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Anomaly Detection in Brushless Fan Systems using integration of wavelet approach and convolutional neural network

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Abstract

In this research, trustworthiness is improved, and the probability of malfunctioning in DC fan systems is decreased was addressed. This research suggests a new method that employs artificial intelligence to detect faults by combining Convolutional Neural Networks (CNN) with wavelet analysis for better anomaly detection. Ten fans were initially used in the experiment; three were faulty, and seven operated correctly. Data for all fans was collected using an Arduino. Wavelet features were employed to identify faults, followed by a CNN classifier (. Specifically, a binary CNN classifier) to determine the presence or absence of faults. The results were very promising, demonstrating significant potential for improving the reliability of DC fan systems.

Keywords— Anomaly detection, deep learning, Convolutional Neural Networks (CNN), wavelet analysis.

1 Introduction

Recently, interest in deep learning has been increasing in the field of industry due to advancements in deep learning and the increase in research and development costs in response to the increase in research and development costs for detection equipment. In particular, it is used as it can replace the time-consuming process of manufacturing caused by human eye inspection or can be used together for fast screening (Al-amri et al., 2021; Demertzis et al., 2020). An array of deep learning studies has been performed on vibration data detection and intensity classification as the Internet of Things (IoT) expands to include vibration-vulnerable equipment, including factories utilizing high voltage power equipment, power plants, and residential thermal power facilities, and at the core of it is the focus on the brushless fan vibration detection(Mohd Ghazali & Rahiman, 2021). The efficiency of the equipment has made brushless fans a key element for cooling in the aforementioned equipment. If a failure happens to the brushless fan elements, secondary damage is caused by thermal change, and when tertiary failure occurs, a failure occurs. At this point of the multitier characteristic, despite the financial effects and production reduction of the terminal equipment, the detection of whether the brushless fans have a potential failure rests with visual inspection of the outer portion of the brushless fan, a costly and time-consuming procedure to complete. In an environment where many of the brushless fans are put into use, the direct monitoring of the brushless fan cannot be completed (Infantraj et al., 2023; Safril et al., 2022). Therefore, outside manufacturing, the effects of brushless fans continue to grow.

In the electronics industry, cooling fans are indispensable because they dissipate the excessive thermal energy of electronic equipment by increasing the convection coefficient. To respond to the needs of the industrial market and reduce the noise of cooling fans, the Brushless Fan, the Brushless DC Motor-driven fan, has been developed and is widely used for cooling electronic equipment. In this system, the feature for high reliability is a Fan Ball Bearing. Nevertheless, due to wear or insufficient lubrication, the Fan Ball Bearing is affected by several

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faults, which may result in significant damage to the fan and the cooling system of the electronic equipment (Khettat et al., 2022).

This study proposes an approach to predict anomalies in Brushless Fans using Deep Learning. First, continuous Harmonic Waves (HWs) embedded with relevant frequencies to extract features from the Brushless Fan signals were identified by Continuous Wavelet Transform (CWT). Then, the Convolutional Neural Networks (CNNs) and the probabilities of the anomalies' occurrences produced by the CNNs were used to construct the Anomaly Predictive Model. The model was constructed using the three, types of fan anomalies' vibrations dataset as the input signal, and both datasets as the required response data. Finally, the anomaly event will occur if the probability of the anomaly's occurrence is above certain **confidence** levels (i.e., both the upper and lower **confidence** levels).

2 Literature review

In general, the BLDC model is suggested to have been derived by applying the similarity of rotary machines. This particular model can represent a real-world fault that has many operating conditions. The fault might develop at any given location on the blades. The modified blade forces will vary due to these particular faults. These variations are tested against experimental vibration signatures (Sun et al., 2022). These tests were designed in such a manner that identified the spectrums from damage detection techniques. With the above three points in view, it became necessary to employ vibration analysis to determine the FFT of fan signals and compare this spectrum with the spectrum from the literature relating to various wavelet coefficients. Therefore, with the above aspects in view, this paper mainly investigates the effectiveness of the CNN and the wavelet analysis for the anomaly detection of the two types of resonance fan stresses, namely, the blade/impeller resonance fan stress and the static/dynamic pressure resonance fan stress, that have been tested under common scenarios (Jagtap et al., 2020).

In this section, we aim to review some of the important works on anomalies in brushless DC (BLDC) fans, namely their associated noises and mechanical faults. It is also important to note here that most of the previous research on anomaly detection in fans is based on problems of noises generated by fans and not the fans themselves (Wang et al., 2024). Therefore, in a bid to extend our work to more general anomaly detection, a discussion of issues related to the mechanical problems of the BLDC fans is important in this literature review. This should motivate other researchers to make use of anomaly detection based on convolutional neural networks (CNNs) and wavelet analysis to solve other types of faults or anomalies in the BLDC fans or other components of the computer. In addition, other important works related to this paper, namely work based on CNN and wavelet analysis, are also reviewed here (Sun et al., 2022).

2.1 Anomaly Detection in Industrial Systems

Anomaly detection in industrial systems refers to the identification of deviations from normal patterns or models, which can be applicable to various fields such as fault detection, data cleaning, or security surveillance. Anomaly detection is crucial in industrial systems, where the doctrine is inspired by preventive maintenance and condition-based monitoring (CBM) (Jiang, 2022). The potential problems would be detected before they lead to catastrophic failures, in contrast to relying on manual inspection or after the catastrophic failures that have occurred. Therefore, the costs that result from shutdowns, unexpected breakdowns, and catastrophic failures, such as the repair, inspection, and replacement of equipment, can be efficiently reduced by employing an automated method to perform anomaly detection in industrial contexts. In this study, the proposed method was designed to improve the anomaly detection performance in brushless fan systems (Arena et al., 2022; Ben-Larbi et al., 2021).

Advantages of Al-Based Anomaly Detection System

Anomaly detection in brushless fan systems is crucial for reliability and failure prevention. This research proposes a deep learning approach using Convolutional Neural Networks (CNN) combined with wavelet analysis to enhance detection accuracy.

We systematically collect and preprocess data from fan systems, encompassing both normal and anomalous instances. Our customized Convolutional Neural Network (CNN), featuring convolutional and pooling layers, effectively captures spatial patterns. Concurrently, wavelet analysis is employed to extract critical time-frequency features. Evaluated using accuracy, precision, recall, and F1-score, our method outperforms baseline and existing approaches, achieving high accuracy. This research enhances the reliability and maintenance of brushless fan systems, enabling timely anomaly detection and mitigation, improving operational efficiency, and reducing downtime.

Convolutional Neural Networks (CNNs)

CNN is a type of feed-forward artificial neural network which is inspired by the visual mechanism of the human brain. Various types of CNN have been applied in the field of image processing on the basis of the basic architecture comprising convolutional layers, fully connected (FC) layers, pooling layers, etc. For object recognition by input image models, scanning (or convolution) areas of the input image and filter weights are compared, changing as the input image scrolls. CNNs, in terms of image scanners, can encode characteristics of the important features of a given image in spatial proximity to one another, regardless of the distance within the same layer of the network. This is why the deep patterns can be understood by backpropagation via backpropagating gradient optimization instead of incorporating features manually. Then, the shallow patterns are highly correlated, whereas the deep patterns have a modular architecture (Celeghin et al., 2023; Yang et al., 2022).

Wavelet Analysis

Wavelets, a class of mathematical functions, are critical in the field of digital signal processing and have been widely applied in many technical fields. After the introduction of wavelet theory into signal analysis from the fields of image and vision, wavelet analysis has become an important practical tool for time-frequency analysis. Using a technique to transform a signal into time and frequency space, the information contained within the signal can be analyzed through scale, location, or frequency. By modifying the length of the windowing function, the wavelet transform provides the time resolution of a Fourier transform while also providing reliable frequency information for the time-frequency analysis (Dong et al., 2023; Guo et al., 2022).

3 Experimental System Design and data collecting

The proposed system is implemented and tested using a specially designed platform to conduct the experiment and collecting data and finally test the built algorithm in real time. The platform is built as in Figure 2 using the following:

1. A wooden of 80* 80 cm base to fit other components of them.
2. Ten computer cooling brushless fans with a dimension of (12*12cm) is fitted on the wooden base with 12V and 0.3A power requirements.
3. 3Each fan can energize separately by a switch
4. A DC power supply with 60 W and 12 V specification
5. Dc to Dc convertor to supply a voltage range from 0-12V
6. Nano 33BLE sense Arduino board which is equipped with IMU module which consist of 3D accelerometer and 3D Gyroscope (LSM9DS1 module)
7. A Laptop for data collection and Arduino programming.

The 12V DC power supply energizes the fans through DC-DC and through the switches. Seven fans kept without any defects to act as normal fans. While the other three fans have intentionally defected to act as anomalous fans. Three deferent artifacts are added to these three fans. The first artifact is generated by adding electrical insulation tape for two blades as shown in Figure 3 while the second is generated by adding the same tape for only one blade and finally the third is generated by adding a mixture of oil and dust for one blade. Three levels of speed are achieved by using three different level of supplying voltage (6, 8 and 12) V. The 3D accelerometer and gyroscope data are collected using the Nano Arduino board and saved on the laptop using IDE 2.0 official Arduino software.

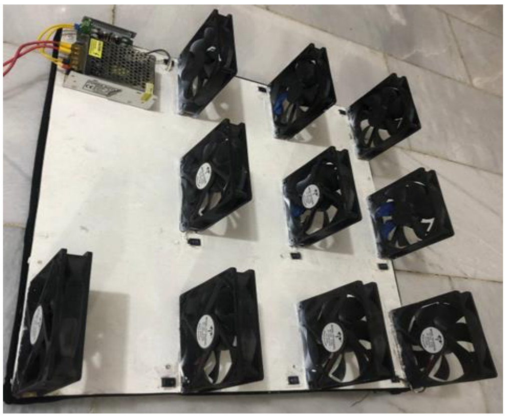


Figure 1: The flow diagram for proposed FASA+FS algorithm

Figure 2: Defected fan with insulation tape on two blades

4 Data Collecting

Data is collected by fitting the Arduino board over each rotating fan for three minutes and the Arduino board is connected to the laptop for data acquisition. The IMU module can provide accelerometer and gyroscope data with a rate of 104 samples/second. This arrangement generates 104*3*60 = 18720 reading for each fan. And as wen mentioned earlier the experiment conducted with three levels of speeds and for all 10 cooling fans. So, the dataset has ($18720 \ * 10 * 3 = \ 561600 \, readings$).

The dataset is a collection of three sets based on three levels of speed. Moreover, 70% of the data is labeled as normal class while the rest 30% is labeled as anomalous class. This dataset is used to build and train the deep learning network (detailed in next section)

The Flow chart with research can be illustrated in Figure 3. Several types of anomalies have intentionally made on our system to simulate the effect of defect on system. In this work we make these artifacts

1. Stick insulation tape on one of the blades of the fan to introduce unbalance effect.
2. Stick insulation tape on two of blades
3. Adding oil and dust of one blade

The experimental setup involves connecting all components on a single board and categorizing the fans into two types: normal and defective. The defective fans are categorized into three distinct types based on the nature of the induced anomalies:

Type 1. Quantity: 2 fans

Modification: One blade of each fan is wrapped with duct tape to simulate imbalance.

Type 2. Quantity: 1 fan

Modification: One blade is wrapped with duct tape, but the extent of wrapping differs from Type 1 to introduce variability in the defect.

Type 3. Quantity: 1 fan

Modification: The fan is subjected to additional oil and dust to create operational hindrance.

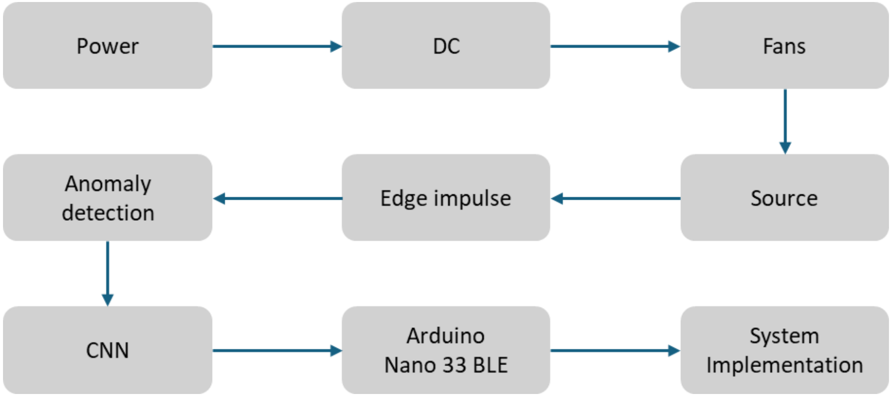


Figure 3: System design Diagram

5 TinyML-Deep Learning Network Architecture and deployment

Deep learning network has gained a positive reputation of high classification performance metrics (Demertzis et al., 2020) and many research papers have used this network successfully to classify their dataset. In this work, a real-time classifier is required to handle the classification mission and distinguish between the normal and anomalous fans.

Convolutional neural network (CNN) is chosen in this work as classification network due to its success in many vibrations driven data. So, one dimensional CNN with the architecture shown in Figure 4 is suggested to handle the classification job. This classifier is built from 1 convolutional layer with 8 kernels and 2 strides. Following by flattened layers and soft-max classifier.

The real-time classifier is designed to be running on microcontroller (MCU) Arduino Nano 33 BLE. It is known that the MCU has limited resources and usually cannot handle the complexity of the deep learning network like CNN. So, with the help of Edge Impulse platform, the proposed 1D classifier is built, trained, and tested to evaluate its performance metrics. The platform helps, with the aid of TinyML framework, to convert the deep learning classifier into lite form to be with the right form and size to be handled by microcontroller resources. Tiny ML generates low resolution version of CNN with small memory size so it can fit the MCU resources and also can have fast inference time.

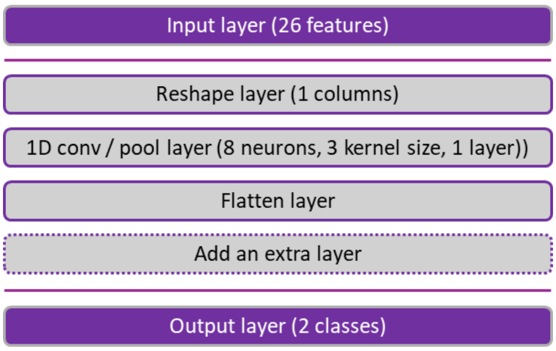


Figure 4: CNN classifier

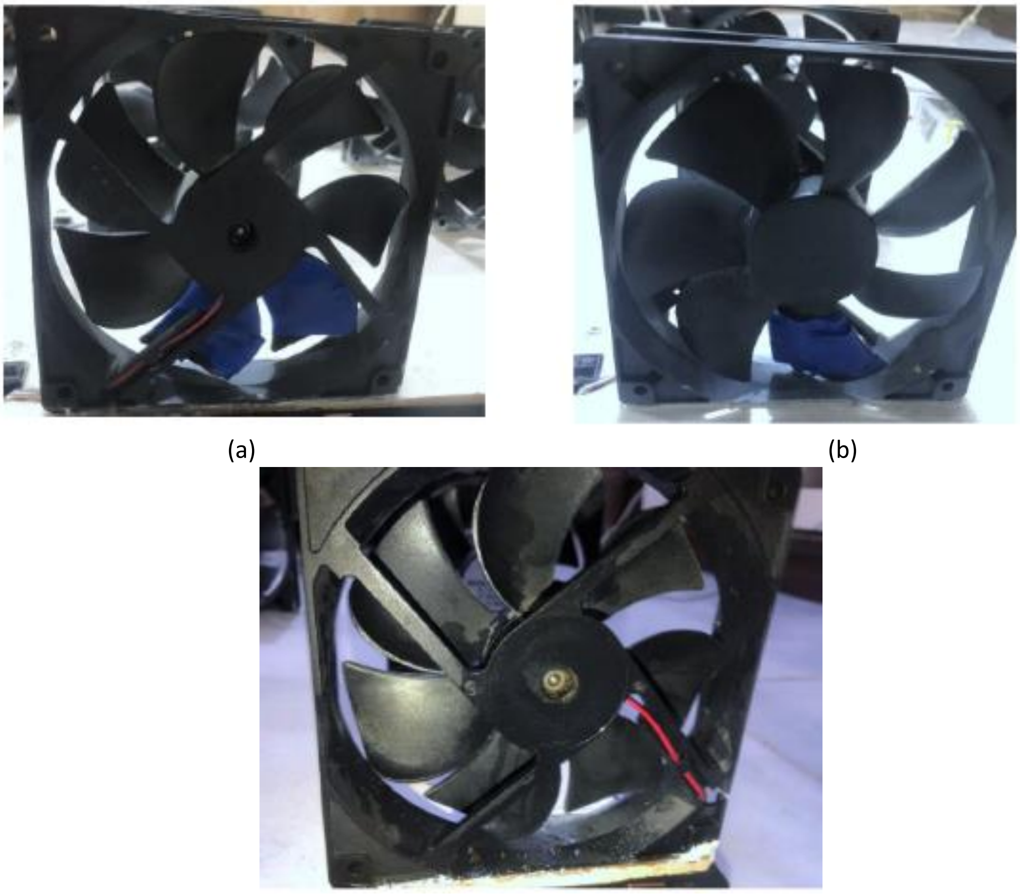
Figure 5: system setup

6 System implementation and Discussion of Results

To address the problem of anomaly detection in brushless fan systems, we propose a method utilizing unsupervised learning techniques, specifically a convolutional neural network (CNN). This approach leverages both the raw sensor data structure and the time-frequency representation of sensor data, allowing for robust anomaly detection without the need for labeled data. Figure 5 illustrates the complete system setup, including the data acquisition process via Arduino Nano. This microcontroller is connected to a computer, where data

collection and storage for subsequent processing take place. The Arduino Nano efficiently captures data from the fan system, recording both normal and anomalous instances.
Several types of anomalies have intentionally made on our system to simulate the effect of defect on system as in Figure 6. In this work the following artifacts have been made:

1. Stick insulation tape on one of the blades of the fan to unbalance effect.
2. Stick insulation tape on two of blades
3. Adding oil and dust of one blade



(a) (b)

(c)

Figure 6: Several types of anomalies

The research focuses on an artificial intelligence-based anomaly detection system to detect anomalies in normal operating systems using massive datasets. The least errors will cause many costly losses. So it founds an anomaly detection system that predicts an error before it happens by artificial intelligence As you train the neural network of artificial intelligence on the systems to be monitored by taking specific steps so that we avoid falling into the plan by conducting proactive maintenance of the system before it fails, and thus we have preserved the data or the system and saved effort, losses, time and money from waste and losses.

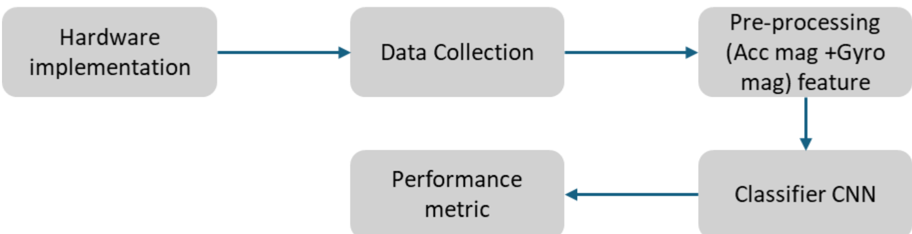


Figure 7: Procedure to detecting anomalies

Figure 7 depicts the block diagram of the procedure to detect the anomalies. So, the criteria for determining whether a fan is faulty are based on the specific modifications and induced anomalies in the fan's operation. The detailed criteria are as follows:

- Vibration Analysis: The primary criterion for detecting a faulty fan is the analysis of vibration patterns. Significant deviations from the normal vibration spectrum, as captured by sensors, indicate potential faults.
- Physical Modifications: Fans were intentionally modified to introduce defects. The specific modifications include:
- Duct Tape Wrapping: Wrapping one or more blades with duct tape to simulate imbalance and airflow disruption.
- Contamination: Adding oil and dust to certain fans to mimic real-world operational hindrances.
- Wavelet Analysis: The time-frequency representation of the fan's operational data is analyzed using wavelet transforms. Significant deviations in the wavelet feature map, especially in the low-frequency components, are indicative of faults.
- CNN Classification: A convolutional neural network (CNN) classifier is trained to distinguish between normal and faulty fans based on the extracted wavelet features. The CNN's decision boundary is learned from labeled training data where the faulty fans are clearly identified.
- Performance Metrics: The high accuracy CNN classifier, as indicated by the confusion matrix, confirms the effectiveness of the fault detection method. The confusion matrix also highlights specific instances of misclassification, allowing for a detailed understanding of the decision criteria.

6.1 Hardware implementation

We connect all the elements together on the board and then divide the fans into two types, the first type consists of 6 fans in the normal case and 4 fans that we cause a defect or add obstacles such as adding some oil or dust or we wrap adhesive tape on the blades of the fans , Unusual fans are divided into 3 types The first is two propellers wrapped with duct tape on one blade only, and the second is a single propeller wrapped on one of its blades with duct tape. The third type is a single fan to which we add some oil and dirt as a hindrance. The board contains a voltage source and a voltage reducer, as can be seen in Figure 8.

Figure 8: Hardware implementation

6.2 Performance metrics

The proposed CNN model was evaluated on the collected dataset, which included both normal and artificially induced abnormal instances. The results demonstrated the model's capability to accurately identify the introduced anomalies. The CNN effectively captured the spatial patterns and variations in the fan system operation data, facilitated by the incorporation of wavelet analysis to extract time-frequency features.
After filtering the data, wavelet analysis was performed to extract time-frequency features from the sensor signals. The wavelet transform provides a detailed view of the signal's frequency content over time, making it an effective tool for detecting transient events and anomalies. To enhance the understanding of wavelet analysis on system performance, a detailed feature extraction is provided. This process involves using a low pass filter with a cutoff frequency of 3 Hz and an order of 6. The following wavelet analysis results were obtained, which are crucial for accurately identifying anomalies in brushless fan systems. Figure 9 shows the decibel (dB) value versus frequency before and after the application of the low pass filter. This comparison illustrates how the filter effectively reduces high-frequency noise while preserving the critical components of the signal needed for accurate anomaly detection.

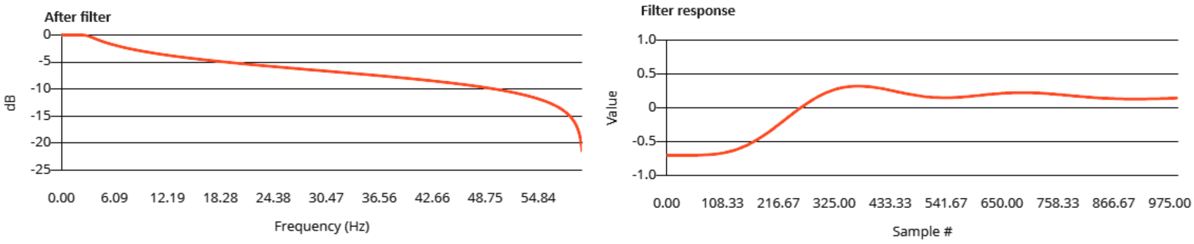


Figure 9: Decibel (dB) value versus frequency before and after the application of the low pass filter

Figure 10 extracts the feature to clear wavelet analysis on system performance.

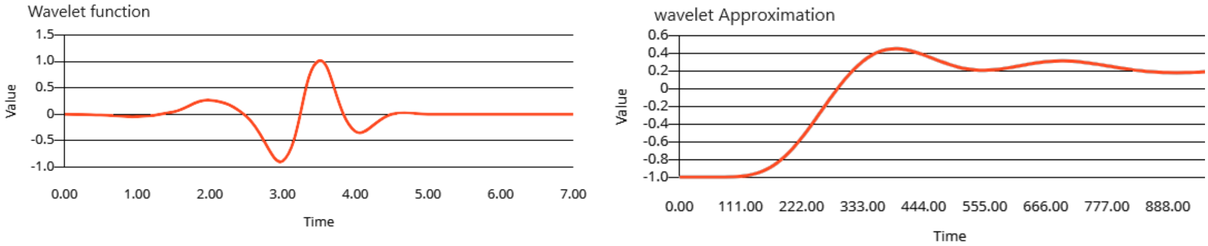


Figure 10: wavelet mother function and the approximation part of the input signal

The classifier has been trained using 70% of the collected data and tested using the rest of the data. The classifier achieved very good performance metrics as the results of accuracy and Loss is illustrated in Table 1

Table 1: Last training performance

Metric	Value
Accuracy	99.2%
Loss	0.12

These metrics indicate a high level of performance, confirming the effectiveness of the CNN-wavelet approach in detecting anomalies in brushless fan systems. Moreover, the confusion matrix shows in detail which part of misclassification take the response for the Loss as shown in Table 2.

Table 2: Confusion matrix

Metric	Anormal	Normal
Anormal	100%	0%
Normal	1.5%	98.5%
F1-score	99%	99%

Another tool for classified data exploration help to overview how good the classifier handles the job and where the failure has happened as shown in Figure 11.

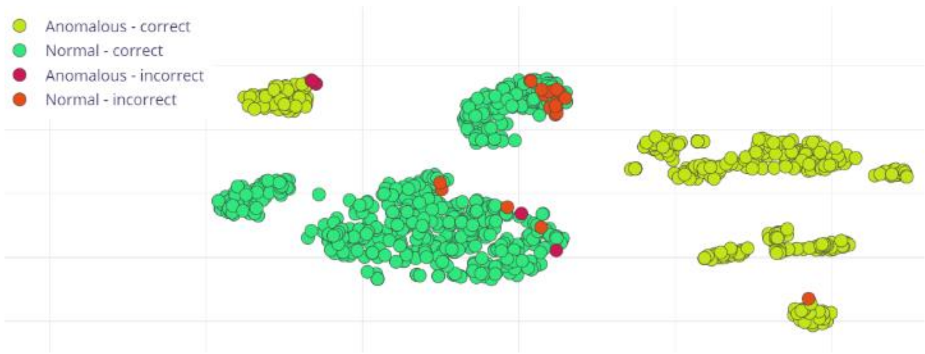


Figure 11: Classified data exploration

Finally, the deployed model is now ready to be installed on the microcontroller (Arduino Nano 33 BE sense). This model will use the flowing resources from the board after deployment as shown in Table 3.

Table 3: On-device Performance

Metric	Value	Total
Inferencing Time	1ms	1ms
Peak Ram Usage	2.0k	2.0k
Flash Usage	24.8k	24.8k

The results from experiments underscore the importance of using advanced deep learning techniques for anomaly detection in industrial applications. The CNN-wavelet approach not only captures the necessary spatial and temporal patterns but also adapts well to different types of anomalies.
Future research should explore the scalability and adaptability of this method to various fan systems and more complex multi-fault scenarios. Additionally, integrating other deep learning architectures, such as recurrent neural networks or attention mechanisms, could further enhance the model's robustness and accuracy.

In summary, our proposed method provides a promising solution for improving the reliability and maintenance of brushless fan systems, offering significant benefits in operational efficiency and fault management.

7 Conclusion

The research suggests a way of applying unsupervised learning methods which are specific for solving the problem of anomaly detection in brushless fan systems, using Convolutional Neural Network (CNN). The method combines information collected by Arduino using time-frequencies representation, with waveforms capturing the complex physics behind brushless fans. Further, it also accepts a wavelet-based feature map that includes information about rotor-stator air gap modulation. The findings indicate that after training with healthy data only, a high detection rate might be achieved using this approach; thus, suggesting its potential as a promising methodology to handle complex dynamics.
A practical model consisting of 10 fans, three of which were faulty, was implemented. This study showcases the superior performance of the CNN-wavelet method in accurately identifying anomalies, holding significant implications for improving the reliability and maintenance of these systems.
In the context of condition-based monitoring, brushless fan systems are widely used to cool various electronic or mechanical systems. Considering brushless fan behavior, anomaly detection may provide good health condition monitoring. This paper addresses the problem of brushless fan anomaly detection where vibrations are considered a critical feature. Although several detection techniques exist in the literature, they usually follow a rule-based algorithm focused solely on physical characteristics. However, these features may not be the most appropriate for brushless anemometer fans or direct detection. The matrices indicate a high level of

performance, confirming the effectiveness of the CNN-wavelet approach in detecting anomalies in brushless fan systems with an accuracy of 99.2% and a loss of 0.12. Moreover, the confusion matrix provides detailed insights into the specific misclassifications that contribute to the overall losses, highlighting the robustness of the proposed method.

This research has important implications for practice. The proposed technique is valuable for online monitoring and early diagnosis of faults in brushless fan systems, which can result in immediate interventions to avoid critical failures and minimize downtime. It boosts operational efficiency while reducing maintenance costs and enhancing overall system performance. Future directions in research include investigating scalability and generalization capability across different types of fan systems and expanding its capacity to deal with intricate multi-fault scenarios.

8 References

Al-amri, R., Murugesan, R. K., Man, M., Abdulateef, A. F., Al-Sharafi, M. A., & Alkahtani, A. A. (2021). A Review of Machine Learning and Deep Learning Techniques for Anomaly Detection in IoT Data. Applied Sciences, 11(12), 5320. https://doi.org/10.3390/app11125320

Arena, S., Florian, E., Zennaro, I., Orrù, P. F., & Sgarbossa, F. (2022). A novel decision support system for managing predictive maintenance strategies based on machine learning approaches. Safety Science, 146, 105529. https://doi.org/10.1016/j.ssci.2021.105529

Ben-Larbi, M. K., Flores Pozo, K., Haylok, T., Choi, M., Grzesik, B., Haas, A., Krupke, D., Konstanski, H., Schaus, V., Fekete, S. P., Schurig, C., & Stoll, E. (2021). Towards the automated operations of large distributed satellite systems. Part 1: Review and paradigm shifts. Advances in Space Research, 67(11), 3598–3619. https://doi.org/10.1016/j.asr.2020.08.009

Celeghin, A., Borriero, A., Orsenigo, D., Diano, M., Méndez Guerrero, C. A., Perotti, A., Petri, G., & Tamietto, M. (2023). Convolutional neural networks for vision neuroscience: significance, developments, and outstanding issues. Frontiers in Computational Neuroscience, 17. https://doi.org/10.3389/fncom.2023.1153572

Demertzis, K., Iliadis, L., Tziritas, N., & Kikiras, P. (2020). Anomaly detection via blockchained deep learning smart contracts in industry 4.0. Neural Computing and Applications, 32(23), 17361–17378. https://doi.org/10.1007/s00521-020-05189-8

Dong, H., Yu, G., Lin, T., & Li, Y. (2023). An energy-concentrated wavelet transform for time-frequency analysis of transient signal. Signal Processing, 206, 108934. https://doi.org/10.1016/j.sigpro.2023.108934

Guo, T., Zhang, T., Lim, E., Lopez-Benitez, M., Ma, F., & Yu, L. (2022). A Review of Wavelet Analysis and Its Applications: Challenges and Opportunities. IEEE Access, 10, 58869–58903. https://doi.org/10.1109/ACCESS.2022.3179517

Infantraj, A., Augustine, M., Raj, E. F. I., & Appadurai, M. (2023). Investigation of Various Laminating Materials for Interior Permanent Magnet Brushless DC Motor for Cooling Fan Application. CES Transactions on Electrical Machines and Systems, 7(4), 422–429. https://doi.org/10.30941/CESTEMS.2023.00048

Jagtap, H. P., Bewoor, A. K., & Kumar, R. (2020). Failure analysis of induced draft fan used in a thermal power plant using coordinated condition monitoring approach: A case study. Engineering Failure Analysis, 111, 104442. https://doi.org/10.1016/j.engfailanal.2020.104442

Jiang, W. (2022). A Machine Vision Anomaly Detection System to Industry 4.0 Based on Variational Fuzzy Autoencoder. Computational Intelligence and Neuroscience, 2022, 1–10. https://doi.org/10.1155/2022/1945507

Khettat, M. A., Hamiche, K., Morvany, R., Annoepel, C., & Omara, A. M. (2022). Low-Cost Sensorless Scalar Control of a Brushless Motor for Automotive Fan System Application. 2022 23rd International Middle East Power Systems Conference (MEPCON), 1–6. https://doi.org/10.1109/MEPCON55441.2022.10021740

Mohd Ghazali, M. H., & Rahiman, W. (2021). Vibration Analysis for Machine Monitoring and Diagnosis: A Systematic Review. Shock and Vibration, 2021, 1–25. https://doi.org/10.1155/2021/9469318

Safril, Mustofa, Zen, M., Sumasto, F., & Wirandi, M. (2022). Design of Cooling System on Brushless DC Motor to Improve Heat Transfers Efficiency. Evergreen, 9(2), 584–593. https://doi.org/10.5109/4794206

Sun, Q., Yu, X., Li, H., & Fan, J. (2022). Adaptive feature extraction and fault diagnosis for three-phase inverter based on hybrid-CNN models under variable operating conditions. Complex & Intelligent Systems, 8(1), 29–42. https://doi.org/10.1007/s40747-021-00337-6

Wang, Y., Yuan, X., Lin, Y., Gu, J., & Zhang, M. (2024). A Semi-Supervised Multi-Scale Deep Adversarial Model for Fan Anomaly Detection. IEEE Transactions on Consumer Electronics, 70(1), 3539–3547. https://doi.org/10.1109/TCE.2023.3267077

Yang, X., Yan, J., Wang, W., Li, S., Hu, B., & Lin, J. (2022). Brain-inspired models for visual object recognition: an overview. Artificial Intelligence Review, 55(7), 5263–5311. https://doi.org/10.1007/s10462-021-10130-z