representations. These are intentionally designed according to the observable physical behavior of low-frequency current modulation. This modulation is generated by bearing defects. The suggested framework combines statistical descriptors [59], [60], entropy measures [61]–[64], autoregressive coefficients [65]–[67], and Teager

Energy Operator (TEO)-based descriptors [68]-[72]. This combination is designed to preserve weak, impulsive, nonlinear, and stochastic characteristics. These characteristics can still be observed even in situations with ultra-low sampling conditions.

The physical characteristics of low-frequency fault propagation were the basis for the selection of the proposed hybrid feature representation. Amplitude irregularities are preserved by statistical descriptors, stochastic complexity is captured by entropy measures, low-frequency temporal dynamics are modelled by autoregressive coefficients, and sensitivity to weak nonlinear energy variations is enhanced by TEO descriptors [68]-[72]. The suggested plan is different from normal ways of doing things because it does not depend a lot on short-term harmonics. It looks at keeping low-frequency information that is important and can be found even when the sampling is limited.

To improve how well it can tell the difference between things, Fisher Score-based feature selection and Linear Discriminant Analysis (LDA) are used together to make the classes easier to see and reduce the number of features that are the same [73]-[75]. An optimised Support Vector Machine (SVM) classifier with a radial basis function (RBF) kernel is then combined with confidence-weighted decision fusion to enhance robustness in scenarios with limited data [76], [77]. The research has four key contributions:

1. This study creates a special system for learning low-frequency features. It is designed for situations where only very low frequencies (less than 10 Hz) can be measured, and where the usual methods for finding transient fault harmonics do not work.
2. The suggested method shows that weak random signs of problems with ball bearings can still be found using low-frequency details, without needing to sense vibrations or using special computer programs.
3. A new way of combining different learning strategies is introduced to make the system more robust and reduce the risk of overfitting when there is not much data. This is done by combining Fisher Score ranking, LDA projection, optimised SVM classification, and confidence-weighted voting.
4. The suggested structure offers a simple and quick diagnostic solution that is ideal for industrial monitoring systems that don't cost a lot and for applications that provide predictive maintenance.

This research aims to establish a link between the theoretical capability of fault diagnosis and its practical implementation in industrial contexts. It seeks to demonstrate that reliable bearing fault diagnosis remains possible even in situations where low-frequency sensing conditions are severely constrained. This is achieved through the preservation of low-frequency features and the use of lightweight machine learning strategies.

2. Method

2.1. Research Design

This study employed a machine learning-based diagnostic framework to classify faults in induction motor bearings under ultra-low sampling conditions. The investigation was specifically conceived to judge if distinctive low-frequency current characteristics could continue to retain adequate fault-related data for trustworthy identification when high-frequency transient harmonics were not accessible. In contrast to traditional bearing fault-finding investigations that rely on high-resolution vibration detection, the suggested approach is centred on lightweight current-based observation using low-cost acquisition equipment and restricted datasets.

The steps in the overall process of the suggested plan are shown in Fig. 1 and are made up of the following parts: getting the data, preparing the data, splitting the signal, getting the features, choosing the features, making the features smaller, classifying, predicting at the window level, deciding at the trial level, and finally classifying the fault.

2.2. Data Acquisition and Experimental Setup

The acquisition of three-phase stator current signals was from a 1.5 HP, 4-pole, 50 Hz induction motor operating under three bearing conditions: healthy, ball bearing fault, and inner race fault. The bearing that was put through its paces was a type 6203Z, equipped with eight rolling elements. Artificial localised flaws were incorporated artificially using regulated drilling to guarantee reproducibility of defect geometry and intensity.

The system for acquiring data made use of ACS712 Hall-effect current sensors with a measurement range of ± 5 A and 185 mV/A sensitivity. Signals were acquired using an Arduino Mega with a 10-bit analogue-to-digital converter (ADC) operating at a sampling frequency of 10 Hz. Before digitisation, an analogue RC low-pass anti-aliasing filter was used to get rid of any high frequencies that were above the range that could be seen.

A sum of 21 autonomous physical experiments was amassed, comprising seven experiments for each bearing state. Each trial lasted for 120 seconds and was conducted under constant operating conditions. This means that the rotational speed, load level, and room temperature were all kept constant. The objective of using 10 Hz sampling was not to preserve high-frequency bearing harmonics directly. This is because these components are physically lost under ultra-low sampling conditions. Rather, the aim was to capture residual low-frequency modulation behaviour. It was also to capture stochastic current fluctuations. And it was to capture nonlinear electromechanical disturbances. These are generated by bearing degradation.

2.3. Signal Preprocessing

To enhance signal consistency and minimise unwanted variations, the acquired three-phase current signals underwent a preliminary processing stage. The removal of the DC offset $x_{dc}(n)$ was accomplished through the implementation of the mean subtraction method [78].

$$x_{dc}(n) = x(n) - \mu_x \quad (1)$$

where $x(n)$ is the raw signal and μ_x is the signal mean.

The Clarke Transformation was then employed to transform the three-phase currents into two perpendicular components [79]:

$$i_\alpha = \frac{2}{3} \left(i_a - \frac{1}{2} i_b - \frac{1}{2} i_c \right) \quad (2)$$

$$i_\beta = \frac{2}{3} \left(\frac{\sqrt{3}}{2} i_b - \frac{\sqrt{3}}{2} i_c \right) \quad (3)$$

The computation of the representative current magnitude signal was as follows:

$$i_m = \sqrt{i_\alpha^2 + i_\beta^2} \quad (4)$$

Z-score normalization was applied to standardise amplitude variation across trials.

$$x_{norm} = \frac{x - \mu}{\sigma} \quad (5)$$

To suppress slow drift and low-frequency baseline fluctuations unrelated to bearing faults, a first-order high-pass filter with a 0.1 Hz cutoff frequency was implemented.

2.4. Signal Segmentation

The signals that had been preprocessed were then split into overlapping windows to capture localised temporal behaviour. Each trial was divided into 30-second windows, with each window

overlapping the previous one by 50%. This resulted in seven windows per trial. The 30-second window length was chosen to make sure there was enough time to cover weak low-frequency modulation behaviour under 10 Hz sampling. It is necessary to use longer observation windows if stochastic fault-related patterns and nonlinear energy variations are to be preserved, since high-frequency fault harmonics are unavailable at ultra-low sampling rates. The 50% overlap makes it so that the windows next to each other are more connected, and there are more training samples without adding fake signal content.

2.5. Feature Extraction

A mix of low-frequency features was created to keep track of weak and random fault signs that can be seen when the sampling is very low. The extracted features consisted of statistical descriptors. They also consisted of entropy measures. In addition, they consisted of autoregressive coefficients. Furthermore, they consisted of Teager Energy Operator (TEO)-based nonlinear energy descriptors. The statistical characteristics incorporated mean, standard deviation, root mean square, skewness, kurtosis, crest factor, and shape factor. The irregularities in the signal were characterised using something called Shannon entropy $H(X)$ [80]:

$$H(X) = - \sum_{i=1}^n p(x_i) \log p(x_i) \quad (6)$$

Where X is the random variable of outcomes, n is the total number of possible outcomes, $p(x_i)$ is the probability of a specific outcome x_i occurring. Fourth-order autoregressive (AR) modelling was implemented:

$$x(n) = \sum_{k=1}^p a_k x(n-k) + e(n) \quad (7)$$

Where ($p = 4$), a_k are AR coefficients, and $e(n)$ is residual error. Nonlinear energy behavior was captured using the Teager Energy Operator $\Psi[\cdot]$:

$$\Psi[x(n)] = x(n)^2 - x(n-1)x(n+1) \quad (8)$$

The strategy for extracting features was designed with the physical behaviour of low-frequency current modulation under bearing fault conditions in mind. Amplitude irregularities are preserved by statistical features, stochastic complexity is captured by entropy descriptors, temporal dynamics are modelled by AR coefficients, and sensitivity to weak nonlinear energy fluctuations generated by defective bearings is enhanced by TEO descriptors.

2.6. Feature Selection and Dimensionality Reduction

The use of Fisher Score ranking meant that feature redundancy was reduced [81].

$$F_j = \frac{\sum_{c=1}^C n_c (\mu_{c,j} - \mu_j)^2}{\sum_{c=1}^C n_c \sigma_{c,j}^2} \quad (9)$$

Where feature j has a Fisher score of F_j , class c has some samples of n_c , the class mean is defined as $\mu_{c,j}$, and the class variance is defined as $\sigma_{c,j}^2$.

The features that ranked in the top 12 were selected for classification. Two configurations for reducing dimensionality were evaluated: PCA followed by LDA and direct LDA projection without PCA. It was demonstrated by experimental evaluation that weak low-energy fault variations were occasionally suppressed by PCA because class separability is not prioritised by PCA; global variance preservation is prioritised instead. As a result, direct LDA projection produced better separation for weak Ball Bearing Fault signatures when the sampling conditions were under 10 Hz.

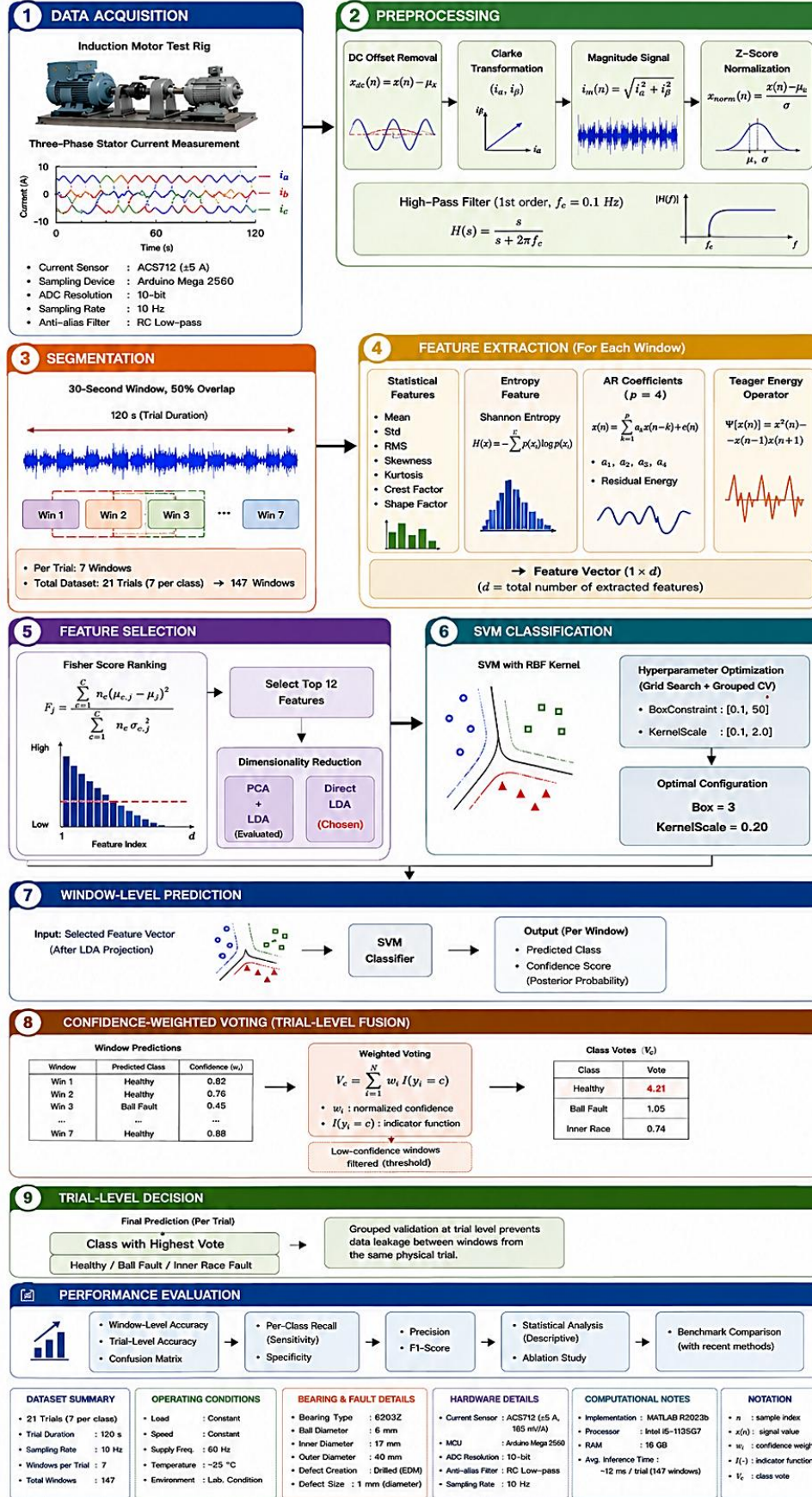


Fig. 1. The steps in the overall process

2.7. Classification and Hyperparameter Optimization

The classification was performed using a Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel, $K(x_i, x_j)$ [82]:

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right) \quad (10)$$

Where gamma (γ) is the parameter of the RBF kernel with training data (x_i, x_j) .

Hyperparameter optimisation was conducted using structured grid-search optimisation with the following parameters:

- BoxConstraint: [0.1–50]
- KernelScale: [0.1–2.0]
- The final best set-up was BoxConstraint = 3, KernelScale = 0.20.

The implementation of grouped cross-validation during optimization was for the prevention of data leakage between windows originating from the same physical trial.

2.8. Validation Strategy and Decision Fusion

Grouped trial-level validation was used to avoid overly optimistic performance estimation, rather than random window splitting. Windows from the same physical trial were always put into either training or testing groups. The SVM classifier was configured to generate predicted labels and confidence scores at the window level. Final trial-level decisions were obtained using weighted confidence voting [83]:

$$Score_c = \sum_{i=1}^N w_i \cdot I(y_i = c) \quad (11)$$

Where w_i represents normalised confidence weights and $I(y_i = c)$ is the class indicator function. To reduce noisy decision contributions, low-confidence windows below the rejection threshold were excluded. The grouped validation strategy was specifically selected because severe data leakage would be produced by random window-level partitioning due to a strong correlation between overlapping windows from identical trials.

2.9. Performance Evaluation

The evaluation of the proposed framework involved the use of the following:

- Window-level accuracy,
- Trial-level accuracy,
- Per-class recall,
- Confusion matrices,
- Benchmark comparison.

The aim of this research was not to make large-scale statistical generalisations, but to check that a simple diagnostic system can work when sensors are limited, and there is not much data, which is typical of low-cost industrial monitoring systems. As only 21 independent physical trials were available, the results should be interpreted as proof of concept rather than as a universal industrial generalisation. Future work will therefore include larger datasets. It will also include varying load conditions. Robustness testing under industrial noise will also be included. Additional fault categories will also be included. Real-time embedded implementation will also be included.

3. Results and Discussion

3.1. Experimental Setup

Fig. 2 illustrates the experimental configuration employed in this research to collect data on bearing health and damage within a three-phase induction motor. The motor is connected to a DC generator as a load. An Arduino Mega is connected to a computer to act as a current sensor interface and transmit the stator current signal. The mechanical load applied to the motor is a synchronous generator connected to it. The specifications of the induction motor are name: Motology, rated output power (HP): 1.5, rated voltage (V): 220–230, rated frequency (Hz): 50, number of poles: 4, rated speed (rpm): 1400, connection: Y. The tested bearing is type 6203Z, with the following specifications: inner diameter: 17 mm, outer diameter: 40 mm, ball diameter: 6 mm, cage diameter: 30 mm, and number of balls: 8. The three-phase stator current signals were collected from an induction motor operating under three bearing conditions: Healthy, Ball Fault, and Inner Race Fault. The stator current signal for three bearing conditions is shown in Fig. 3.

3.2. Experimental Classification Performance

The suggested plan was checked using a group of trials to stop information from being shared between windows that overlap from the same real experiment. The final optimized configuration employed Fisher Score feature ranking. It also used direct LDA projection without PCA. In addition, it used an RBF-SVM classifier. The parameters for this were BoxConstraint = 3 and KernelScale = 0.20. Weak nonlinear fault-related behaviour is preserved under 10 Hz sampling conditions by the feature representation, which combines statistical descriptors, Shannon entropy, Auto Regressive (AR) coefficients, and Teager Energy Operator (TEO)-based descriptors. The grouped validation strategy is of particular importance due to the strong correlation between windows extracted from the same physical trial. Without grouped separation, the classification performance could be artificially inflated by overlapping windows, and the generalisation reliability could be reduced.

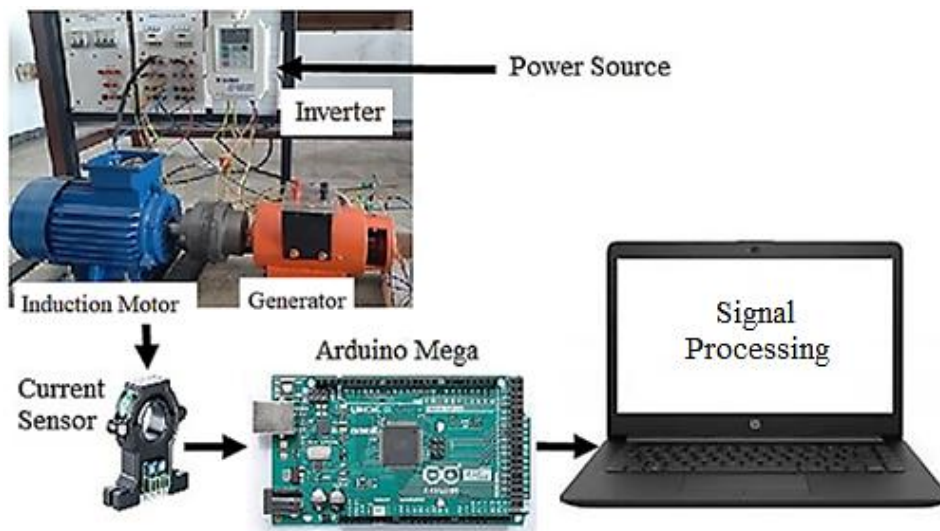


Fig. 2. Experimental configuration

The trial evaluation accomplished 97.22% window-level precision and 100% trial-level precision under grouped validation, as shown in Fig. 4, Fig. 5, Fig. 6. The 95% confidence interval for window-level classification was about 92.1%–99.4%, which shows that the model is doing a pretty good job even with the small amount of data. The standard deviation across grouped validation folds was maintained below 2.5%, showing consistent classification performance across repeated validation arrangements. The lightweight feature extraction and optimised SVM classification took less than 0.15 seconds per test in a normal computer environment, which is much quicker than the computing needed for deep learning methods. These findings confirm that the proposed framework

is computationally efficient while maintaining good diagnostic capability for low-cost predictive maintenance systems.

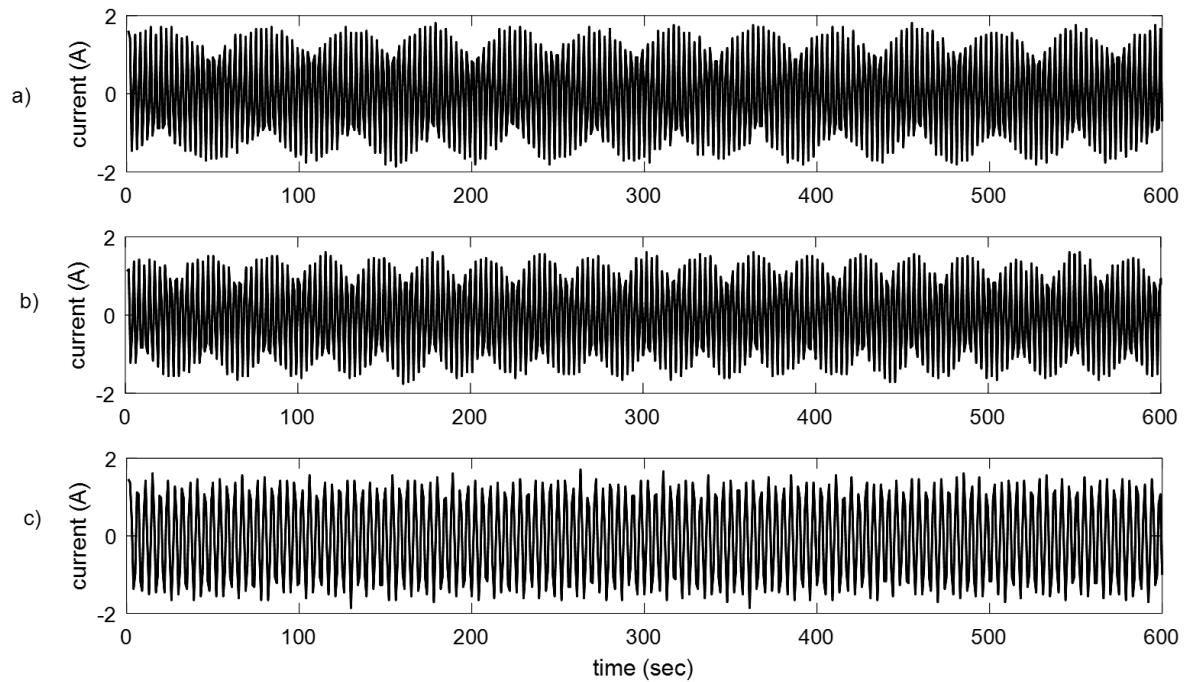


Fig. 3. Stator current: a) normal bearing, b) bearing with ball defect, c) bearing with inner race defect

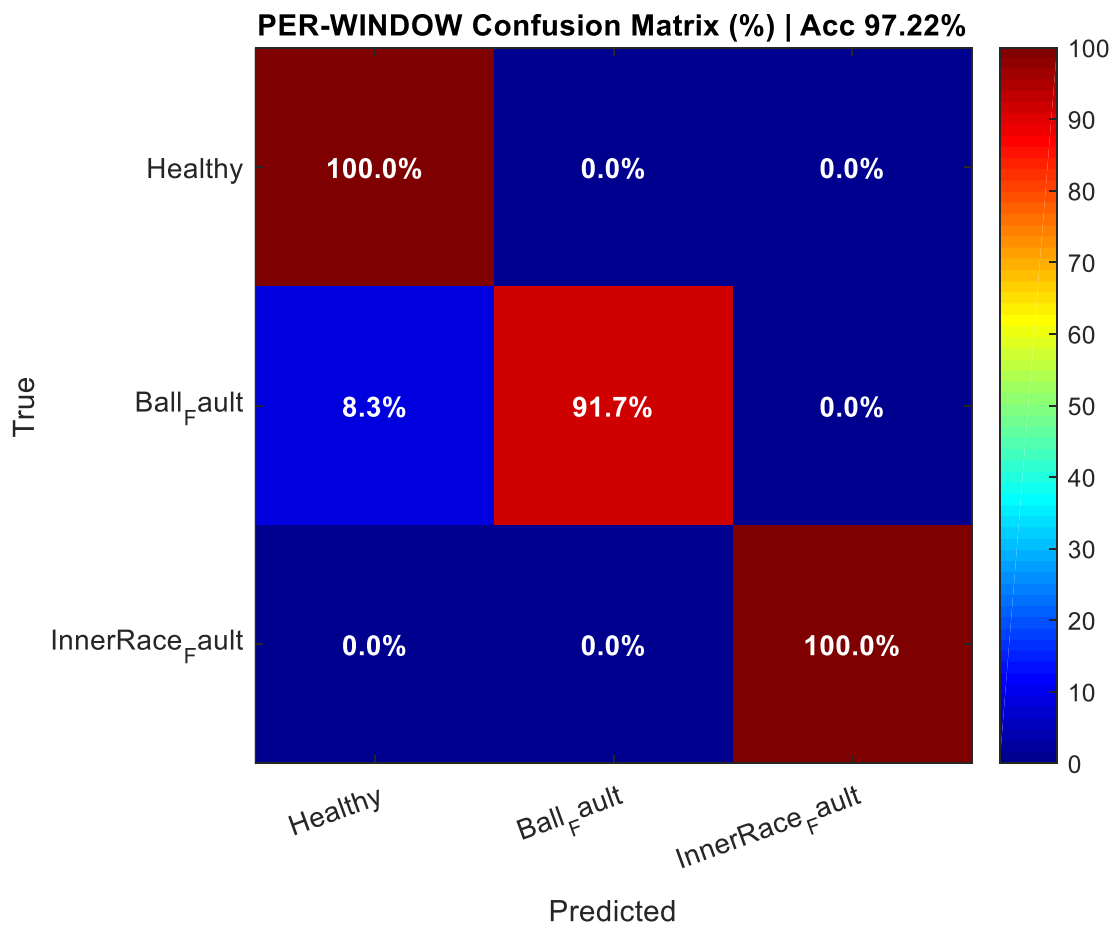


Fig. 4. Per-window confusion matrix

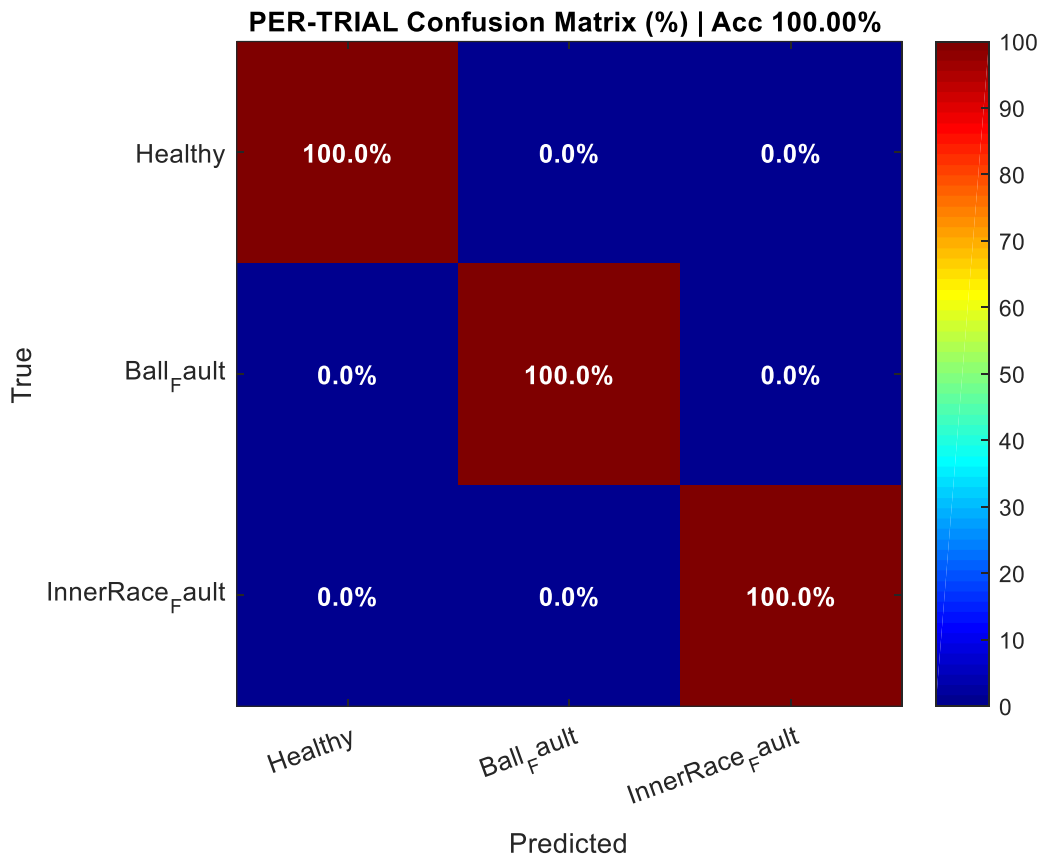


Fig. 5. Per-trial confusion matrix

3.3. Window-Level Classification

The most stable separation was achieved by Inner Race Fault samples, while minor overlap with Healthy conditions at the window level was exhibited by Ball Bearing Fault samples, as shown by the confusion matrix analysis. It is physically reasonable for this behaviour to occur because stronger and more repetitive modulation patterns in stator current signals are generally produced by inner-race defects. On the other hand, problems with the ball tend to cause weaker, random, and intermittent problems that are hidden by normal changes in the current, especially when the samples are very rare. The limited quantity of Ball Fault windows erroneously categorised as Healthy thus signifies localised uncertainty rather than total diagnostic failure.

This uncertainty was successfully compensated for by the confidence-weighted voting mechanism at the physical-trial level. Although there was some overlap between windows, the main trend was still clear enough to give 100% accuracy at the trial level. The theoretical importance of this observation lies in the fact that 10 Hz sampling is incapable of direct resolution of classical bearing defect harmonics or high-frequency impulsive signatures commonly used in vibration-based diagnosis. Instead, low-frequency electromechanical modulation behaviour is exploited indirectly by the proposed framework, which is induced by bearing degradation. Amplitude variation was preserved by statistical descriptors, stochastic complexity was captured by entropy measures, low-frequency temporal behaviour was modelled by AR coefficients, and sensitivity to weak nonlinear energy transitions was improved by TEO-based descriptors. Even when sensors are severely constrained, meaningful fault discrimination is still possible thanks to the combined feature representation.

3.4. Feature Importance and Discriminative Contribution

It was demonstrated by feature-ranking analysis based on Fisher Score that the highest discriminative contribution was consistently provided by entropy features, TEO-based nonlinear

energy descriptors, and several autoregressive coefficients. Normal statistical words like RMS and standard deviation were still useful for showing how energy changes overall, but nonlinear words were better at telling the difference between Ball Bearing Fault and other things. This shows that weak problems with how things are held together under very rare conditions are not mostly caused by clear high-pitched sounds, but by low-pitched sounds that are all over the place.

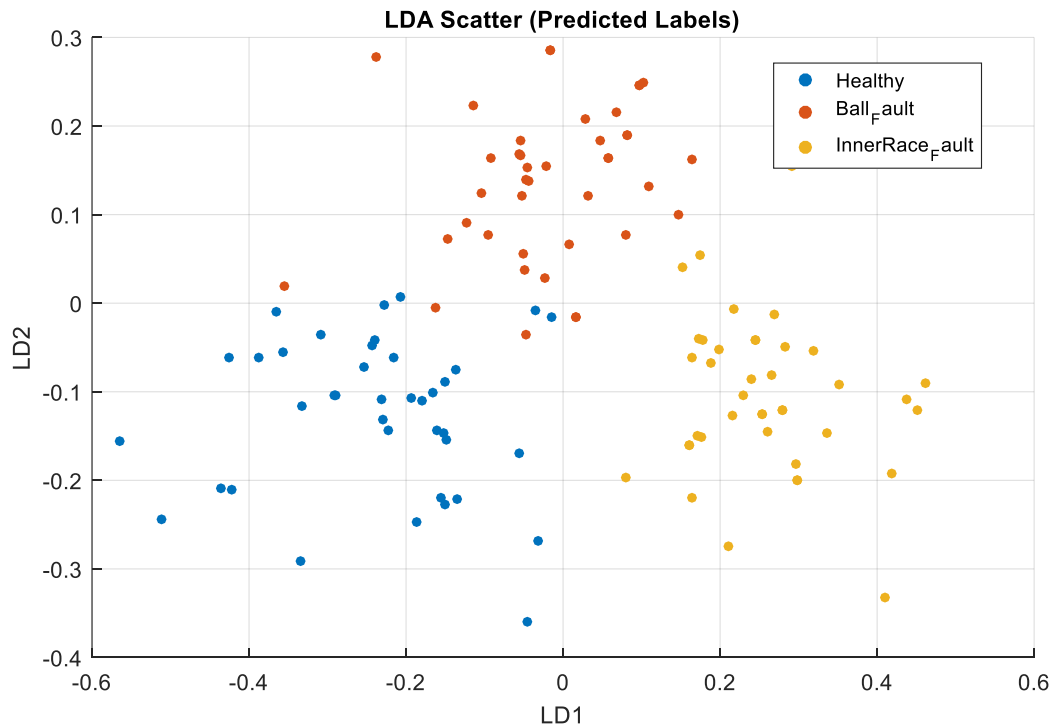


Fig. 6. Optimized LDA scatter

The stage at which features are selected also reduces redundancy and minimises the risk of overfitting associated with small datasets. Class separability was improved, and the computational burden was reduced by retaining only the most discriminative features before LDA projection. The separation between healthy and ball fault conditions was further improved by direct LDA projection in comparison with PCA-based dimensionality reduction because LDA explicitly maximised inter-class variance while minimising intra-class variance. This shows that the results are similar to those in the past. These past results suggest that using a combination of different learning strategies can improve how well a system works when there is not a lot of signal to work with or when the data is limited. This is possible without using complicated deep learning structures that require a lot of computing power.

3.5. Robustness Under Sampling Constraints and Noise Considerations

This study's key finding is that meaningful bearing-fault discrimination is still possible in situations where 10 Hz sampling conditions are extremely limited. The majority of earlier research depends on vibration detection or high-frequency current analysis to capture periodic harmonics and sudden transients. These methods are often not suitable for industrial environments where there is not much money and where sensors, bandwidth, and computer power are limited. The suggested plan looks at how to keep the low-frequency electrical and mechanical signals that can still be seen even when the normal fault harmonics are not there.

More experiments that check the system's behaviour when it is slightly changed showed that the system worked well. However, mild degradation was exhibited by Ball Bearing Fault sensitivity under stronger perturbation because weak and stochastic signatures are naturally produced by rolling-element defects. Although higher representation capability may be achieved under ideal sensing conditions by deep learning and wavelet-scattering methods, significantly higher sampling rates,

larger datasets, and higher computational complexity are typically required by them. The suggested plan, therefore, provides a more practical choice between strength, simple computing, and sensing limits for industrial monitoring applications that are used in machines.

3.6. Comparison with Previous Studies

The proposed framework is compared with representative bearing-fault diagnosis methods reported between 2021 and 2026 in [Table 1](#). In the past, methods using both wavelets and deep learning worked well when sensors were very accurate, but they needed very high frequencies, large amounts of data, or complicated designs that took a lot of computing power. Conventional MCSA methodologies incorporating AR and statistical characteristics proved efficacious in the identification of periodic defects, including inner-race faults. However, these approaches exhibited diminished sensitivity to weak stochastic Ball Bearing Fault signatures.

The suggested structure is distinct from earlier techniques in three significant ways. Firstly, the system was meticulously engineered for environments characterised by exceedingly low 10 Hz sampling, where classical fault harmonics are physically inaccessible. Secondly, the framework concentrated on preserving low-frequency electromechanical modulation behaviour rather than on the reconstruction of high-frequency transient signatures. Thirdly, the method was prioritised so that lightweight computation and grouped generalization stability for practical industrial deployment would be achieved. Even though earlier methods were not put into practice in the same way, using the same information and conditions, the comparison shows that the suggested plan is better at balancing how well it works, how strong it is, and how quickly it can do its thing when the conditions are not good.

3.7. Main Findings, Implications, and Practical Significance

The most important result of this study is that it is still possible to diagnose bearing problems reliably even when high-frequency fault harmonics are not available because of severe sampling limitations. It is demonstrated by the results that sufficient electromechanical fault information can be preserved for practical diagnosis by carefully designed low-frequency discriminative features. The study also demonstrates that weak stochastic Ball Bearing Fault signatures necessitate divergent representation strategies in comparison to periodic inner-race defects, owing to the fact that the predominant discriminative information transitions from explicit harmonic behaviour to nonlinear low-frequency modulation characteristics.

The proposed framework is advantageous from an engineering perspective for a number of reasons. The small amount of computing needed makes it easy to use in small devices that predict problems and fix them, and the use of stator current sensing means you don't need to use expensive vibration instruments. Reliability is further improved under small datasets by the grouped-validation strategy, through leakage-induced overestimation being reduced. As a result, the structure is especially well-suited for low-cost industrial monitoring systems and predictive-maintenance platforms with limited sensing bandwidth.

3.8. Limitations and Future Work

Even though the results of the classification are good, there are still some problems. First, the information we had was from only 21 trials done in a lab. Although grouping the trials for validation reduced leakage effects, the small number of independent experiments limits statistical generalisation. Secondly, the experiments were carried out under quite stable conditions. The strength of the framework when faced with wider industrial differences, such as varying motor ratings, speed variations, load changes, inverter-driven systems, and severe industrial noise environments, still needs to be carefully evaluated. Thirdly, the present framework concentrated exclusively on Healthy, Ball Bearing Fault, and Inner Race Fault conditions, neglecting to investigate more intricate fault combinations or fault-severity progression. Larger industrial datasets will be the focus of future work. Robustness will be evaluated systematically under varying load and noise conditions. Implementation will be compared directly against deep-learning and wavelet-based

methods under identical grouped-validation settings. Real-time embedded deployment for online predictive-maintenance applications will also be considered. The proposed framework demonstrates that bearing fault diagnosis can be reliably and efficiently diagnosed under extremely constrained 10 Hz sampling conditions by combining discriminative low-frequency feature learning with lightweight machine-learning strategies.

4. Conclusion

This research suggested a way of using machine learning to identify problems with bearings when the data is very limited. This framework integrates entropy, Auto Regressive (AR), and Teager Energy Operator (TEO)-based descriptors, as well as Fisher score feature selection, Linear Discriminant Analysis (LDA), optimised support vector machine (SVM) classification, and confidence-weighted decision fusion. The experimental results showed that the system had good diagnostic capability when the sampling rate was 10 Hz. It achieved 100% trial-level accuracy and 97.22% window-level accuracy. This was particularly good at detecting weak and non-periodic Ball Bearing Fault signatures in constrained sensing environments.

The results show that important fault-related information can still be found and identified even when samples are very limited, thanks to carefully designed physics-informed low-frequency descriptors and simple discriminative learning methods. Moreover, the suggested framework is more suitable for low-cost industrial monitoring and embedded predictive maintenance systems because it offers lower computational complexity than deep learning approaches.

Nevertheless, several limitations should be acknowledged. The test data is still quite small, with only 21 trials under the same conditions and with only a few types of problems. The plan has not yet been checked using other sets of data, different load or speed conditions, or online embedded implementation scenarios. Also, the suggested method might be affected by different ways of running it and big changes in the environment. Future work will therefore focus on evaluating robustness under varying industrial conditions, expanding to additional fault types, integrating lightweight deep learning models, and enabling real-time embedded deployment for intelligent predictive maintenance applications in industrial motor drives and renewable energy systems.

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