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Predictive Maintenance for Bird Feeder Motors via Time-Series Current Analysis

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Abstract. Automated outdoor electronic device systems have been deployed widely for their high efficiency. However, environmental vulnerabilities could be a severe issue. To be more specific, high humidity outdoors causes feed agglomeration, therefore leading to fatal problems like mechanical jamming and motor burnout. According to current techniques, although deep learning model achieves the high accuracy of diagnosis, the heavy load is not suitable for a low-cost edge artificial intelligence (AI) controller. At the same time, traditional signal processing methods based on threshold values can easily cause false alarms in a noisy environment. This paper adopts lightweight sensorless predictive maintenance method, combining it with the motor current characteristic analysis (MCSA) and random forest classifier, and extracting the variance and peak amplitude features via Fast Fourier Transform (FFT) in the frequency domain. The result shows that by this method, the accuracy on the test data is up to 96.80%, which is superior to the standard deep neural network (89.30%) and maintains an extremely low inference latency, which is suitable for edge AI deployment.

Keywords: Edge artificial intelligence (AI), sensorless predictive maintenance method, motor current characteristic analysis (MCSA), random forest classifier, Fast Fourier Transform (FFT)

1. Introduction

The automated bird feeder has many advantages, which are mainly manifested in precise timing, quantified feeding, and outstanding environmental adaptability. In the process of distributing grains, the frequency of feeding and the single discharge volume can be precisely set through an internal Motor drive mechanism and microcontroller [1]. This design helps birds build regular foraging habits and effectively prevents bird food from deteriorating in the tray due to accumulation. In addition, a fully enclosed silo is usually adopted, and a rainproof eave design to a large extent isolates from external moisture, preventing seeds from getting moldy and saving food [2]. However, outdoor feeding activities face severe environmental challenges.

The mechanical crisis exists in the missing steps of the stepping motor. When environmental moisture permeates into the internal devices, the moisture content of biological materials will also increase internally. Grains get wet and clump together [3]. This forces the agitator to generate a

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higher torque, which could become a mechanical stall, leading to motor damage. During the period of stall, the specific input frequency of the stepping motor could generate a resonance that is lower than the standard frequency.

Early failure elimination for induction motors is vital, with criteria being vibration and current. Three possible methods are listed to detect the two criteria. Based on the frequency-time wavelet transform, and Wigner-Ville decomposition, the short-time Fourier transform (STFT) realize the motor failure justification. The high computational demand may cause frequent false alarms when being put into a noisy environment. For the single DNN model, the data shows accuracy of STFT is up to 89.3%, and the SWT-LSTM-DNN model achieved a higher prediction accuracy rate of 96.24%, which shows more comprehensive performance in accuracy and precision [4]. However, these high-precision models have extremely high computational complexity and cannot be deployed on inexpensive microcontrollers. There is a huge gap in the edge artificial intelligence (AI) area.

To address the aforementioned challenges, this paper proposes a physics-driven, sensorless detection approach based on Back-Electromotive Force (Back-EMF) analysis. By using Fast Fourier Transform (FFT) dimensionality reduction to extract the variance and peak value, this paper deploys a method called a Random Forest classifier to operate a Majority Voting. In this method, the model achieves deep-learning-level accuracy with millisecond-level latency, making it the perfect fit for low-cost edge AI deployment.

2. Proposed methodology

2.1 The establishment of the model

Based on the Blondel-Park two-reaction theory, the stationary stator variables of the motor can be transformed into an equivalent two-phase configuration within a synchronously rotating d-q reference frame [5]. The mathematical models thatcontrol the stepper modelscan be expressed as

$$u_{dref} = Ri_{dref} + L\frac{di_{dref}}{dt} - Li_{qref}\omega_{ref} + k_m\omega_r \sin\left(\Delta\theta\right) \tag{1}$$

$$u_{qref} = Ri_{qref} + L\frac{di_{qref}}{dt} + Li_{dref}\omega_{ref} + k_m\omega_r \cos\left(\Delta\theta\right) \tag{2}$$

Where i_{dref} and i_{dref} are the respective phase currents ; $R\,and\,L$ is the stator phase resistance and inductance; ω_r is the real rotor speed (Mechanical variable); k_m is the magnetic flux motor constant; k_m magnetic flux motor constant; $\Delta\theta$ represents the electrical angle between the reference frame and the rotor frame.

The electromechanical coupling within this system is governed by the Back-EMF which is expressed in the formula as $k_m\omega_r \sin(\Delta\theta) and\, k_m\omega_r \cos(\Delta\theta)$. The high mechanical speed of the rotor generates a large amount of counter electromotive force in the operation, which oppose supply voltage to keep phase current at a standard range. However, when an abnormal situation occurs, especially when feed lumps and clogs the mixer due to high moisture, the mechanical rotor stops suddenly, and the rotor speed declines to zero, and the back-EMF vanishes in the formula. The sudden elimination of this reverse force allows the entire power supply voltage to be applied to the stator resistance and inductance, leading to a current peak.

This physical model collects data by repeatedly inducing a hard mechanical stall; it may cause permanent thermal damage and motor burnout risks. This is the reason for fitting a high-precision synthetic time series dataset in MATLAB based on the established equation, as shown in Figure 1.

DOI: 10.54254/2755-2721/2026.37452

This model captures a transient current anomaly driven by a drop in back-EMF [6]. In addition, it also provides a safe and mathematically solid basic foundation for the following feature extraction and AI training [7].

As shown in Figure 1, the synthetic time-series clearly captured the transient electrical response during a physical stall. In normal operation, the phase diagram remains stable and periodic in amplitude.

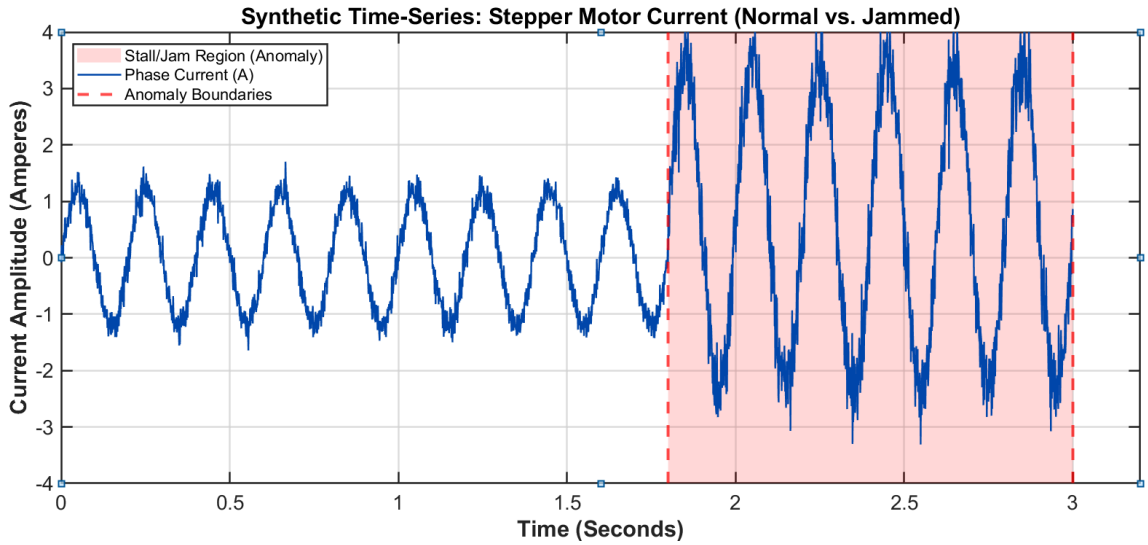


Figure 1. Synthetic time-series of the stepper motor phase current (picture credit: original)

2.2 Feature extraction and frequency-domain analysis

2.2.1 Potential frequency domain solution based on FFT

In real outdoor electromechanical systems, the initial current signals are usually veiled by large quantities of unpredictable environmental noise. Therefore, it is difficult to separate other interference factors, and it could result in severe overfitting eventually [8].

To overcome a limitation in the time domain, this essay adopts a frequency domain transformation method and replicates plots using MATLAB signal processing architecture. By applying the Fast Fourier Transform, complex and noisy time-domain current signals can be mathematically divided into a composition of frequencies. This vital transformation lets mechanical stall (especially stepper motors stalling) demonstrate obvious high-frequency spectral characteristics [9]. FFT can isolate specific peaks instead of extracting data from a confused time-domain waveform, which better acts as electrical fingerprints and identifies fault characteristics more clearly without being disturbed by environmental noise.

2.2.2 Robust feature engineering for AI

To test the reliability of the predictive maintenance system and avoid the unpredictability commonly found in black box deep learning models, it adopts a strict filter before classification. The proposed Random Forest model does not input the entire spectrum into the algorithm, but is trained only from FFT-extracted specific target spectrum signatures [9]. In the detailed procedures, the variance is extracted to capture high-frequency mechanical vibration noise, and the peak amplitude value is extracted to capture a sudden Back EMF decline. These statistical characteristics that represent

DOI: 10.54254/2755-2721/2026.37452

physical meaning into filters are input to realize large-scale dimensionality reduction. By this method, it also offers highly robust input data for low-delay edge AI calculation.

Simulated time-domain phase current generated in MATLAB is shown in Figure 2, illustrating the ideal clean signal versus the highly fluctuating noisy signal superimposed with simulated outdoor environmental interference.

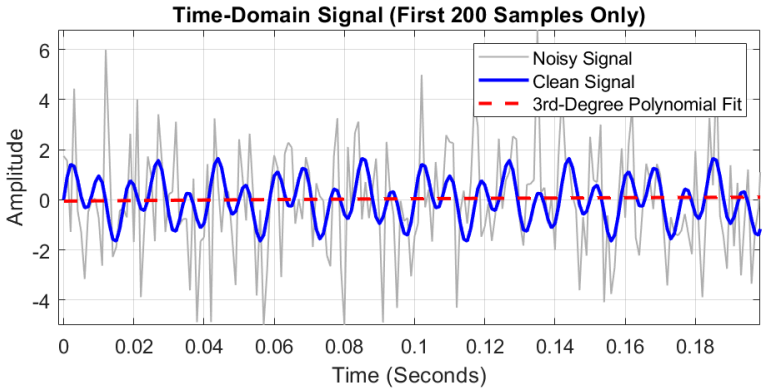


Figure 2. Simulated time-domain phase current (picture credit: original)

In Figure 3, the single-sided amplitude spectrum of the noisy signal is obtained via FFT. The distinct spectral peaks serve as the primary features extracted for the subsequent anomaly detection model.

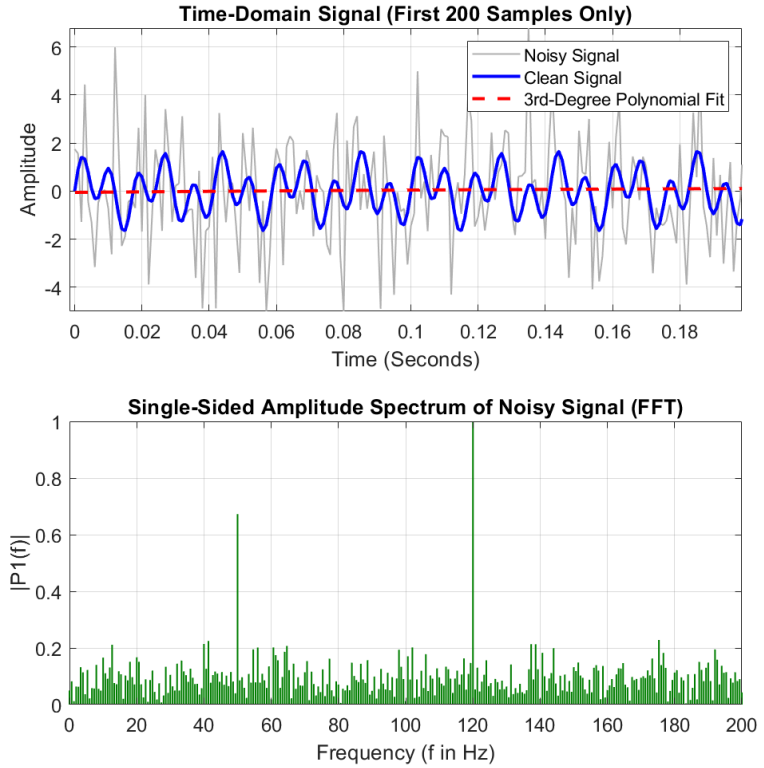


Figure 3. Single-sided amplitude spectrum of the noisy signal (picture credit: original)

DOI: 10.54254/2755-2721/2026.37452

2.3. AI pipeline and edge-optimized ensemble learning

2.3.1 Feature engineering and data division

To make the AI model efficiently deal with continuous phase current, it is better to implement the sliding window technology, which can be explained as a continuous current record being divided into a hundred-millisecond discrete processing window. The model will not accept initial raw sequential arrays, they could conduct training according to specific statistical characteristics and electromechanical features. To be more specific, capturing a sudden current decline driven by a Back EMF via extracting the amplitude peak value. Meanwhile, calculating variance (σ^2), defined mathematically as Equation (3), to quantify the generated high-frequency vibration noise when the motor rotor physically stalls.

$$\sigma^2 = \frac{\sum(x_i-\mu)^2}{N} \tag{3}$$

Where x_i denoteseach individual sampled data point; μ is the mean (average) value of all the current samples within the given window; N represents the total number of samples (data points) in that specific 100-millisecond processing window.

2.3.2 Algorithmic selection and decision logic

Traditional fault detection methods rely on hard-coded current thresholds. However, in an unpredictable outdoor environment, a single threshold is prone to misclassification because of an instant mechanical shock. To resolve this crucial problem, this paper implements a Random Forest Classifier, whose fundamental robustness of the algorithm can be illustrated by the composition of decision trees, as shown in Figure 4 [8]. If a random outdoor shock leads to the peak value surpassing the threshold (like node A: Amplitude > 2.5A). The hard-coded system will immediately trigger a false alarm. Instead, the decision trees will start a following evaluation (node C: Variance Question). For a sudden physical shock or lack of high-frequency vibration, stall like a mechanical stall, its variance will remain relatively low (Variance < 0.4 A²); the algorithm can safely route the classification to node B (normal operation). Only if all of the standards concerned with amplitude and variance can be satisfied at the same time, it could be marked as an anomaly (node D).

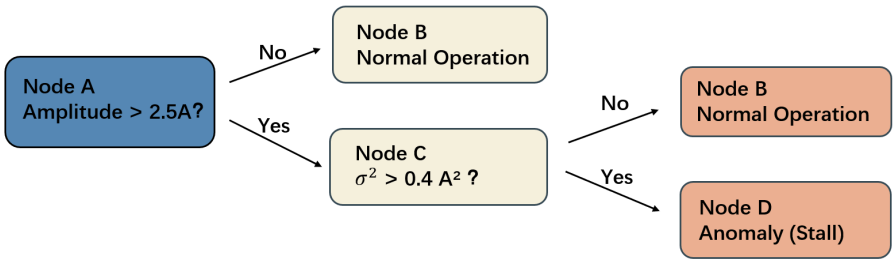


Figure 4. Random Forest Classifier (picture credit: original)

2.3.3. Ensemble Robustness and edge computing viability

The reliability of the Random Forest Classifier originates from its integrated learning architecture. By constructing multiple unrelated decision trees and adopting the Majority Voting mechanism, this

DOI: 10.54254/2755-2721/2026.37452

model reduces the influence of random environmental noise and isolated misreadings [10]. Furthermore, this structure, aimed at edge AI deployment, experiences a series of advancements. It is different from heavyweight deep learning networks that require matrix multiplication; the process of deduction of the Random Forest Classifier is compiled into a series of basic if-else gates. This design generates low calculation complexity of $O(log\ N)$, ensuring a short inference delay. The automated bird feeder makes use of this model to operate a lightweight calculation and finally meet the target of a low-cost, low-power-consuming microcontroller in a real-time close loop execution.

3. Results

3.1. Signals transformation and detection

To systematically let physical signals transform into structure learning of machine models, the time domain has been divided into discrete 100-millisecond sliding windows. Each split window in Table 1 is represented as an independent sample, involving two major features in the FFT extraction method: the amplitude (I_{max}) and variance (σ^2). Furthermore, this synthetic dataset verifies the decision logic in part 2.3.2. For instance, #017 has a high amplitude and low variance, responding to the transient environmental shock correctly instead of continuously false alarms (#018). This structured format effectively transforms chaotic time series signals into high-quality feature matrices, paving the mathematical foundation for the following classification tasks.

Table 1. Selection and decision logic detection

Window ID	Time (s)	Peak Amplitude Imax (A)	Variance σ2 (A2)	Ground Truth Label	Model Prediction
#004	0.40 - 0.50	1.35	0.12	0 (Normal)	0 (Normal)
#012	1.20 - 1.30	1.42	0.15	0 (Normal)	0 (Normal)
#017	1.70 - 1.80	2.95	0.28	0 (Normal)	0 (Normal)
#018	1.80 - 1.90	4.05	0.88	1 (Stall)	1 (Stall)
#019	1.90 - 2.00	4.12	0.95	1 (Stall)	1 (Stall)
#024	2.40 - 2.50	2.1	0.35	1 (Stall)	0 (Normal)

3.2. Confusion matrix application

To thoroughly evaluate the robustness of the proposed Random Forest classifier, this model adopts an equilibrium dataset including two thousand discrete sliding windows, through the confusion matrix, visualises the predictive performance. As shown in Figure 5, the random forest classifier evaluated on 2,000 test samples are shown in the confusion matrix. The vertical axis represents the real physical state of the motor (True Class). The horizontal axis represents the diagnostic of the

DOI: 10.54254/2755-2721/2026.37452

algorithm's prediction (Predicted Class). The color gradients correspond to the density of samples in each phase. Dark blue distinguishes the high density of correct classifications on the main diagonal, verifying the stable accuracy of the model. This model correctly identifies 970 normal function samples (true negatives) and successfully detects 966 mechanical stall problems (true positives). This matrix demonstrates a strictly controlled margin of error: only thirty times false alarms derived from simulated instant noise (false negatives) and only 34 missed reports of minor freezes (false negatives). This specific distribution transformed into an accuracy of 96.80% and a recall rate of 96.60%. This index indicates that the classifier maintains high sensitivity under environmental influence and mechanical stall conditions.

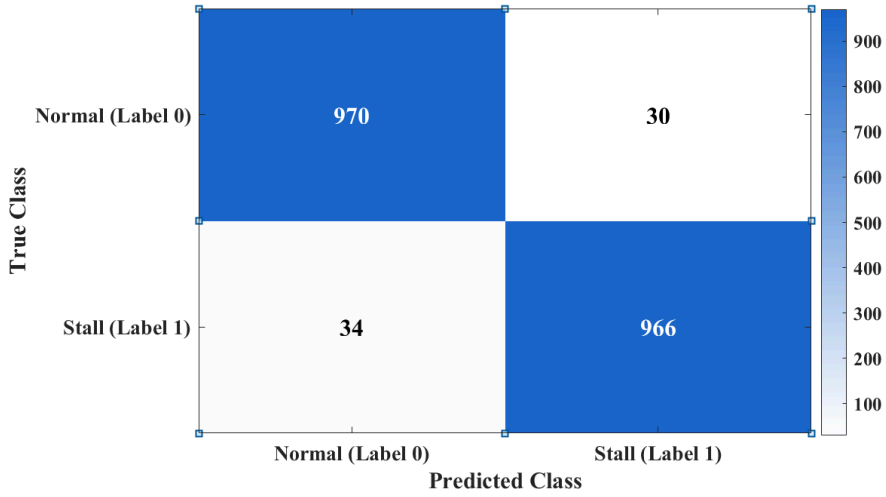


Figure 5. Confusion matrix of random forest classifier (picture credit: original)

3.3. Evaluation metrics and baseline comparison

To strictly evaluate the performance of the mentioned algorithm, this paper uses a 10-Fold Cross-Validation method, ensuring an accurate evaluation of the mean and median values. We have benchmarked and compared the proposed random forest model for edge optimization with two of the most advanced neural network structures: a standard Deep Neural Network (DNN) and a hybrid Stationary Wavelet Transform Long Short-Term Memory DNN (SWT-LSTM-DNN). As shown in Figure 6, a standard DNN model achieves an average accuracy of 89.30%. However, it cannot capture complex high-frequency transient dynamics when mechanical jamming occurs. In contrast, a more advanced SWT-LSTM-DNN obtains a higher accuracy, 96.24% [4].

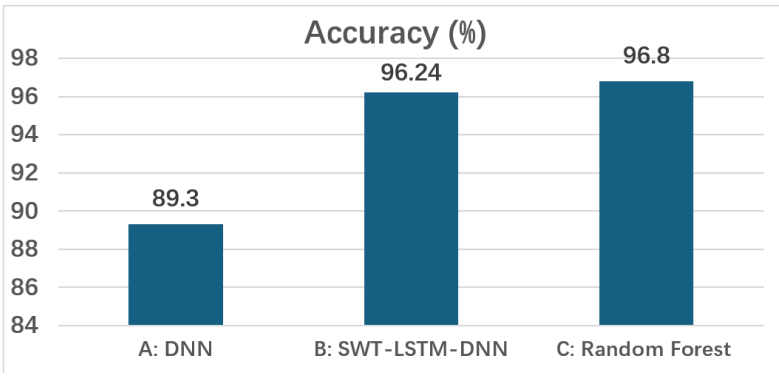


Figure 6. Accuracy comparison of anomaly detection algorithms (picture credit: original)

DOI: 10.54254/2755-2721/2026.37452

3.4. Performance and edge viability

Although accuracy evaluates the overall correctness, due to the inherently unbalanced nature of industrial operation data, evaluating F1-Score is particularly crucial for anomaly detection. F1-score provides a harmonic mean of Precision and recall, balancing the trade-off between false positives (false positive) and missed negatives (false negative). SWT-LSTM-DNN has a very high diagnostic accuracy rate. However, its huge number of parameters and complex matrix operations have brought about a high intensity of computational load. This makes it more challenging to deploy onto an edge AI controller. As shown in Figure 7, comparison matrix of the proposed Random Forest classifier evaluated on the synthetic dataset (N=2,000). The matrix visualizes the high True Positive rate for stall detection and effectively captures the Precision and Recall distribution, minimizing false alarms in noisy conditions. The proposed Random Forest classifier achieves 96.79% F1-Score, which surpasses the standard DNN (88%) and SWT-LSTM-DNN (95.0%) structure (Table 2). Besides, this kind of light computational model could satisfy the strict hardware limitations of edge AI and guarantee real-time, low-power stall detection without relying on cloud processing.

Table 2. Performance and complexity comparison of different models

Algorithm Model	Accuracy (%)	F1-Score (%)	Computational Load	Edge Deployment Viability
A: DNN	89.3	88	High	Poor
B: SWT-LSTM-DNN	96.24	95	Very high	Unviable
C: Random Forest	96.8	96.79	Extremely Low	Excellent

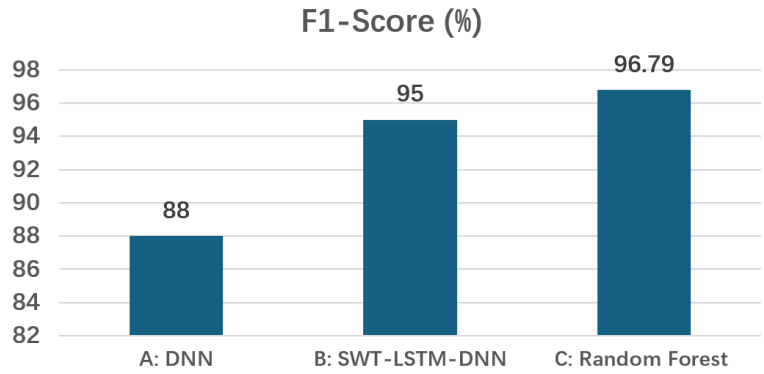


Figure 7. F1-Score comparison of anomaly detection algorithms (picture credit: original)

4. Discussion

4.1. System-level impact and ecological benefits

The sensorless predictive maintenance system provides huge engineering and ecological value, meeting the expanding demand of reducing wildlife device failures and declining maintenance costs.

From the perspective of function, this equipment prevents feed clumping and overflow waste, saving food resources. In financial terms, it precisely predicts mechanical stalls and stops the stepper motor in advance before a catastrophic failure occurs. The system to a large extent extends

DOI: 10.54254/2755-2721/2026.37452

automated feeding maintenance periods, therefore reducing labor costs and the related carbon footprint.

4.2. Future steps

The urgent task in the future is to bridge this simulation-reality gap by assembling a physical hardware prototype. The immediate plan is to integrate a physical ACS712 current sensor to obtain empirical operation data in different environmental conditions. After that, Transfer Learning techniques will be applied to fine-tune the random forest model, which could assist AI in adapting to the thermal drift of the real world independently and complicated outdoor noise distribution.

5. Conclusion

This paper proposes a physically driven sensorless motor fault detection system based on a Random Forest classifier to address the widespread problem of false alarms when bird feeders suffer transient environmental shocks in outdoor environments. Considering the destructive hardware damage and high cost, the Digital Twin methodology could be a solution by establishing d-q axis electromechanical equations in MATLAB and generating high precision Synthetic dataset. In this experiment, continuous time-domain signals are divided into 100-millisecond sliding windows, and the peak amplitude and variance are extracted through the Fast Fourier Transform (FFT). These characteristics assist decision trees in strictly classifying the difference between external vibration and internal mechanical stall.

In the evaluation of the dataset, which includes two thousand samples, the proposed model achieves 96.80% accuracy and a 96.79% stable F1-Score. Compared with standard deep learning models: DNN and SWT-LSTM-DNN, Random Forest classifier achieves a high accuracy, it also reduces the computing load to $O(log\ N)$. By this way, it guarantees millisecond-level latency and make it accessible in edge deployment when using limited resources, eventually provides a low cost and highly reliable predictive maintenance solution. The future work will focus on transfer learning (Sim-to-Real, deploying the verified algorithm into microcontrollers). This post-optimization will play a role in interaction with wildlife regardless of environmental factor.

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