

Article

Image-Based Fault Detection and Severity Classification of Broken Rotor Bars in Induction Motors Using EfficientNetB3

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Abstract

Broken rotor bar faults (BRBFs) in induction motors (IMs) present significant challenges in industrial applications, particularly due to the need for large labeled datasets and fast processing. This study addresses these issues by leveraging transfer learning with classical diagnostic techniques, using experimental 3-phase current and 3-axes vibration signals. The Gramian Angular Field (GAF) technique has been utilized to transform time series data into 2D images, enabling fine-tuning of an EfficientNetB3 model, which achieved 99.83% accuracy in classifying five BRBF severity levels. The proposed strategy also outperforms the state-of-the-art methods using the same experimental data. Similarly, validation with features extracted using Continuous Wavelet Transform (CWT) and Short-Time Fourier Transform (STFT) further confirmed its reliability and superiority. This study also offers enhanced interpretability through Grad-CAM visualizations of the best model, which highlights the critical regions contributing to fault classification. These visualizations enable deeper and simpler understanding of fault mechanisms and support subsequent risk analysis, making the developed model actionable and user-friendly for industrial applications.

Keywords: broken rotor bar fault; continuous wavelet transform; gramian angular field; fast fourier transform; classification; transfer learning; machine learning

1. Introduction

The detection of broken rotor bar faults (BRBFs) in induction motors (IMs) is a critical area of focus due to the implications such faults have on operational efficiency and safety in industrial applications. Various strategies have emerged over the years, leveraging advancements in signal processing, machine learning, and multi-sensor data fusion techniques.

Historically, fault detection in IMs has relied on techniques such as vibration analysis, current signature analysis, and thermal imaging. These methods, while useful, often suffer from limitations related to data interpretation and the need for expert knowledge. For instance, Garcia et al. [1] highlight that traditional methods can struggle to accurately diagnose faults under varying operational conditions, which is a common scenario in industrial settings. As a result, there has been a growing interest in leveraging AI to automate and enhance the diagnostic process.

AI-based systems have emerged as a powerful alternative to traditional diagnostic methods. Machine learning algorithms, particularly deep learning models, have shown



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promise in automating the feature extraction process and improving diagnostic accuracy. Xiang et al. [2] discuss the application of deep transfer learning (DTL) in machinery fault diagnosis, emphasizing its ability to adapt to different operating conditions. This adaptability is crucial for diagnosing BRBFs, as the characteristics of these faults can vary significantly based on the motor's operational environment.

Transfer learning, a subset of machine learning, allows models trained on one dataset to be fine-tuned for another, often smaller, dataset. This capability is particularly beneficial in industrial applications where obtaining large labeled datasets can be challenging. Yan et al. [3] illustrate this concept by demonstrating how transfer principal component analysis can enhance fault diagnosis accuracy in IMs. Their findings indicate that transfer learning can effectively minimize the discrepancies between different operational domains, leading to improved diagnostic performance. Moreover, the authors of [4] proposed a transfer learning-based rotor fault diagnosis method using vibration signals. Their approach effectively utilized pretrained models to extract features from vibration data, leading to improved fault classification accuracy.

Similarly, researchers in [5] introduced a transfer learning architecture that addresses the challenge of missing data due to multi-rate sampling. Their method combines a pretrained convolutional neural network (CNN) for feature extraction with a fully connected layer trained on gearbox fault data. This dual approach allows for effective fault diagnosis even in scenarios where data may be incomplete or inconsistent. Additionally, Dişli et al. [6] highlighted the application of deep transfer learning in diagnosing broken rotor faults by analyzing the voltages and currents of the motor's three phases, alongside acceleration and velocity signals. This method builds upon traditional signal processing techniques, enhancing the accuracy of fault detection through advanced feature extraction and classification capabilities inherent in deep learning frameworks.

The integration of deep learning with transfer learning has proven particularly effective in diagnosing BRBFs. For example, the authors of [2] developed a DTL method that combines model-based and feature-based transfer learning to enhance the versatility of CNNs under variable operating conditions. Their approach demonstrated significant improvements in fault detection accuracy, highlighting the potential of combining these two powerful methodologies.

Furthermore, Chen et al. [7] conducted a systematic review of DTL applications in fault diagnosis, emphasizing its growing importance in the field. Their findings suggest that deep learning models, when combined with transfer learning techniques, can achieve superior performance compared to traditional methods, particularly in scenarios with limited training data.

In addition to machine learning techniques, signal processing methods remain relevant in the diagnosis of BRBFs. Halder et al. [8] introduced an innovative approach that employs inverse thresholding on spectrograms to detect broken rotor bars. This method capitalizes on the frequency domain characteristics of the signals, allowing for the identification of fault signatures that may not be readily apparent in the time domain. The integration of these signal processing techniques with machine learning models can potentially enhance diagnostic accuracy and reliability.

Moreover, the fusion of multi-sensor data has been explored as a means to improve fault diagnosis. By combining data from multiple sensors, researchers can obtain a more comprehensive view of the motor's condition, leading to improved fault detection capabilities. Azamfar et al. [9] discuss the use of a 2D CNN combined with motor current signature analysis for gearbox fault diagnosis, which can be analogous to BRBF detection. This multi-sensor approach allows for a more comprehensive analysis of the motor's operational state, leading to better fault identification and characterization.

While AI-based fault detection methods have made impressive strides, several challenges still need to be tackled. One major hurdle is the requirement for large labeled datasets to effectively train machine learning models. In industrial environments, collecting and labeling such datasets can be expensive and time-consuming. At the same time, there is a growing need for low-cost edge devices that can handle these models efficiently and provide real-time results, which would significantly improve decision-making. To address these challenges, researchers are turning to semi-supervised learning and transfer learning approaches. By blending traditional diagnostic methods with advanced AI techniques, a more reliable and effective fault detection system can be developed, ultimately boosting the performance and lifespan of IMs. In this context, this paper aims to alleviate the aforementioned challenges by leveraging transfer learning combined with classical strategies for BRBF detection. The main contributions of this study are as follows:

- **Lightweight Model Training:** A pretrained image classification model from the “EfficientNet” family has been fine-tuned using experimental data, including 3-phase current and 3-axes vibration measurements.
- **Fault Severity Classification:** The proposed model is able to classify five different levels of BRBF severity, including the healthy class (experimental signatures).
- **Innovative Data Encoding:** Building on prior preprocessing methods as highlighted in the previous study [10], the proposed strategy employs the traditional Gramian Angular Field (GAF) technique to transform time series data into 2D images, which are subsequently fed into the pretrained EfficientNetB3 model.
- **Superior Classification Performance:** By fine-tuning hyperparameters and benchmarking against state-of-the-art techniques, the proposed strategy demonstrates superior classification accuracy on the experimental test set. Additionally, to validate the effectiveness of the approach, we also trained models using features extracted through Continuous Wavelet Transform (CWT) and Short-Time Fourier Transform (STFT) with the EfficientNetB3 model, providing further confirmation of the results.
- **Model Explainability:** The results of the best-performing model, which is based on vibration signatures, are explained using Grad-CAM visualization to provide deeper insights into the classification process.

This paper is organized as follows: Section 2 highlights the key feature extraction techniques employed in this study, which also serve as benchmarks for the GAF strategy. Section 3 provides details on the experimental dataset, the evaluation metrics used for classification, model hyperparameter tuning, and the criteria for comparison. Section 4 elaborates on the generated features utilized for training, followed by the presentation and discussion of results in Section 5. Section 6 compares the outcomes with other state-of-the-art techniques, and finally, Section 7 concludes the paper.

2. Feature Definition (Theory)

2.1. Continuous Wavelet Transform (CWT)

The wavelet transform is a combined function of one-dimensional data and a wavelet function of finite duration to generate a two-dimensional map of wavelet coefficients. The coefficients are calculated by moving the wavelet function along the signal at time intervals and correlating it with the normalized wavelet function at chosen scales. The absolute value of the wavelet coefficients is the scalogram. The wavelet basis function is defined as

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-\tau}{s}\right), \quad s, \tau \in \mathbb{R}, \quad s \neq 0 \quad (1)$$

where s is the scaling factor that controls the width of the wavelet and τ is the shifting parameter that controls the location of the wavelet. Given a time series $x(t) \in L^2(\mathbb{R})$, its CWT with respect to ψ is a function of two variables, $CWT_{x,\psi}(\tau, s)$.

$$CWT_{x,\psi}(\tau, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi^* \left(\frac{t - \tau}{s} \right) dt \quad (2)$$

The time domain position of the wavelet is given by τ and the position of the wavelet in the frequency domain is given by s . Morlet wavelets are the most responsive wavelets while dealing with vibration signals. Equation (3) defines the complex Morlet wavelet.

$$\psi_{\text{Morlet}}(t) = \frac{1}{\sqrt{\pi f_b}} e^{j2\pi f_c t - \frac{t^2}{f_b}} \quad (3)$$

where f_c is the center frequency and f_b is the bandwidth.

2.2. Gramian Angular Field (GAF)

The GAF [11] is a transformation technique that encodes time series data into a two-dimensional image format, which enables the application of image processing techniques to time-series analysis [12]. It achieves this by capturing temporal dependencies and structural patterns in the time series. Moving on, given a time series $X = \{x_1, x_2, \dots, x_n\}$ of n real-valued samples, input X is firstly rescaled between $[-1, 1]$ using

$$\tilde{x}^i = \frac{(x_i - \max(X)) + (x_i - \min(X))}{\max(X) - \min(X)} \quad (4)$$

Furthermore, the rescaled times series $\tilde{X}$ is then represented in polar coordinates by encoding each sample as the angular cosine and the time stamp as the radius using the given equation:

$$\begin{cases} \phi = \arccos(\tilde{x}_i), \tilde{x}_i \in \tilde{X} \\ r = \frac{t_i}{N}, t_i \in \mathbb{N} \end{cases} \quad (5)$$

where t_i is the time stamp and N is a constant factor to regularize the span of the polar coordinate system.

Upon transforming the rescaled time series into the polar coordinate system, the angular perspective is exploited by considering the trigonometric sum or difference between each point, which helps identify temporal correlations across different time intervals. The Gramian Summation Angular Field (GASF) quasi-Gramian matrix is defined as follows:

$$GASF = \begin{bmatrix} \cos(\phi_1 + \phi_1) & \cos(\phi_1 + \phi_2) & \cdots & \cos(\phi_1 + \phi_j) \\ \cos(\phi_2 + \phi_1) & \cos(\phi_2 + \phi_2) & \cdots & \cos(\phi_2 + \phi_j) \\ \vdots & \vdots & \ddots & \vdots \\ \cos(\phi_i + \phi_1) & \cos(\phi_i + \phi_2) & \cdots & \cos(\phi_i + \phi_j) \end{bmatrix} \quad (6)$$

2.3. Short-Time Fourier Transform (STFT)

The STFT is a widely utilized technique for analyzing the time-frequency characteristics of a signal. This method integrates one-dimensional signal data with a sliding window function of finite duration, thereby producing a two-dimensional representation of the signal's frequency content over time [13,14]. The computation of the STFT coefficients involves multiplying the signal by the window function and subsequently applying the Fourier Transform to each segment. The resulting matrix of coefficients constitutes the

signal's spectrogram, which effectively illustrates the evolution of the signal's frequency content over time.

The STFT is defined as

$$STFT_x(t, f) = \int_{-\infty}^{\infty} x(\tau)w(\tau - t)e^{-j2\pi f\tau}d\tau \quad (7)$$

where $x(\tau)$ is the input signal, $w(\tau - t)$ is the window function centered at time t , f is the frequency variable, and t is the time variable.

The window function $w(t)$ controls the time localization of the analysis. Common window functions include Hamming, Hann, and Gaussian, each of which influences the time-frequency resolution trade-off.

The time-frequency resolution trade-off is governed by the width of the window $w(t)$. Narrow windows provide better time resolution but poorer frequency resolution, while wider windows achieve better frequency resolution but sacrifice time localization.

To this end, the features listed in this section have been used to detect BRBFs in IMs and for a comparative analysis to determine the best feature engineering technique. The study has utilized three separate feature extraction techniques. Namely Continuous Wavelet Transform, Short-Time Fourier Transform, and Gramian Angular Field. All three have been used to encode time series data into three-dimensional images.

3. Proposed Methodology

3.1. Dataset Description

Data acquisition was the first step in this study. The IEEE dataset [15] was used for this study, which contains the three-phase currents, three-phase voltages, and five vibration signals for healthy and 1–4 BRBFs. The ratings of the IM under test are presented in Table 1. The load torque of the system was adjusted by varying the field winding voltage of a direct current generator. The IM was tested under varying load conditions, specifically at 12.5%, 25%, 37.5%, 50%, 62.5%, 75%, 87.5%, and 100% of its full load capacity. The experimental setup is shown in Figure 1. To simulate BRBFs in a three-phase induction motor, holes were drilled into four rotors to create faults: the first rotor had one broken bar, the second had two adjacent broken bars, the third had three, and the fourth had four. Healthy (class 1), 1BRB (class 2), 2BRB (class 3), 3BRB (class 4), and 4BRB (class 5) make up the five classes in this study.

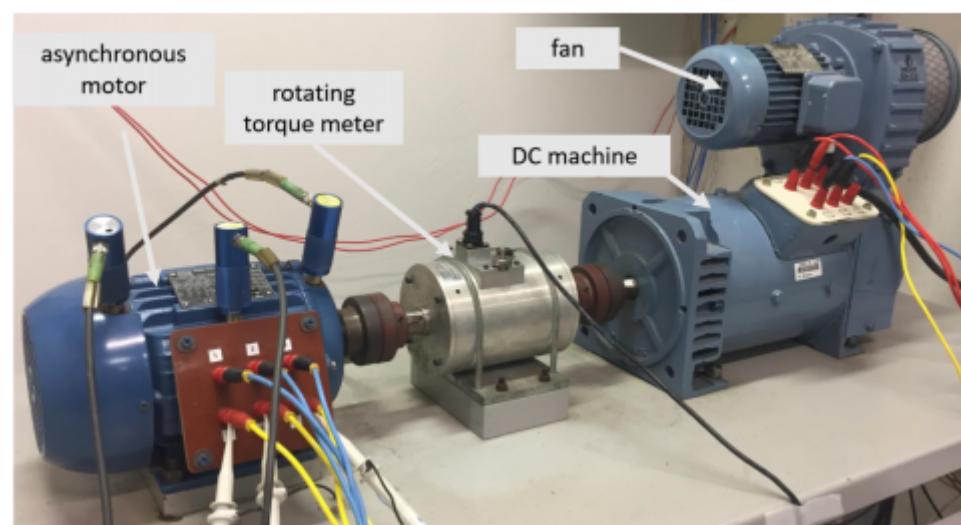


Figure 1. BRBF emulation experimental setup.

Table 1. Ratings for the induction motor under test.

IM Ratings			
Power	1 hp	Frequency	60 Hz
Rated Current	1.75 A	Nominal Torque	4.1 Nm
Rated Voltage	380 V	Rotor Bars	34
Number of Poles	4	Rated Speed	1715 rpm

The whole dataset contained 10 trials of data. The steady-state three-phase current (i_a, i_b, i_c) and vibration data ($V_{axial}, V_{acpi}, V_{acpe}$) from trials 3 and 4 have been used to train, validate, and test the EfficientNetB3 model. Trials 3 and 4 were selected because they provide stable steady-state operating conditions with consistent load levels. Prior to analysis, all available trials were visually inspected and evaluated based on signal continuity and noise level. Trials 3 and 4 exhibited no missing samples and only minimal disturbances in the recordings, making them suitable for reliable feature extraction and model evaluation. Additionally, the statistical properties of the remaining trials were examined and found to be comparable, indicating that the use of trials 3 and 4 does not introduce bias into the results. The sampling frequency for current is 50 kHz and 7.6 kHz for acceleration. Data for all loads have been combined into one dataset rather than treating each loading condition as a separate dataset. This approach has been adopted to better simulate real-world industrial scenarios, where motors frequently operate under varying loading conditions rather than a single, constant load. By combining data for all loads into one dataset, the model can learn to handle and predict performance across a range of operating conditions, thereby enhancing its robustness and applicability in practical settings. Each loading condition consists of 208,000 samples per class. In total, 1,664,000 data samples have been used for each of the five classes.

3.2. Feature Extraction—Time Series to Image Conversion

Consider the time series data $\{x_t\}_{t=1}^N$, where N is the length of the time series. The sliding window with a length of W samples and an overlap of O samples can be represented as follows:

For the k -th window starting at t_k , the starting index is

$$t_k = 1 + k \cdot (W - O) \quad (8)$$

Each window will then contain the sequence S_k :

$$S_k = \{x_{t_k}, x_{t_k+1}, \dots, x_{t_k+W-1}\} \quad (9)$$

where k ranges from 0 to $\left\lfloor \frac{N-W}{W-O} \right\rfloor$.

To convert the time series data to images such as scalograms, spectrograms, and GAF (Section 2), the sliding window was utilized (Equations (4) and (5)) with a length of 100 samples and zero overlaps. A 100 sample window strikes a balance between time localization (capturing transient BRB signatures under variable load) and sufficient frequency content for downstream 2D encodings; larger windows increased accuracy marginally but degraded class separability under mixed-load training, while shorter windows amplified noise. The sliding window was applied to both the current and vibration datasets. There were three vibration signals ($V_{axial}, V_{acpi}, V_{acpe}$) and three current signals (i_a, i_b, i_c). The sliding window was applied to all three signals of each type and the resulting images were concatenated onto one another to form an image of size $100 \times 100 \times 3$ for the two separate signal types. In total, 83,200 images were generated from each distinct signal type. Of these,

66,560 images were used for training and validation (10% of training images), while the remaining 16,640 images were used for testing (20% of 83,200 images).

The parameters for each time series to image method is provided in Table 2.

Table 2. Key parameters for GAF, CWT, and STFT feature extraction methods.

Parameter	Description/Value
GAF	
Image size	100 × 100 pixels (determined by sliding window length)
Polar encoding	Gramian Angular Summation Field (GASF)
Rescaling	Min–max normalization to [−1, 1]
Sliding window	Length = 100 samples, overlap = 0 (non-overlapping)
Channels	3 vibration/current signals concatenated (V_{axial} , V_{acpi} , V_{acpe})
CWT	
Wavelet type	Morlet wavelet
Scale/frequency range	1–2000 Hz (captures fault-related frequencies)
Sampling frequency	7.6 kHz for vibration, 50 kHz for current
Sliding window	Length = 100 samples, overlap = 0 (non-overlapping)
Channels	3 vibration/current signals concatenated
STFT	
Window type	Hamming window
Window length	100 samples
Overlap	0 samples (non-overlapping)
FFT length	256 points
Sampling frequency	50 kHz
Channels	3-phase current signals/three vibration signals combined into a single image via magnitude
Image size	100 × 100 pixels (resized after plotting)
Normalization	Magnitude converted to dB, min-max scaled to [0, 1]

3.3. Classification and Hyperparameter Optimization

This study uses the EfficientNetB3 model to classify the levels of faults in the rotor of an induction motor through the use of images. Three distinct feature engineering techniques, discussed in Section 2, were employed in this study to convert time series data into images for input into the classifier. It must be noted that before any feature engineering, the raw time series data was used for classifying these faults using a 1D-CNN. However, the accuracy was not favorable (see Table 5).

Hyperparameter optimization was conducted using Bayesian optimization to enhance the model's performance. A detailed description of Bayesian hyperparameter optimization can be found in Kumar et al. [16]. This process involved tuning three key parameters such as learning rate, dropout rate, and L2 regularization to maximize the validation accuracy. The search was carried out within a predefined range for each hyperparameter shown in Table 3 for 5 trials, and the optimal combination was selected based on the highest validation performance using cross-validation. Although the Bayesian search was limited to five trials, this setting was chosen to balance tuning depth with computational cost, and preliminary experiments showed that additional trials produced only marginal gains; moreover, the goal of the search was not exhaustive optimization but ensuring consistent and reproducible improvements over baseline settings. The hyperparameters obtained through Bayesian optimization are listed in Table 4. The model was retrained from scratch using these parameters to ensure it learns the data with the most effective settings from the start and ensures that the model is more robust and better generalizes to unseen data, improving its overall performance on the test set. This ensures suboptimal parameter

settings do not cause bias in the model during the initial training. The final model was then evaluated on a test set to ensure robustness and generalizability.

Table 3. Predefined ranges for hyperparameters.

Parameter	Range
Learning rate	1×10^{-5} to 1×10^{-2} (log scale)
Dropout rate	0.2 to 0.7 (step = 0.1)
L2 regularization	1×10^{-5} to 1×10^{-2} (log scale)

A single random seed was used for all experiments to ensure reproducibility within the computational constraints. While evaluating stability across multiple seeds could provide additional insights into the model's robustness, training a large CNN model such as EfficientNetB3 on thousands of images is computationally intensive and time-consuming; therefore, a single-seed approach was adopted for this work. Future studies could extend the hyperparameter search with more trials and assess performance stability across multiple seeds to further validate generalizability.

Table 4. Best hyperparameters for EfficientNet-B3.

Hyperparameters	Current Signatures			Vibration Signatures		
	GAF	CWT	STFT	GAF	CWT	STFT
Learning Rate	0.0005	0.0004	0.0012	0.0001	0.0010	0.0021
Dropout Rate	0.3	0.3	0.3	0.5	0.2	0.5
L2 Regularization	1.1083×10^{-4}	1.2116×10^{-5}	5.4005×10^{-5}	1.0×10^{-4}	1.0×10^{-4}	1.8820×10^{-5}

3.4. Comparison Criteria

The evaluation began by identifying where the highest accuracy was achieved in the trained EfficientNetB3 model, followed by examining which method was used to encode the time series data into images. Subsequently, the specific time series data—either current or vibration—used for the conversion was analyzed. This approach helped pinpoint the optimal combination of conversion methods and data types for accurate BRBF detection. The other evaluation metrics used to evaluate the classifier include recall score, F1 score, false discovery rate (FDR), false negative rate (FNR), and precision. The comparison criteria for the classifiers in this study are set out as follows:

1. Accuracy: This is the number of correctly classified instances from the total number of instances in the dataset.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)$$

2. Precision: Positive predictive value (PPV) is a measure of the accuracy of a classification system. It is defined as the ratio of true positive predictions to the total number of positive predictions (both true positives (TPs) and false positives (FPs)).

$$Precision = \frac{TP}{TP + FP} \quad (11)$$

3. Recall (sensitivity): Defined as the ratio of true positive predictions to the actual number of positives, which includes both true positives and false negatives (FNs).

$$Recall = \frac{TP}{TP + FN} \quad (12)$$

4. F1 Score: This provides a balance between precision and recall and is useful when there is an uneven class distribution.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (13)$$

5. False Negative Rate: Represents the proportion of actual positives that were incorrectly classified as negatives. This is the opposite of recall.

$$FNR = \frac{FN}{FN + TP} \quad (14)$$

6. False Discovery Rate: This is the proportion of FPs among all positive predictions made by a model.

$$FDR = \frac{FP}{FP + TP} \quad (15)$$

7. Confusion matrix: This provides a comprehensive view of the model's performance by showing the counts of TPs for each class (diagonal values) and misclassifications (off-diagonal values).
8. State-of-the-Art Techniques: The method proposed in this paper has been compared with previously published methods that utilized the same dataset.

4. Feature Generation

4.1. Gramian Angular Field (GAF)

Figures 2 and 3 illustrate GAF images generated from time series data of three-phase currents and vibration signals, respectively, providing visual representations of different fault conditions in an induction machine, ranging from class 1 (healthy) to class 5 (4 BRBs), along with their corresponding Grad-CAM images. For both current and vibration data, class 1, which represents a healthy state, exhibits regular and symmetric patterns with smooth color transitions, indicating stable correlations over time and minimal anomalies. As the severity of faults increases from class 2 to class 5, the GAF images for both currents and vibration signals display increasingly distorted and chaotic patterns, reflecting growing instability and abrupt changes in the data. This is seen more in the vibration-based GAFs (Figure 2). In both cases, the color intensities transition from cooler tones (green, blue, purple) in healthy conditions to warmer and more intense hues (yellow, red, pink) as faults worsen, signifying higher correlations and disruptions in the signals. These distinct visual patterns and color variations across different classes serve as unique visual signatures that will enable models to effectively learn and classify various fault types, leveraging both current and vibration data for comprehensive fault diagnosis in induction machines.

The corresponding Grad-CAM images for both current- and vibration-based GAFs illustrate clear class separability by showing distinct activation patterns for each fault condition, from healthy (class 1—Figures 2f and 3f) to the most severe fault (class 5—Figures 2j and 3j). Each image highlights specific regions of interest in the vibration signal data, with differences in the distribution and intensity of red and yellow activation areas. For example, class 1 shows diffused, low-intensity activations, indicating the absence of localized anomalies, while class 5 exhibits concentrated, high-intensity regions reflecting severe faults. While intermediate classes' Grad-CAMs also display specific patterns unique to each severity level, it is observed that these patterns do not always depict a gradual progression in fault severity. This could be due to overlapping features, signal preprocessing limitations, or complex fault dynamics. However, the authors were more concerned with achieving clear class separability, which ensures that each class occupies a unique feature space, making it easier for the classifier to learn and accurately differentiate between fault conditions.

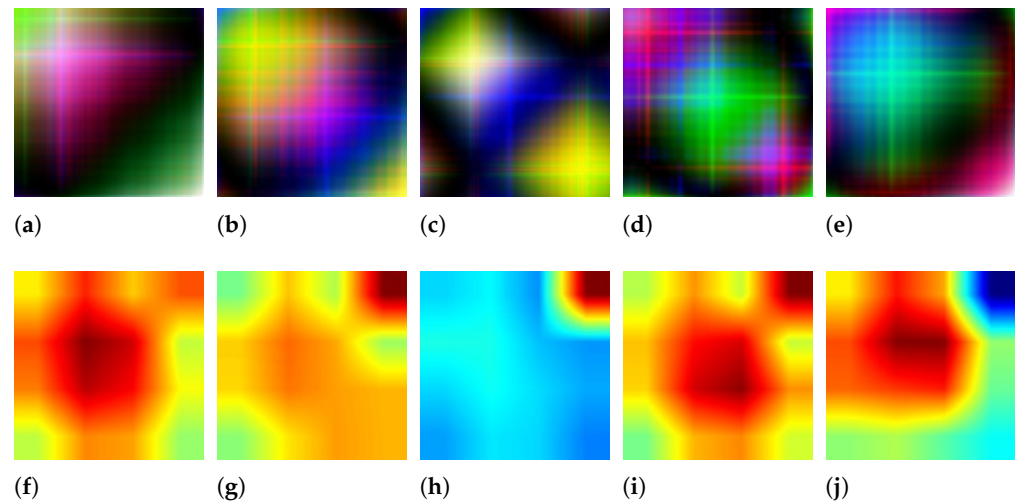


Figure 2. Vibration-based GAF generated images: (a) Class 1, (b) Class 2, (c) Class 3, (d) Class 4, (e) Class 5; and its corresponding Grad-CAM images: (f) Class 1, (g) Class 2, (h) Class 3, (i) Class 4, (j) Class 5.

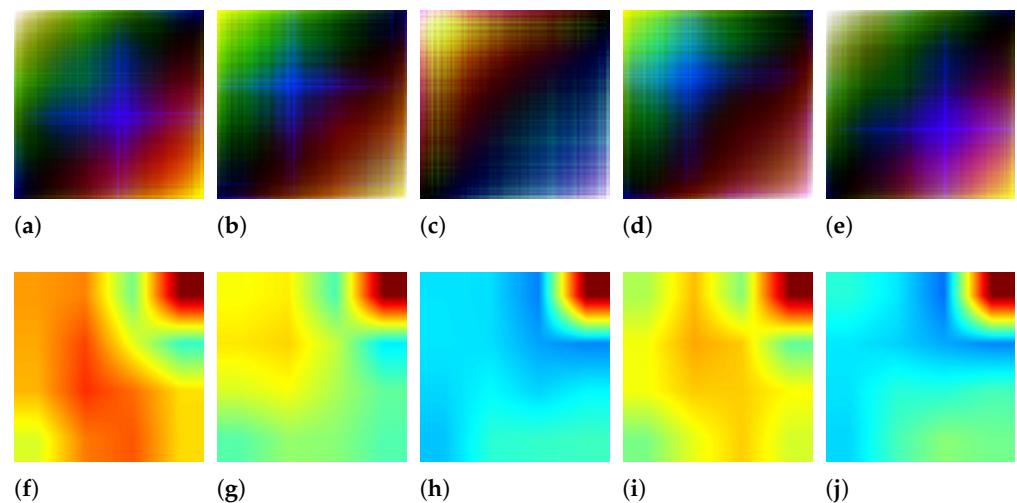


Figure 3. Current-based GAF generated images: (a) Class 1, (b) Class 2, (c) Class 3, (d) Class 4, (e) Class 5; and its corresponding Grad-CAM images: (f) Class 1, (g) Class 2, (h) Class 3, (i) Class 4, (j) Class 5.

4.2. Continuous Wavelet Transform (CWT)

The scalograms generated using time series vibration and current data are presented in Figures 4 and 5 with the corresponding gradcam images. The first image in both figures represents the mildest fault or possibly a healthy state and displays the smoothest gradient transitions with a balanced mix of blues, yellows, and pinks, suggesting minimal signal disturbance. The second image, depicting a less severe fault, has balanced color transitions and softer gradients, indicative of a milder fault. The third image, associated with moderate fault conditions, features lighter tones and more evenly distributed purples and greens, reflecting reduced signal variations. The fourth image, representing a slightly less severe fault, has smoother color transitions, blending greens, purples, and yellows, indicating less pronounced activity. The fifth image, indicating the most severe fault, shows strong contrasts between dark and vibrant hues, suggesting significant signal variations. The current signal based scaograms are slightly different from that of the vibration signal based-signals. These scalograms in Figure 5 portray a darker version of what is seen in Figure 4. However, the gradient and color mixes are very similar in both. These scalogram images are able to somewhat separate the classes by visualizing the varying energy and signal characteristics associated with different severities.

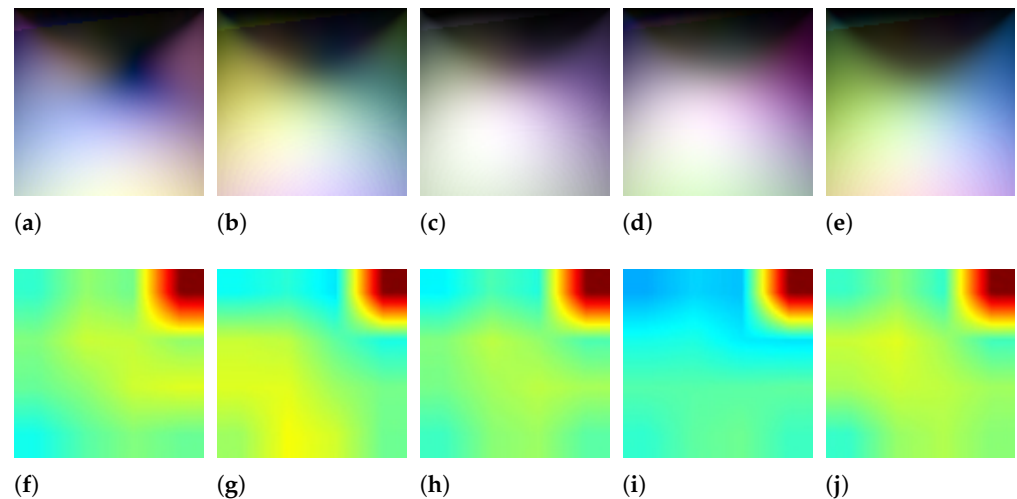


Figure 4. Vibration-based scalograms: (a) Class 1, (b) Class 2, (c) Class 3, (d) Class 4, (e) Class 5; and its corresponding Grad-CAM images: (f) Class 1, (g) Class 2, (h) Class 3, (i) Class 4, (j) Class 5.

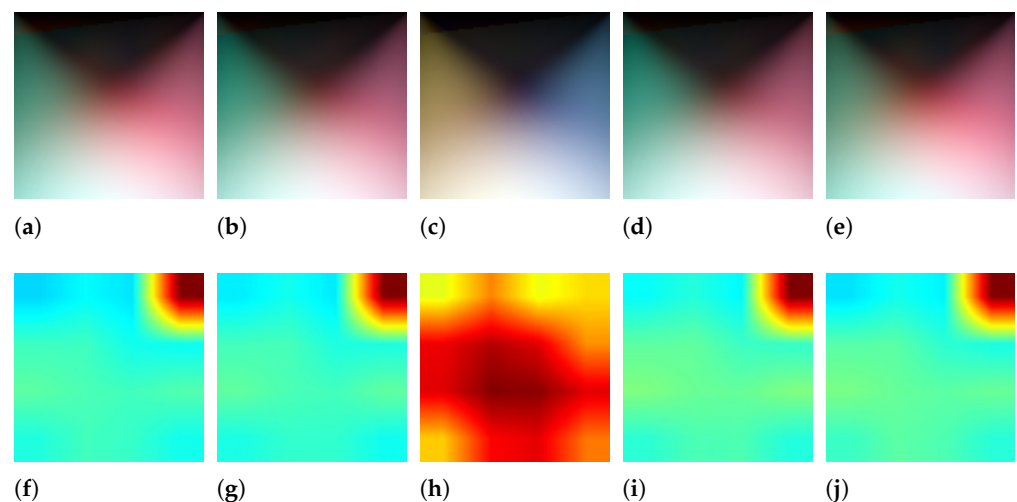


Figure 5. Current-based scalograms: (a) Class 1, (b) Class 2, (c) Class 3, (d) Class 4, (e) Class 5; and its corresponding Grad-CAM images: (f) Class 1, (g) Class 2, (h) Class 3, (i) Class 4, (j) Class 5.

The Grad-CAM images for the scalograms provide a limited degree of class separation, though not as distinct as observed in the Grad-CAM images of the GAFs. The Grad-CAM images for vibration data show subtle variations in patterns for each class, as illustrated in Figure 4f–j, in contrast to the scalograms of current data. The vibration Grad-CAM images exhibit varying patterns in yellow and green, surrounded by subtle hints of blue. When compared to the current Grad-CAM images, there are very few, if any, distinct patterns. The only notable difference is that class 3 (Figure 5b) shows a completely different pattern compared to both vibration and current Grad-CAM images. This observation indicates that vibration based scalograms will perform better than current-based scalograms.

4.3. Short-Time Fourier Transform (STFT)

The spectrograms generated from both vibration and current data effectively illustrate the progressive deterioration of a machine from a healthy state (class 1) to a severely faulty condition (class 5) as shown in Figures 6 and 7. In the case of the vibration-based spectrograms, class 1 exhibits a smooth and consistent pattern with a narrow, bright band at the center, indicating stable vibration levels. As the classes transition from class 2 to class 5, there is a visible increase in irregularities and disturbances. Class 2 shows

mild distortions with slight broadening of the central band, while classes 3 and 4 exhibit increasingly pronounced irregularities and a broader energy spread, signaling moderate to advanced fault progression. Finally, class 5 displays chaotic patterns and a high-intensity central region, indicating imminent failure. Similarly, the current-based spectrograms also demonstrate a gradual transition from healthy to faulty conditions. In class 1, the current signal is concentrated in a narrow, bright central band, indicating stable condition. As the machine's condition worsens, the spectrograms for classes 2 to 5 reveal widening central bands and increasing irregularities. Class 2 shows small fluctuations in the current signal, indicating early electrical anomalies, while classes 3 and 4 exhibit heightened disturbances, reflecting moderate-to-severe faults. Finally, class 5 exhibits widespread high-intensity areas, signaling severe disruptions in the electrical current due to extensive machine failure. In both vibration and current spectrograms, the transition from class 1 to class 5 mirrors the machine's progressive deterioration. The widening of the central band and the increasing irregularities in both sets of spectrograms visually illustrate the gradual degradation.

The Grad-CAM images for the spectrograms are presented in Figures 6f–j and 7f–j. The STFT spectrogram Grad-CAM images exhibit minimally distinct patterns corresponding to each class. The vibration Grad-CAM images display similar patterns for class 1 and class 2 (Figure 6f,g), a completely different pattern for class 3, and similar patterns for class 4 and class 5 (Figure 6i,j). A similar observation is made for the current Grad-CAM images, where class 1 and class 2 share similar patterns, class 3 is entirely different, and class 4 and class 5 show comparable patterns. This observation indicates that STFT spectrograms may not be well-suited for the classification of BRBs, as both the spectrogram and Grad-CAM images do not provide sufficient class separation or distinct visual patterns to reliably differentiate between the fault conditions.

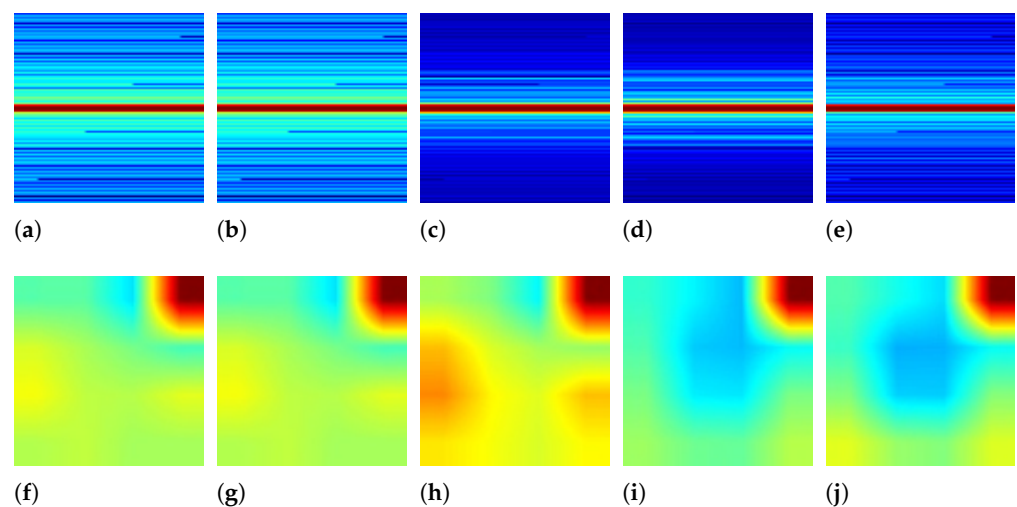


Figure 6. Vibration-based spectrograms: (a) Class 1, (b) Class 2, (c) Class 3, (d) Class 4, (e) Class 5; and its corresponding Grad-CAM images: (f) Class 1, (g) Class 2, (h) Class 3, (i) Class 4, (j) Class 5.

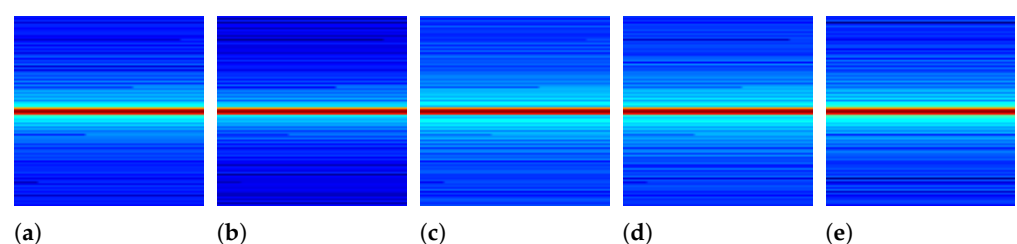


Figure 7. Cont.

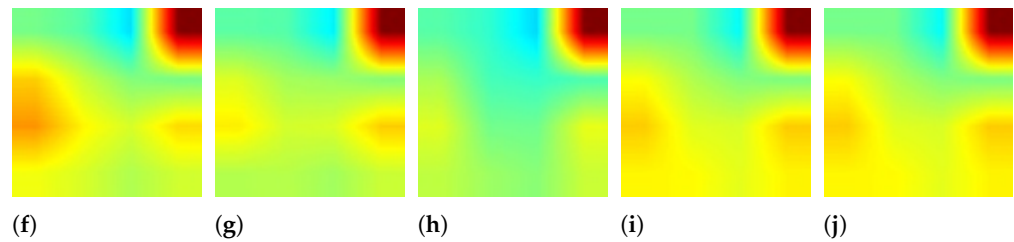


Figure 7. Current-based spectrograms: (a) Class 1, (b) Class 2, (c) Class 3, (d) Class 4, (e) Class 5; and its corresponding Grad-CAM images: (f) Class 1, (g) Class 2, (h) Class 3, (i) Class 4, (j) Class 5

5. Classification Results

Table 5 provides a detailed comparison of the three FE techniques applied to two types of signal data: current signatures and vibration signatures in addition to raw time series data. These include GAF, CWT, STFT, and raw time series data. Each technique's performance is assessed using training, validation, and test datasets, with a measure of both loss and accuracy. The significant variation in performance depending on the FE technique and the signal type indicates that the choice of the FE method has a direct impact on accuracy and generalization. Notably, the results demonstrate that vibration signatures outperform current signatures, with lower loss values and higher accuracies across all techniques.

In terms of current signal performance, the CWT achieves the highest test accuracy of 89.27%, with a corresponding test loss of 0.324, followed closely by GAF with 86.32% test accuracy and a test loss of 0.499. Both techniques significantly outperform STFT and raw time series, which yield test accuracies of 76.06% and 50.73%, respectively, indicating weaker performance in capturing relevant features from current signals.

Meanwhile, for vibration signal data, both GAF and CWT achieve nearly perfect results, with test accuracies of 99.83% and 99.80% and test losses of 0.006 for both techniques. STFT also demonstrates good performance on vibration signals, with a test accuracy of 94.53% and a test loss of 0.198. However, raw time series data consistently underperforms, with a test accuracy of only 80.13% and a test loss of 0.459.

The GAF proved to be the best technique for detecting BRB faults due to their unique ability to transform time series data into 2D representations while retaining critical temporal dependencies and encoding angular relationships [11]. These properties provide a structured and interpretable format, perfectly suited for CNNs. GAF outperformed CWT and STFT by offering robust multi-resolution capabilities without requiring complex pre-processing or parameter tuning, such as wavelet selection or window size adjustments. The test confusion matrix for the vibration-based GAF is shown in Figure 8, where the diagonal elements represent correct classifications, demonstrating extremely high accuracy for each severity level. The off-diagonal elements denote misclassifications, which are minimal. The convergence curves are shown in Figure 9. Additionally, GAF effectively captures both global and local patterns in time series data, enabling clear class separability, which was evident in the distinct Grad-CAM patterns associated with different fault conditions (see Figures 2–7). Unlike CWT and STFT, which are susceptible to noise amplification [17] and feature redundancy, GAF offers a noise-resilient transformation that preserves temporal correlations. Furthermore, GAF's visually interpretable outputs align well with domain knowledge, making it particularly effective for deep learning models to detect and classify BRB faults with high accuracy and reliability. These advantages collectively explain why GAF performed better than other techniques in this application.

Table 5. EfficientNetB3 trained using different feature extraction techniques.

FE Technique	Loss			Accuracy (%)		
	Training	Validation	Test	Training	Validation	Test
Current Signatures						
Gramian Angular Field	0.062	0.482	0.499	97.87	87.05	86.32
Continuous Wavelet Transform	0.073	0.338	0.324	97.38	89.11	89.27
Short-Time Fourier Transform	0.324	0.493	0.499	83.55	77.60	76.06
Time Series Raw	1.096	1.109	1.103	51.65	51.04	50.73
Vibration Signatures						
Gramian Angular Field	0.009	0.002	0.006	99.64	99.94	99.83
Continuous Wavelet Transform	0.010	0.002	0.006	99.64	99.94	99.80
Short-Time Fourier Transform	0.051	0.199	0.198	98.37	94.49	94.53
Time Series Raw	0.365	0.458	0.459	84.18	80.94	80.13

Furthermore, Table 6 shows the performance metrics for the best method for detecting broken rotor bar faults through vibration signals converted to images using GAF. These metrics include FNR, FDR, PPV, recall, F1 score, and AUC. The metrics reveal the GAFs high performance across all five classes, with extraordinarily low FNR and FDR values, indicating extremely low misclassifications. For instance, class 1 and class 3 have an FNR of 0.0% and FDR of 0.1%, showcasing perfect recall and nearly perfect precision, resulting in F1 scores of 99.9%. Similarly, class 4 achieves a perfect PPV (100%) and nearly perfect recall (99.9%), further reflected in an F1 score of 100%. Class 2 and class 5, while slightly lower in performance, still achieve remarkably high F1 scores of 99.7% and 99.6%, respectively.

The AUC values, which range from 0.9977 to 0.9997 across all 5 classes, demonstrate that the model has the ability to distinguish between different fault severities with near-perfect accuracy. The consistently high scores across all metrics indicate the robustness and reliability of the vibration-based GAF method for classifying fault conditions. These results affirm its suitability for applications requiring precise fault detection and classification, with class 4 achieving the best overall performance in terms of F1 score and AUC.

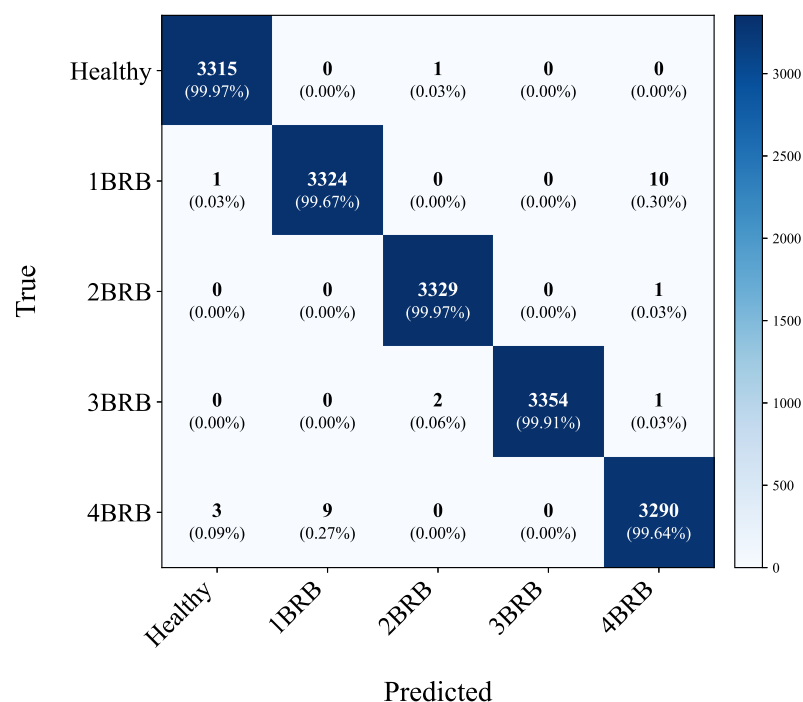
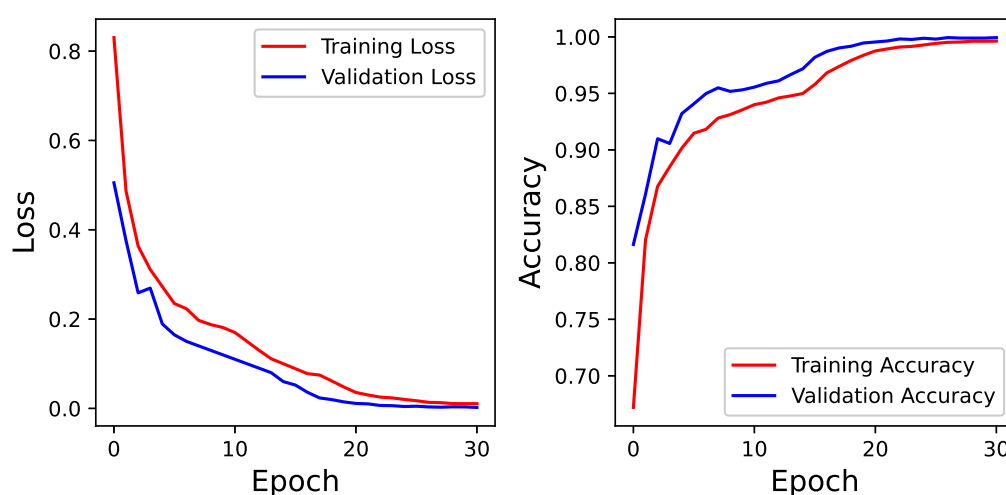
**Figure 8.** Confusion matrix of GAF vibration based model.

Table 6. Evaluation metrics for the best method (vibration-based GAF).

Class	FNR (%)	FDR (%)	PPV (%)	Recall (%)	F1 Score (%)	AUC
1	0.0	0.1	99.9	100	99.9	0.9997
2	0.3	0.3	99.7	99.7	99.7	0.9980
3	0.0	0.1	99.9	100	99.9	0.9997
4	0.1	0.0	100	99.9	100	0.9996
5	0.4	0.4	99.6	99.6	99.6	0.9977

**Figure 9.** Convergence curves of vibration based model.

6. Comparison with State of the Art

Further analysis of the proposed method was conducted by comparing it with other state-of-the-art techniques that utilized the same dataset as shown in Table 7, particularly vibration signatures, as this study proposes a method based on vibration signatures. Such a comparison helps establish a clear benchmark, validating performance claims by isolating improvements attributable to the method itself rather than variations in the datasets. This approach will demonstrate the robustness and potential generalizability of the proposed method (vibration signal-based GAF) to similar problems.

Table 7. A summary of state-of-the-art methods.

Technique	Ref.	Accuracy (%)
Vibration GAFs with EfficientNetB3	Proposed	99.83
Vibration signals with multi-layer DNN	Vezeteu et al. [18]	99.36
SVM with RBF Kernel	Mellal et al. [19]	98.02
Vibration STFT spectrograms with MobileNetV2	Misra et al. [20]	97.67
Discrete wavelet transform with BiLSTM	Rayhan et al. [21]	95.31
Current FFT with Decision Jungle	Hadraoui et al. [22]	90.38

Vezeteu et al. [18] proposed a deep neural network (DNN) optimized with dropout and regularization, which used five principal components from the PCA transformed raw vibration signals as input to the classifier. The method achieved a test accuracy of 99.36%, significantly outperforming support vector machine (SVM) by 19.68%. In comparison, our method performs better without requiring any dimensionality reduction step. Mellal et al. [19] have used a SVM with the Radial Basis Function (RBF) kernel for the similar problem. Feature selection was conducted using the one-way ANOVA F-test to identify the most critical features from time domain and frequency domain features in this study. It

must be noted that this study only focuses on four fault severities (healthy, 1BRB, 2BRB, and 3BRB) and not all severities as compared to our study. Misra et al. [20] proposed a fine-tuned MobileNetV2 CNN model, leveraging transfer learning on STFT spectrograms generated from vibration signals, achieved the highest accuracy of 97.67%, significantly outperforming traditional machine learning models like Random Forest (85.92%), kNN (80.53%), and Decision Trees (81.71%). The final two studies, [21,22], utilize current data for BRB fault detection. While these studies outperform the current signature-based approach proposed in this study, our method demonstrates greater accuracy when evaluated more broadly rather than being limited to current data alone. The approach proposed in [21] has not been evaluated on new, unseen data (test set), which may expose potential limitations in its generalizability and robustness.

A deeper examination of the results reveals why the proposed GAF+EfficientNetB3 framework surpasses existing SOTA methods such as STFT+MobileNetV2 [20] or discrete wavelet transform with BiLSTM [21]. First, GAF offers a more discriminative representation of the vibration signals by preserving temporal dependencies and encoding angular relationships, resulting in a structured 2D image that is highly compatible with convolutional architectures. Unlike STFT, which requires careful tuning of window size and is sensitive to noise amplification and feature redundancy, GAF provides noise-resilient, parameter-free transformations with clear global and local patterns. These properties enhance class separability, as also evidenced by the distinct Grad-CAM activation regions for different BRB severities. Second, EfficientNetB3 contributes significantly to the performance gains through its compound scaling strategy, which balances network depth, width, and resolution. This allows EfficientNetB3 to extract richer hierarchical features from the GAF images compared to lightweight models such as MobileNetV2, which has more limited representational capacity. The combination of a robust feature encoding (GAF) and a high-capacity, efficiently scaled CNN (EfficientNetB3) results in superior generalization, reduced misclassification, and higher accuracy, particularly when distinguishing subtle BRB severity levels. These factors collectively explain the improved performance over prior works.

7. Conclusions

This study introduced a robust method for detecting and classifying BRBFs in IMs by leveraging GAF transformations and the EfficientLiteB3 model. The proposed approach achieved an experimental test accuracy of 99.83% on vibration data, showcasing its ability to effectively classify fault severities. By transforming time series data into interpretable 2D images, the method captured critical temporal dependencies, enabling precise fault diagnosis. Furthermore, the use of Grad-CAM visualizations enhanced explainability by identifying key regions contributing to classification, providing actionable insights for industrial applications. While the proposed strategy excelled with vibration data, the analysis of current signals yielded slightly lower accuracy due to overlapping features and inherent noise. Nonetheless, the GAF-based transformation demonstrated potential for meaningful representation, and future work could refine preprocessing techniques to improve current signal analysis.

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