Fault Modeling to Determine the Reliability Status of Rotating Machines Using Deep Learning Methods Based on Vibrations from Acoustic Emissions from Cooling Fans

T N F Joseph[1]*, T N Dianorré[1], O Florence[2], N F Edgar[3], and M P Marcelin[4]

[1]Laboratory of Mechatronics, Energiatronics and Sustainable Mobility (LaMEMD), Department of Automotive and Mechatronics Engineering, National Higher polytechnic School of Douala, University of Douala, Cameroon
[2]Laboratory of Mechanics and Materials (LaMM), Department of Mechanical Engineering, National Higher polytechnic School of Douala, University of Douala, Cameroon
[3]Technology and Applied Sciences Laboratory, University of Douala, Cameroon
[4]Higher Technical Teacher's Training College, Depaartment of Renewable energy, University of Buea, Cameroon.

*Corresponding author's email: nonofernand18@gmail.com

Abstract. Modern industrial production acknowledges the increasing significance of maintenance. As of right now, maintenance is seen as a service that aims to maintain the effectiveness of systems and installations while adhering to quality, energy efficiency, and protection standards. An inventive technique to automate rotating machine maintenance procedures has been created in this study. To identify failures and flaws in the motors through their supports, where the fan blades are attached, a technique based on capturing the noises produced by their cooling fans and utilizing deep learning to diagnose problems was investigated. Two operational circumstances were envisioned: the absence of fault and the presence of fault. The machine is correctly powered and running in ideal circumstances when it is not having any issues. In contrast, failures were gradually created purposefully and then documented in order to better understand the faults. Utilizing a pre-trained network (SqueezeNet) built on the ImageNet database, the convolutional neural network (CNN)-based technique was constructed. Applying transfer learning to the spectrograms obtained from the sound emission recordings of our machine's fan in both working modes demonstrated outstanding performance (accuracy = 0.987), confirming the methodology's outstanding quality.

Keyword: Rotating machine, CNN, deep learning, reliability

1. Introduction

For industrial installations to be dependable and efficient, rotating machinery problem diagnosis is essential. Unexpected repairs and downtime can be very expensive. One non-destructive method for detecting noises caused by defective events, including cracks or material deformations, is acoustic emission (AE). This approach has the benefit of simplifying maintenance and enabling real-time machine monitoring, which enables timely intervention before significant issues arise [1]. Unplanned maintenance on moving machinery lowers output and may compromise safety. Increased repetition, planned intervention to identify issues that may result in extended downtime, and condition monitoring are some strategies to lessen this effect [1]. Vibration analysis is frequently used to monitor machine conditions. However, motion observation is usually less accurate at detecting damage already present, which is a major obstacle for vulnerable systems. On the other hand, sound emission methods are gaining in importance due to their ability to detect damage at an early stage while at the same time allowing increased sampling rates, leading to a considerable amount of larger data. In addition, EA and motion tracking require signal pre-processing and analysis such as wavelets, fast Fourier transform, band filtering, among others [2]. This is expensive and time-consuming work that requires specialist engineering skills. Machine learning methods have become increasingly popular for fault diagnosis and prediction. The majority of these shallow models rely heavily on manual feature recognition and collection [3;4], and [5].

Complex features of audio data can be extracted by neural networks, including convolutional neural networks (CNNs), improving diagnostic accuracy [5]. Research has shown that the use of deep learning to examine AE signals promotes significant accuracy in fault categorization [6]. As highlighted in [7], the success of these techniques relies on the correct operation of the hand-built features, which of course requires a significant understanding of the degradation mechanisms of the device.

Several studies have investigated the application of EA in combination with deep learning methods. For example, Liu et al. in 2019 [6] proved that convolutional neural networks are able to effectively classify sound emission signals, allowing for accurate defect detection. In addition, recent research has shown that the use of deep learning models can identify delicate imperfections that conventional techniques might miss [8]. The ability to spot faults quickly is particularly crucial for bearings, which are frequently the source of many problems in moving machinery. Studies have shown that artificial intelligence, combined with machine learning methods, is capable of detecting bearing faults at a rate of 97.3% [5]. This method facilitates the implementation of predictive maintenance strategies, helping to reduce costs and optimize machine availability [8].

In order to overcome these challenges, we suggest a technique based on deep neural networks to diagnose defects. It operates on large raw auditory signals and facilitates the automatic extraction of hierarchical features "layer by layer" to acquire complex interpretations of the information. Initially, information regarding various operating conditions was collected. Two operating conditions were identified: no fault and fault. In the No-Fault state, the fan of our motor receives optimal power and does not experience any overload or issues. On the other hand, in the Fault situation, the motor is not fully powered and presents several problems that have been artificially designed to replicate those usually encountered during the normal operation of the machine. A dichotomous categorization allowed for the correct classification of the fan's sound emission measurements under various usage conditions (without fault, with fault). The collected data was used to create a convolutional neural network (CNN) algorithm aimed at automatically recognizing the features of the fan. The structure of the article is as follows:

This article presents an innovative method for diagnosing faults in rotating machinery, using convolutional neural networks (CNN) applied to acoustic emissions from cooling fans. Our model achieves 98.7% accuracy and 95.0% recall, surpassing the performance of previous approaches. It promotes proactive maintenance by detecting anomalies early, reducing downtime and associated costs. By integrating transfer learning, we optimize training time and generalization of results, while ensuring practical application in real industrial environments, thus providing an effective solution for rotating machine management.

Section 2 provides an in-depth description of the engine's features and the data collection process. Moreover, the methods for identifying features and designing algorithms based on deep learning are discussed. Section 3 presents the results of the application of this methodology, accompanied by a brief summary of its strengths and a list of its weaknesses. Section 4 concludes by summarizing the results of this research.

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2. Materials and Methods

This research, we are developing a technique for automatically detecting faults in a moving machine using the sounds generated by the machine's fan. As a result, the system informs us of the condition of the machine and specifies the categories of anomalies in order to plan an appropriate maintenance intervention. Figure 1.

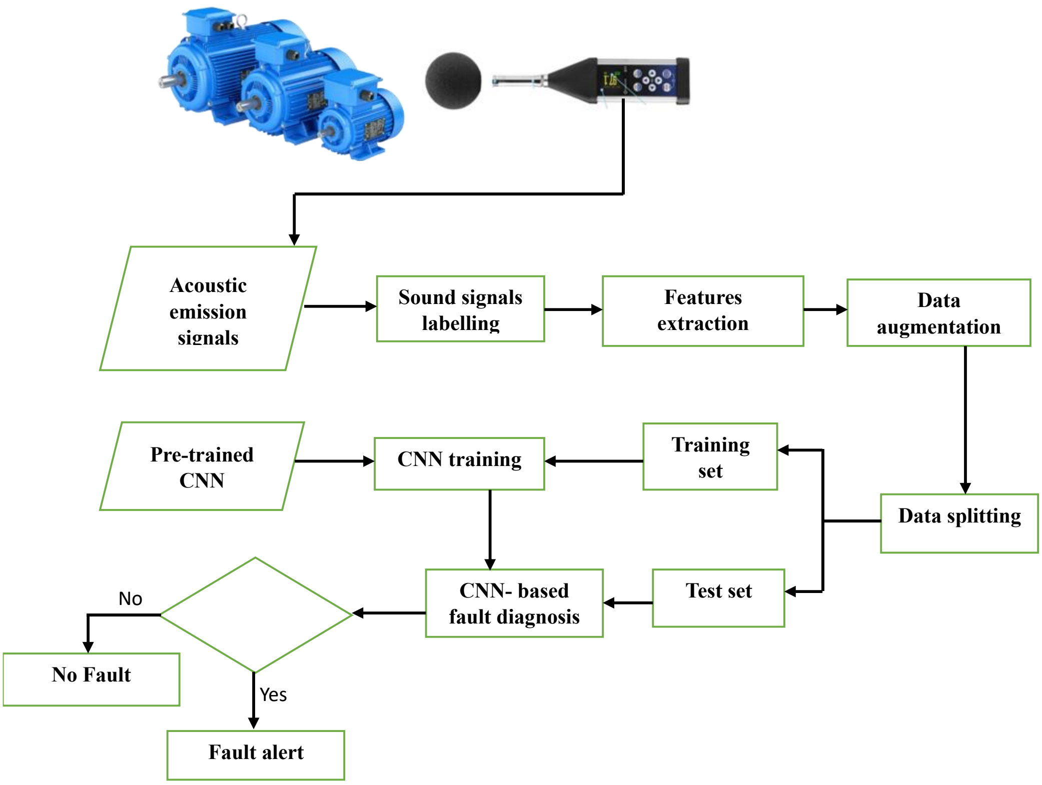

Figure 1. Flow chart of the automated engine failure detection system.

The technique illustrated in Figure 1 can anticipate the urgency of a maintenance intervention to remedy the problem or fault signaled by the cooling fan noise. In this way, we take action only when it is required, preventing production from being halted if it is not requested.

2.1. Introduction to fan cooling systems for rotating machinery

In a rotating machine, a fan is permanently installed on the rotor or the machine's shaft. It harnesses mechanical energy to maintain a constant airflow at a fixed voltage without altering its density, thanks to one or more blades. Thus, the main objective of a fan is to allow the circulation of a precise amount of air at a sufficiently high pressure to heat the internal components of the device to which it is connected. Various types and sizes of fans can be used depending on the specific needs in terms of airflow and air pressure. It is therefore necessary to choose the ideal fan for each situation by taking into consideration criteria such as machine performance, available space, the blade-fixed machine model, noise level, mechanical and aerodynamic efficiency, mechanical resistance, and finally, cost [7]. We could mention a few. For centrifugal fans: They use a rotor to draw in air and distribute it through a diffuser. Particularly suited for applications requiring high pressure. Axial fans: The air is transported parallel to the movement of the fan; Designed for significant air movements at high pressure. Cross-flow fans: The air flows and exits parallel to the fan axis; frequently used in climate control devices.

Propeller fans are characterized by blades with a helical shape and are intended for low-pressure applications. Tube fans: They draw in and expel air through a duct, frequently used in air conditioning systems. Radial flow fans: Designed to produce radial airflow, frequently used in industrial fields. Cooling fans: Specifically designed for the heating of equipment or machines. Thermal fans: Used to recover and reuse heat in ventilation systems.

The selection of each type of fan is based on the specific usage requirements, such as air volume, pressure, or sound. Depending on their design and adaptations in rotating machines, several types of fans can be distinguished, such as: Centrifugal fans: which use a rotor to capture air and move it through a diffuser. Perfect for applications that require high pressure. Axial fans: Air is transported parallel to the fan axis; Designed for high airflow at high pressure. Cross-flow fans: Air enters and exits parallel to the axis of the fan, frequently used in air conditioning systems. Propeller fans are distinguished by their blade shape, and they are mainly used for low-pressure applications. Tube fans: Air is drawn in and expelled through a tube, frequently used in air conditioning units. Radial fans: Designed to produce a radial airflow, frequently used in industrial applications. Cooling fans: Specifically designed for the heating of equipment or machines. Thermal fans: Used to recover and reuse heat in ventilation systems. Centrifugal and axial air conditioning systems. In axial fans (Figure 2), the airflow primarily passes through the fan blades parallel to the axis of rotation of the impeller, while maintaining the average flow direction unchanged, despite the emergence of swirling phenomena related to the movement of the blades. The blades primarily exert force in the axial direction, from the inlet to the outlet, which results in an increase in pressure. The essential properties of an axial fan vary considerably depending on the number of blades and their position relative to the airflow. These fans are better suited for circumstances where the flow-to-pressure ratio is important.

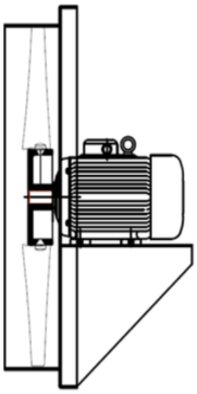

Figure 2. Axial fan scheme (front and side view).

2.2. Noise produced by a cooling fan on a rotating machine

In a rotating machine, the noise generated by a fan is generally unavoidable and can vary in intensity. The air is moved to cool the internal parts of the machine thanks to the rotation of the blades. The noise can be light and soothing at a low setting, while at an increasing speed, it can become a more disruptive hum. This noise is crucial for operation, as it helps prevent overheating. However, a noise that is too loud can signal mechanical issues, such as an imbalance or degradation of parts. Manufacturers are making every effort to create quieter fans by using absorbent materials and aerodynamic configurations.

The fluctuating forces associated with rotating parts and the turbulence of the airflow generate mechanical noise, which originates from the structural radiations of the motor block and other connected components [8]. Anti-vibration seals and supports can reduce the sound emission caused by mechanical noise, just like adding foundation weights to minimize structural vibrations. Aerodynamic noise comes from the regular impulses that each blade sends to the air, as well as the contributions generated by the vortices in the turbulent flow of wind around these blades. The first disturbance resulting from the rotation of the blades constituting the fan arises from pressure fluctuations caused by the recurring changes in force within the fluid. This type of noise originates from the thrust forces moving through the air, due to the impulsive interaction of the blades with the incoming wind, which is not ideally straight, and due to any nearby obstacles [9]. Since the passage of the blades is regularly performed near the machine windings, the noise produced is tonal in nature,

$$BPF = Z \times n \tag{1}$$

where Z is the number of blades and n is motor shaft rotation frequency.

Therefore, despite the normal nature of the noise, its intensity can be regulated to optimize the auditory comfort of users. Ultimately, the regulation of noise from rotating machines generally comes from their cooling fans and represents a major engineering challenge. This type of noise is caused by variations in fluid forces in temporal and frequent spheres. It essentially depends on the flow velocity, the fan design, as well as the size and roughness of the segments [10].

In rotating machines, aerodynamic noise is produced through several key processes. Turbulence, caused by the irregular flow of air around the blades, leads to pressure fluctuations that generate noise. Blade interactions also contribute, as the contact between blades and airflow—along with interferences among the blades themselves—produces sound waves. Aerodynamic drag on the surfaces of blades and rotors creates noise disturbances, particularly noticeable at low speeds. Under certain conditions, cavitation may occur, where the formation and collapse of bubbles around the blades result in intense noise. Structural vibrations of machine components, which are amplified by the airflow, further add to the overall aerodynamic noise. Additionally, variable flow conditions, such as changes in wind speed and direction, play a significant role in influencing noise generation.

These devices are generally interconnected, which makes managing aerodynamic noise complicated in moving machines. This means that the configuration of a fan's blades has a notable impact on sound emissions and characterizes its noise. The accumulation of material on a fan's blades or inadequate power supply, which actually alters its characteristics, consequently causes a change in its audio performance. The objective of this research is to automatically identify this operational state of the machine by characterizing its auditory performance.

2.3. Maintenance of the cooling fan on a rotating machine

It is crucial to maintain a fan in a rotating machine to ensure its efficiency, reliability, and longevity. Fans are essential for cooling electrical machines, by eliminating the heat produced by internal losses during energy conversion. To prevent overheating of components and prolong the longevity of insulating materials, it is crucial to maintain optimal air circulation. According to research conducted by Barlow et al (2017) [11], it is crucial to have efficient ventilation to minimize mechanical losses caused by air friction, which optimizes the overall performance of the machine.

According to [12], the main maintenance operations include visual inspection, cleaning, lubrication, and checking the blade balance. The latter is crucial for removing dust and debris that could compromise the fan's operation. Moreover, it is crucial to maintain good blade balancing in order to minimize vibrations that can cause mechanical problems or undesirable sounds [13]. According to research by [14], it is also crucial to monitor the fan's performance by conducting frequent checks on air flow and pressure. These checks ensure that it operates at the intended speed and with the expected efficiency. A meticulous monitoring of performance allows for anticipating maintenance needs and avoiding costly malfunctions.

To conclude, it is crucial to document maintenance operations for optimal management of moving machines. Keeping a log of the interventions carried out, the parts changed, and the observations made facilitates the preparation for future inspections and improves the performance of the fans. Furthermore, it is essential to raise staff awareness about proper maintenance and safety methods to ensure the optimal and safe operation of the machines [12].

2.4. Measurements of acoustic emission from the blades of a cooling fan on a rotating machine

It is essential to quantify the sound production of fans in a moving machine to assess their efficiency and ecological footprint. Various mechanisms, such as air turbulence, vibrations, and aerodynamic interactions, contribute to the noise production by fans. Several measurement and analysis techniques are employed to quantify these emissions. Sound measurement techniques include the use of omnidirectional microphones positioned at precise distances from the fan. These microphones capture sound pressure levels, which are then examined to calculate the noise in decibels (dB). Standards such as ISO 3744 or ISO 9614 are frequently used to ensure the accuracy and reproducibility of the measurements. These standards determine the test conditions, including the position of the microphones and the environmental settings.

Two operating conditions have been established: (1) normal operating conditions and (2) abnormal operating conditions. In the normal operating condition, the fan is tested under normal operating conditions, that is, at its rated speed and load. This includes adhering to the manufacturer's specifications regarding airflow and static pressure. Testing under these conditions allows for data that reflects the usual behavior of the fan, which is crucial for diagnosing potential problems. Deviations from normal performance can indicate mechanical or wear-related issues. Meanwhile, in the abnormal operating conditions, the faults were artificially induced on the motor, such as variations in rotational speed, current, supply voltage, misalignments, imbalances, overloads, and bearing faults, to simulate those that normally occur during the motor's normal operation.

In an anechoic chamber (12 m by 10 m), as illustrated in Figure 3, we conducted sound tests at advanced hours to ensure optimal sound quality and achieve impeccable sound, with absorbing corners and a cutoff frequency of 100 Hz: Thus, the reflection of signals on the walls is considerably reduced. This evaluation technique poses no difficulties in the face of overheating, as it does not require direct contact between the sensor and the moving device, unlike vibration detection. The machine is placed at an angle in the laboratory to create a fixed source and receiver system, correct the positioning error, and capture the signal correctly to reproduce the operating conditions.

Figure 3. Measurement setup in a laboratory. The decision to place the sound level meter on a frame very close to the machine itself is well placed to avoid the influence of noise.

The 01 dB SoundLevel Meter shown in Figure 4, which complies with the UNI EN ISO 3745:2012 standard, was used to carry out the acoustic measurements [15]. The horizontal position of the sound level meter on a stand, at the height of the machine and close to the fan, together with its positions adjusted below a 90-degree offset angle, enabled the sound vibrations of the machine fan to be accurately characterized. The information gathered was used to program an algorithm using convolutional neural networks to automatically detect the operating conditions of the machine based on the noise of its fan.

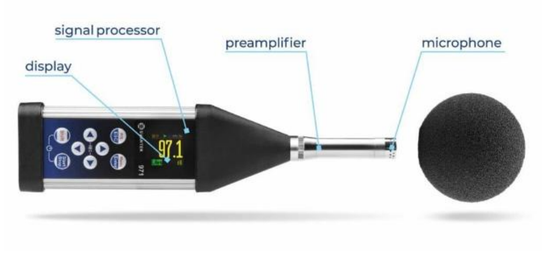

Figure 4. Sound level meter

2.5. Feature Extraction

In order to identify the elements that could be used to determine the damage, an analysis of the recorded audio signals was carried out. This is a crucial step in determining the damage. In fact, the descriptors sampled will be used as an entry point both in the classifier training process and in the test that follows [16]. We have previously pointed out that differentiating between good and bad fan operation is a complex task that cannot be reduced to identifying sound triggers capable of distinguishing between the two modes of operation. A temporal study would not be sufficient to distinguish the two fan states. So, in order to evaluate energy levels in various frequencies, it is necessary to focus our research on the frequency field. To achieve this, we can use the Fourier operator, which facilitates the transition from the time field to the frequency field by projecting the signal evaluated in time onto an orthonormal basis of complex expressions [17]. Equation (2) is used to determine sound pressure levels (SPL) based on sound pressure measurements (p),

$$L_P = 20\, Log10\left(\frac{P}{P_0}\right) \tag{2}$$

where Lp is the sound pressure level in decibels (dB), p is the sound pressure measured in pascals (Pa), and P_0 is the reference pressure, generally set at 20 µPa.

This formula converts the measured sound pressure to a logarithmic scale, which is more in line with human perception of sound. Once the data has been collected, pre-processing is carried out, including filtering to eliminate unwanted noise and normalization to ensure data consistency.

The extraction of acoustic characteristics involves several analysis methods. Temporal characteristics, such as signal energy, are measured using the following formula (3):

$$E = \int_0^T x\,(t)^2\, dt \tag{3}$$

where E is the energy of the signal, x(t) is the acoustic signal as a function of time, T is the recording time. This integration of the square of the signal amplitude highlights the contributions of the higher values, which is important for sound.

At the same time, frequency analyses using the Fourier transform are used to obtain the frequency spectrum of the signal, given by formula (4)

$$E(f) = \int_{-\infty}^{\infty} x(t)\, e^{-j2\pi f t}\, dt \tag{4}$$

where X(f) is the Fourier transform of the signal, f is the frequency, and j is the imaginary unit.

Finally, the extracted characteristics are analyzed to detect potential anomalies. The use of machine learning models, such as random forests or neural networks, can be used to interpret the data and diagnose mechanical problems. Formula (5) illustrates that the centroidal frequency fc can be calculated to give a measure of the 'position' of the power spectrum.

$$f_c = \frac{\sum_i f_i p(f_i)}{\sum_i p\,(f_i)} \tag{5}$$

where f_c is the frequency at the index i and $P(f_i)$ is the power at frequency fi.

These methods for extracting acoustic characteristics are supported by research that highlights their importance for the diagnosis and optimization of rotating machines [15; 16], and [17].

To make an accurate transition from the time domain to the frequency domain, the discrete Fourier transform (DFT) considers a signal sample in a time window. We are therefore able to evaluate the complex component in the frequency domain using equation (6).

$$X_K = \frac{1}{N} \sum_{n=0}^{N-1} x_n e^{2nk\frac{n}{N}} \tag{6}$$

where x_n is the n-th sample of the signal, N is the number of samples contained in the window, and k is the index of discrete frequencies.

Energy and sound pressure levels are evaluated to obtain an overall view of the fan's operation. In addition, the use of the Fourier transform for frequency analysis makes it possible to identify the predominant frequencies and harmonics associated with the fan's operation. DFT derives a vector of complex numbers. DFT assumes that the signal is static, but most signals are constantly changing. The sound signal is segmented into segments with an amount of overlap to overcome this limitation, each segment being multiplied by the Hanning window to reduce the beginnings and ends of the segment.

Thus, the ShortTerm Fourier Transform (STFT) is performed by segmenting the signal into partially overlapping segments using a windowing method and determining the DFT for each segment. The STFT can be viewed using a coefficient matrix, arranging the DFT coefficients for each segment in various columns. The column index symbolizes time, while the row index determines the frequency of the associated coefficient. The matrix produced can be considered an image, and the evolution of the signal in the time-frequency domain can be illustrated by determining the modulus of each coefficient. The spectrogram produced by STFT is also referred to as a linear spectrum since its amplitude changes linearly as a function of its frequency [18].

2.6. Diagnosis of engine failures based on the acoustic emissions of its cooling fan using the CNN model

The suggested approach based on CNN relies on a data corpus created by AE monitoring of an experimental rotor, as illustrated in Figure 5. The configuration includes: (1) Voltmeter, (2) Ammeter, (3) Rheostat, (4) Power Source, (5) Micro acoustic emission sensors, (6) Rotor and shaft carrying the cooling fan, (7) Rotating machine: Asynchronous Machine (MAS), and (8) Terminal plate for couplin.

It is essential to conduct a frequency search, as ambient noise encompasses a wide spectrum of frequencies. This is referred to as the signal spectrum, which corresponds to a Cartesian diagram illustrating the difference between the sound frequencies and its energy content [19]. The signals detected through the operation of the engine in the laboratory were previously processed to deduce their characteristics [19]. The spectrogram was chosen, relating three crucial factors to illustrate a sound: its frequency, its duration, and its intensity. A color map is used to illustrate these three variables in a two-dimensional diagram: The abscissa represents time, the ordinate represents frequency, and the colors represent sound intensity. The dark shades indicate a low sound intensity, while the light shades signal a high sound intensity [20]. To determine the sound emission and identify distinctive trends that allow for the distinction between the two processes, it is crucial to use the spectrogram. The latter allows for establishing the sound intensity while highlighting the moments when frequency variations occur.

A CNN-based classifier received the collected features (the spectrogram of the two operating conditions) as input: due to their ability to detect adjacency patterns, CNNs served as a source of information. CNNs, thanks to an adaptive learning process that moves from lower to higher degrees, have demonstrated effectiveness in data characterization using a grid topology. Thanks to their attributes, they are particularly beneficial for object recognition in the field of computer vision [21]. Convolutional neural networks operate on matrix images, illustrated by two-dimensional arrays where each pixel ranges from 0 to 255: CNNs connect neighboring pixels to create a pattern. Those neural networks link to the network's weights.

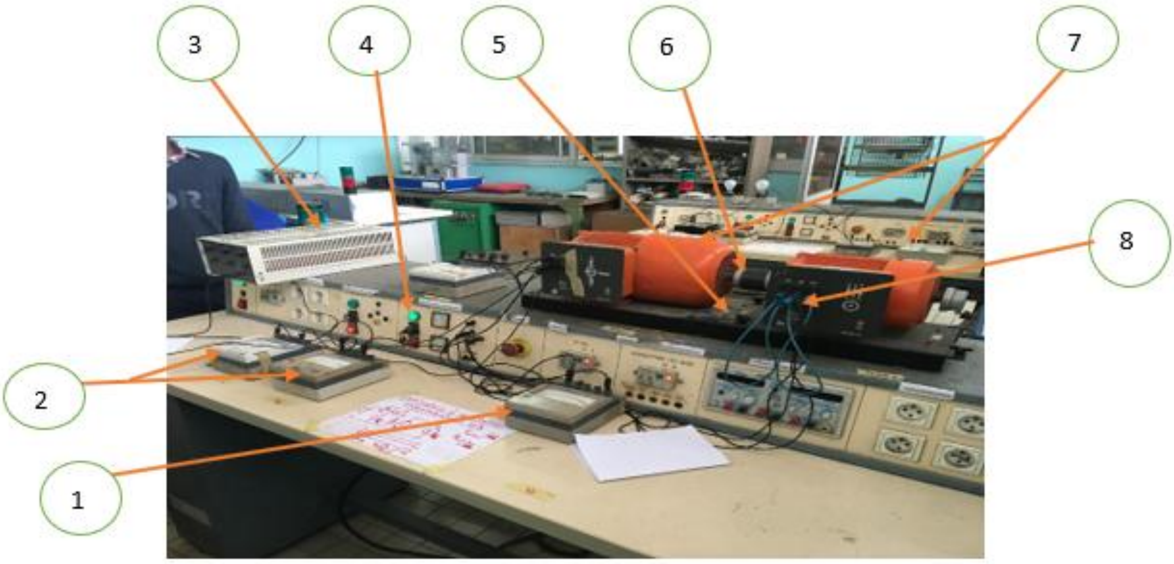

Figure 5. Experimental motor setup

The technology indicates the fundamental particularity of this type of artificial neural network (ANN), namely the convolution process which involves generating points between two matrices, creating a similar structure in the input [22]. Thus, two-dimensional CNNs are characterized by the presence of a convolutional layer that serves as input for an image. RGB images (RED, GREEN, BLUE) consist of several matrices that control the intensity of the primary colors in relation to each pixel. Therefore, the classic measurements of an image (height and width) are now associated with another measurement: depth. The three dimensions will be present in the input layer, while the subsequent layers will exhibit a multidimensional structure and conform to the essential distinctive characteristics for classification.

A CNN is an ANN that is closely related to a convolution operation performed in the first layer. It employs grid structures with geographical connections between cells, allowing the identification of small local areas that have passed through a layer. The initial layers define information matrices, referred to as activation maps or feature maps, while the trainable parameters of the network are tensors known as kernels. The structure of a CNN consists of the following layers: the convolutional layer, the activation layer, the pooling layer, and the fully connected layer (Figure 6).

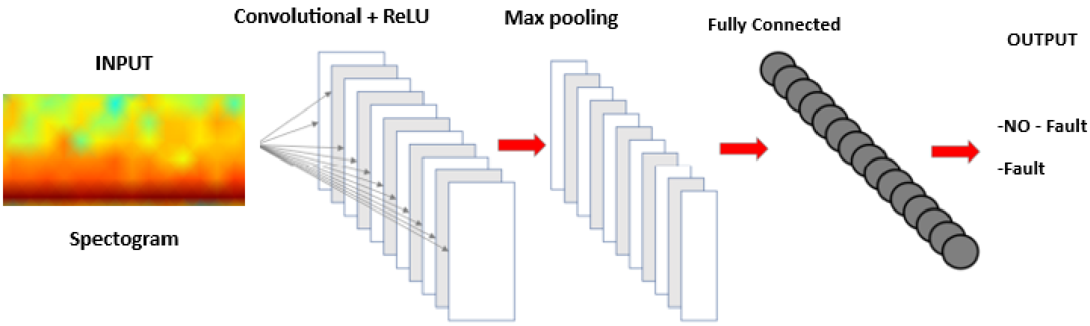

Figure 6. CNN Architecture for Classification.

The convolution layer positions a filter (kernel) in key segments of the image and indicates the dot product between the kernel and the input matrix, also called the "receptive field," a part of the image that has the same proportions as the kernel [23]. The filter is moved by an amount proportional to the stride until it reaches the edge, where it convolves the entire image. Another matrix, called a feature map, is generated at the end of the convolution and focuses on a specific part of the image. Thus, the simultaneous use of multiple filters to perform recognition will result in the formation of an output tensor whose depth corresponds to the number of filters used. The activation operation, which is not linear, should be presented immediately after the convolution. Each convolutional layer uses the activation function to process a layer of identical dimension, whose values are bounded by thresholds [24].

The purpose of the pooling layer is to adjust the dimension of the feature maps while preserving the essential features. In max pooling, a 2x2 filter is usually used, which moves across the feature map in a stride of the same size. The pooling filter allows for the identification of receptive fields and establishes the maximum value for each field. Finally, fully connected layers are then added which proceed with the classification and generate the final output of the CNN. This layer of levels feeds the matrix modified by the previous levels, generating a vector of dimension N corresponding to the number of classes to be predicted.

2.7. Data Augmentation

For increased accuracy, convolutional networks require a multitude of input data during the training process: The more frequent analysis of images during training is due to a small quantity, which we call overfitting. Significantly, a convolutional neural network begins to show satisfactory accuracy on several thousand images used for the training process. In situations where collecting a large volume of training data is complex, methods allow for identifying differences through artificial transformations of images [25]. To increase the number of available training examples, we have the option to apply the following transformations: Flip, Crop, Rotate, Translate, Distort, Change brightness, Adjust contrast.

It is essential to choose these transformations based on the images they need to convert, as the transformation must incorporate information without causing distortions [26]. It is clear that in our situation, culture must be removed as it would have stolen relevant information, thus removing a portion of the spectrogram that constitutes the source of the features [27]. The general idea to follow is to optimize the diversity of transformations of objects within each class while minimizing the differences between different categories. The use of data augmentation leads to a slower convergence of the training model, which is unnecessary in the presence of increased accuracy during testing [28].

2.8. Transfer Learning

A network initialized with random values requires a specific training period: The fundamental concept of transfer learning is to minimize training times by using pre-existing networks for the recognition of objects with generic attributes [29]. Transfer Learning (TL) precisely refers to the ability to adjust and transfer loads, thereby allowing the exploitation of knowledge to achieve various objectives. Almost all layers of the neural network are initially trained on a considerable and generic volume of data, facilitating the creation of global concepts. Next, the specific data volume is used to prepare the remaining layers, and it is determined whether the errors should be propagated through fine-tuning [30].

On one hand, the knowledge of a neural network can be reused, but it is still important to grasp its particularities, especially if the final problem does not closely match the initial problem. The recognition of very generic features is addressed in the initial layers of a CNN, while those that stem from the final layers become specialized and are associated with the dataset [31]. Furthermore, under certain circumstances, weight transfer can lead to a significant enhancement of the generalization capability, thereby improving the overall accuracy of the central neural network.

We have pre-trained models that allow for continued specialized training. For larger datasets, it is recommended to allow the transformation of the fully connected final layers, while for even larger volumes of data, the weights of the upper convolutional layers can be adjusted. Generally, the base layers of the mesh extract common features for each object, such as edges [32].

2.9. Performance evaluation

The performance measures used in this study include accuracy, recall and F1-Score which are defined as follows. Using three important classification metrics that were computed for this study-accuracy, recall, and the F1 score-as shown in equations (19-22), we saw improvements in our findings. Recall, sometimes referred to as sensitivity, gauges how well the model can distinguish positive results from all actual positive cases [31], Conversely, accuracy measures how well the model can forecast positive outcomes out of all projected positive occurrences. Last but not least, the F1 score-the harmonic mean, recall-offers a holistic assessment of the model's quality, especially when the distribution of classes is unbalanced.

The collection of these metrics offers a thorough assessment of the model's categorisation performance. We required the quantity of true positives (TP), false positives (FP), and false negatives (FN) for every class in order to calculate these metrics. TP: The true-positive of a class is the total number of correct predictions for this labeled class. FP: The false-positive of a class is the total number of incorrect predictions that predicted this class. FN: The false-negative of a class is the total number of false predictions for the data labeled in that class.

Accuracy, as indicated in equations (7), measures the proportion of correct predictions out of the total number of observations. It is an overall measure of model performance. Accuracy: Measure of the proportion of correct predictions among all predictions

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \tag{7}$$

Recall measures the model's ability to correctly identify positive instances. This is crucial to ensure that all defects are detected. It is calculated as follows, as presented in equation (8).

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{8}$$

F1-Score is the harmonic mean of precision and recall, providing a single measure that balances both. It is calculated using equation (9).

$$\mathrm{F1} = 2 \times \frac{\text{Précision} \times \text{Rappel}}{\text{Précision} + \text{Rappel}} \tag{9}$$

2.9.1. Implementation of CNN

The following hardware configuration was used at the University of Douala's Electrical Engineering, Reliability, and Intelligent Maintenance Laboratory at the Douala University Institute of Technology (IUT) to obtain the results presented in the following section: an Intel Core i7-6700K 64-bit processor, 32 GB RAM, and an NVIDIA Titan XP GPU.

3. Results and Discussions

The proposed CNN method is compared to other shallow models that have already been illustrated above but which lack convolutional layers. This allows us to assess the impact on the diagnostic performance of convolutions. The sound level meter was positioned on a structure at the height of the motor and very close to the fan. It is also positioned on a base insulated from the motor. Measurements were taken in three phases, with the fan on the motor rotor [23]. Three measurement sessions were carried out according to the conditions of use, corresponding to the three distinct speeds of the motor. Table 1 shows the sound pressure levels (dB Lin) for the three speeds detected by the microphone.

Table 1. Sound pressure level (dB Lin) measured

Speed in tr/min	Power supply 15–25A, 230/400V – 50Hz	Sound level in dB				
		70 - 80	80 - 90	90 - 100	100 - 110	120 and more
Minimum speed 500 tr/min	GOOD	70	81	90	Dysfunction	Failure
	MAL	Alimentation	Alimentation	Dysfunction	Dysfunction	Failure
Average speed 1000 tr/min	GOOD	76	84	94	Dysfunction	Failure
	Mal	Alimentation	Alimentation	Dysfunction	Dysfunction	Failure
Maximum speed 1500 tr/min	GOOD	80	87	96	Dysfunction	Failure
	Mal	Alimentation	Alimentation	Dysfunction	Dysfunction	Failure

In order to describe how the engine works, we first need to look at the frequency field. This is done by means of a spectral examination of sound emission levels. Figure 6 illustrates the 1/3 octave sound emission levels. The three rotation speeds and the three measurement points show average spectra in the band from 50 Hz to 16 kHz.

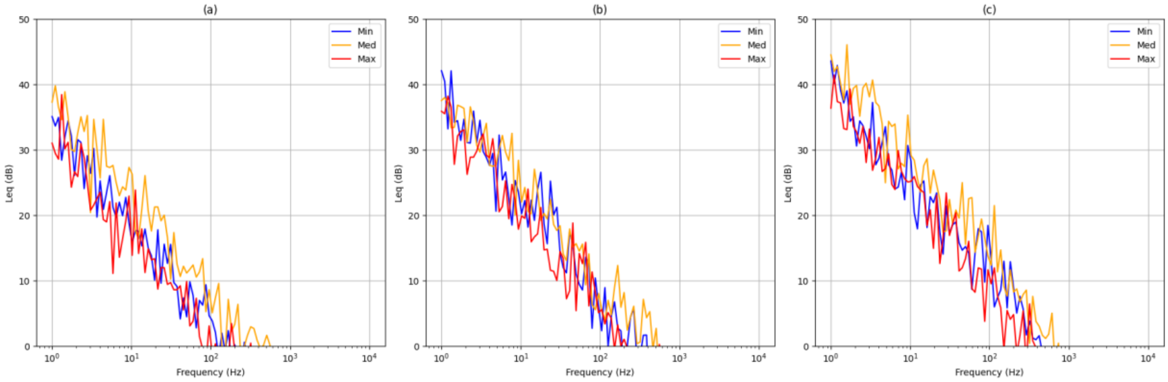

Figure 7. Spectral levels in a one-third octave range, from 20 Hz to 16 kHz, for the three operating scenarios during the measurement session at the three microphone locations (dB Lin). ((a): 80, (b): 90, (c): 100)

According to figure 7, the energy content emitted at low frequency is the most significant, both at low and medium frequency. Fan installation. As mentioned earlier, it should also be noted that the microphones have the highest energy level at 100 dB, both at low and mid frequencies. Furthermore, as we have already anticipated, the fan's optimum operating speed results in greater noise emission, both at low and medium frequencies. Sound emission, which can be low or medium frequency.

3.1. Simulation of load variations on the motor with effects on the cooling fan

As mentioned previously, this research aims to detect the problem based on deep learning. To detect an overload on the motor, it is possible to obtain the sound emission from the blades of a cooling fan. We have planned two operating conditions: Without anomaly, with anomaly. In the situation Without anomaly The engine's power supply is impeccable and its operation is normal. Moreover, the fan is in good working condition and does not produce any undesirable noise emissions. However, in case of malfunction, negative noise emissions were observed on the cooling fan. We artificially generated various faults on the engine to reproduce those that typically occur during normal engine operation. Normalization of the equipment's operation. In order to reproduce the various engine failures using the cooling fan noises, we set up a rheostat that was installed on the engine. The surface area. The selection of the rheostat is motivated by its ability to simultaneously modulate voltage and current in power circuits. It is also necessary to ensure operating conditions in complex and changing contexts such as industrial environments, where production is frequent and requires a machine in good condition. The industry where production fluids play a crucial role requires constantly advanced machines. Given that changes in voltage and current in a motor impair its proper functioning, it is particularly crucial for the fan of these machines, which is connected to the shaft (the rotor) of the machine. This aspect has been considered in the application of our model. Figure 8 presents a comparison between the heat images collected under the two operating conditions and the two modes of the cooling fan.

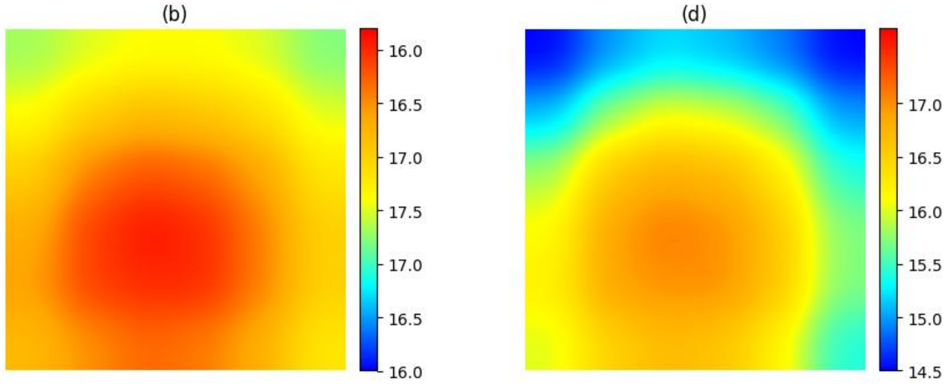

Figure 8. The fan of our machine operates under both conditions: (b) Without defect: the machine is fully powered and the fan does not generate any sound emissions suggesting a malfunction. Moreover, its thermal image of the machine's fan under flawless operating conditions is impeccable; (d) Defect: the machine does not benefit from optimal power supply and has a few minor defects. Moreover, its thermal image of the machine's fan is malfunctioning under unusual operating conditions.

The analysis of the thermal images of the machine's fan in both operating modes (without defect - Figure 8(b), with defect - Figure 8(d) reveals that the one of the defect-free machine is clearer than that of the machine with defect. This explains the malfunction of the machine and its consequences on its fan, as it is connected to the machine's rotor shaft. The anomaly affecting the fan, located on the rotating axis (the rotor) of the device, causes increased temperatures due to the heat generated from the device's poor power supply, which will result in unusual sounds. Due to the irregularities on the fans caused by the malfunction of the machine's rotor. This anomaly generates additional vibrations on the machine structure where our fan blades are located, producing sounds distinct from the usual operating conditions.

3.2. Extraction of Acoustic Emission Features

We employed an algorithm based on a 2D CNN to classify the operating conditions of our machine's fan: For both operating conditions, we decided to extract the spectrograms from the recordings made during our test. Indeed, convolutional neurons have demonstrated their performance in image processing. The spectrogram is composed of the abscissa, an indicator of time, the ordinate, an indicator of frequency, and colors, symbolizing the intensity of the sound. In the final image, the dark shades symbolize a low-intensity sound, while the lighter shades symbolize a high-intensity sound. The bright hues symbolize a sound of high intensity. The spectrogram reproduces the frequency content of the temporal progression of a signal towards a signal.

To obtain an adequate number of samples for the training and testing stages, each recording was initially segmented into 5-second segments. 120 samples were taken and fairly distributed between the two identity verification categories (No-Fault, Fault). The spectrogram was determined for each sample, as illustrated in Figure 8, which presents two spectrograms related to the two categories of identity proof. We compare two spectrograms related to the two operating conditions.

The analysis of the two spectrograms for two signals aims to understand how they can be used to determine the operation of the machine. The diagram of the sound emissions from the cooling fan showing a total value of The initial signal (figure 9 a), generated based on a 5-minute audio recording, illustrates that the spectrogram of the fan's sound emissions shows a fully powered and defect-free machine. In order to identify the frequencies likely to influence the functional conditions, we limited the frequency spectrum to 20 Hz-20 kHz. The second signal illustrates the spectrogram of the fan's sound emissions, with a poorly powered device and several failures, leading to the creation of some defects unintentionally (Figure 9 b). It can be observed that the second signal has a greater frequency content, particularly at low frequencies, illustrating the imbalance of the rotation axis caused by the artificially generated defects. Each sample received a spectrogram, which was then converted into a 800 × 800 pixel png image.

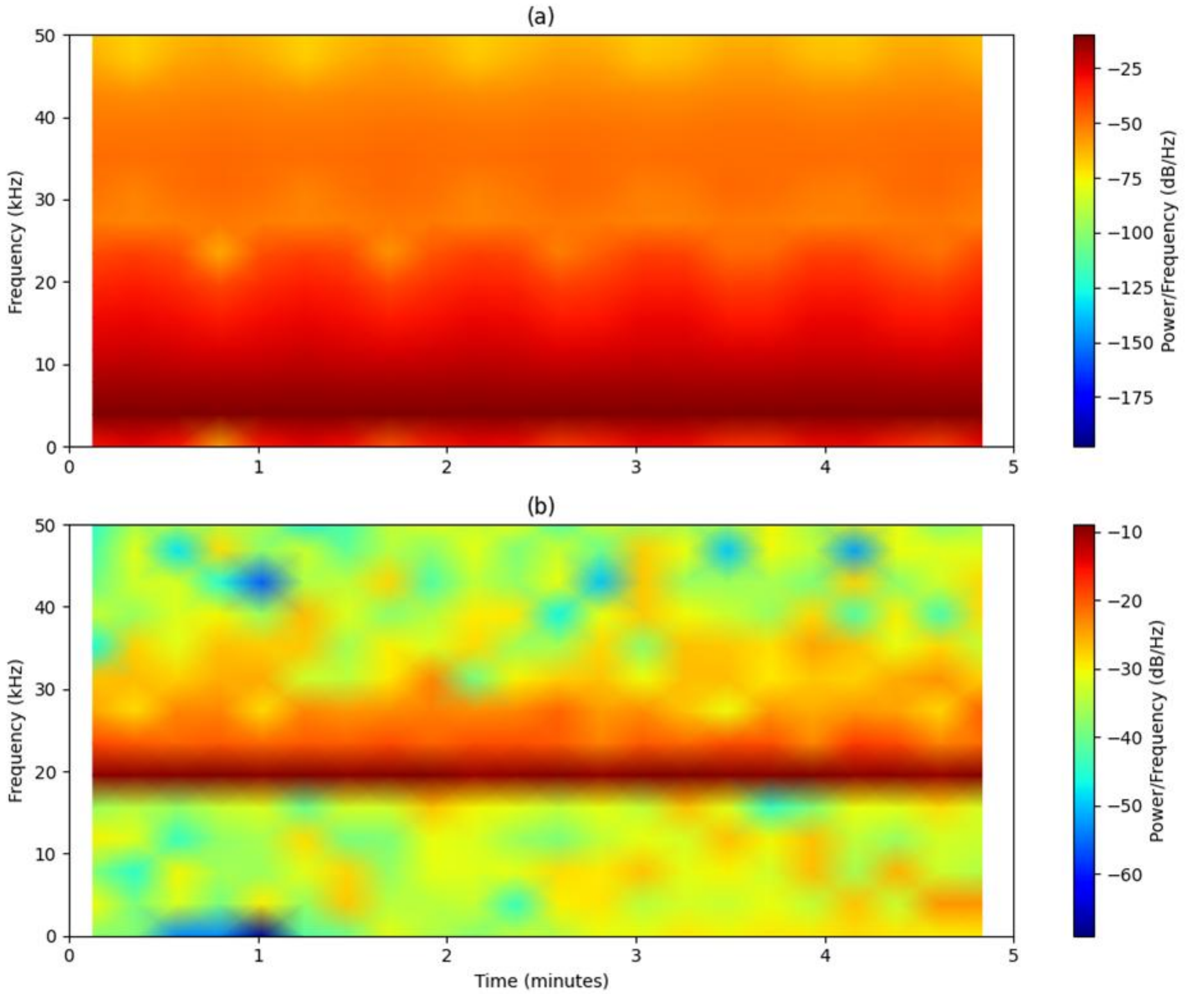

Figure 9. Spectrograms of the two signals: (a) No-Fault: The motor is well powered and has no faults, so there is no acoustic emission from the fan; (b) Fault: The motor is not well powered and has faults due to artificially created problems, so there is acoustic emission from the fan.

3.3. Diagnosis of rotating machine cooling fan faults using a convolutional neural network

In order to increase the number of samples used during the model training phase, the spectrograms of the segmented signals were subsequently transformed. The transformations were selected based on the available samples, with the aim of enriching information without causing distortions. In this perspective, culture was initially neglected, as it would have stolen relevant information, removing part of the spectrum. This initial step aimed to optimize the diversity of object transformations within each class and to minimize the difference between these same transformations as much as possible. We carried out transformations such as rotation, resizing, and reflection.

The example of applying image augmentation on two spectrogram samples related to the two operating conditions is illustrated in Figure 10. Thanks to the increase in information, the initial data volume grew from 120 samples to 840 samples. The use of data augmentation caused a slower convergence of the algorithm during the model training process, while allowing for increased accuracy during testing.

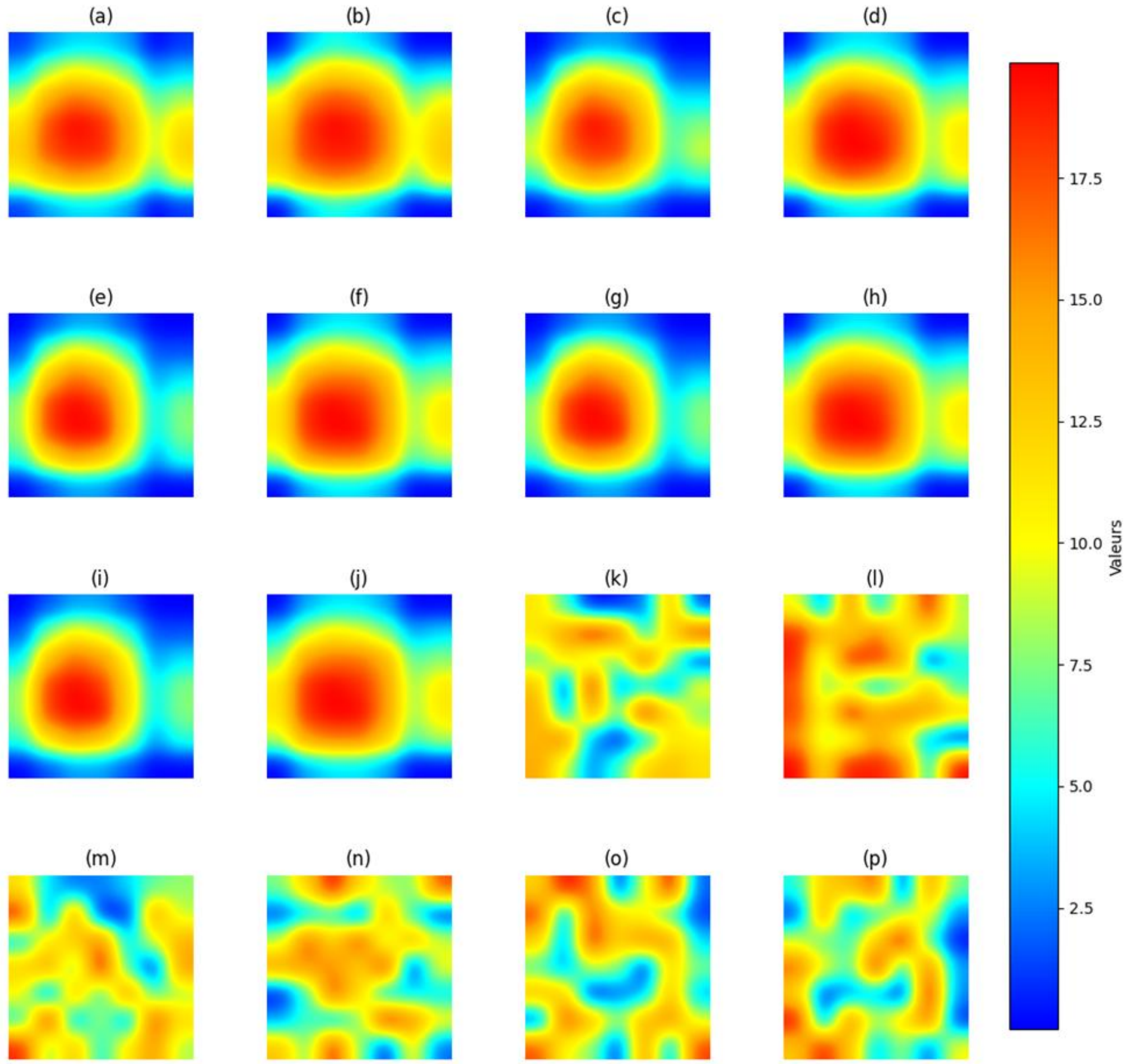

Figure 10. Example of image augmentation: In the starting images of (a) to (j), the starting images are relative to the absence of defect and are shown. Images in (k) a (p) line (b) shows the starting image relating to the fault condition.

We opted for transfer learning by employing a pre-trained network for image recognition. This allows us to benefit from the small number of samples used during the training process and to reduce the training time required when a network is initialized with unexpected values.

The MATLAB environment offers a multitude of pre-trained models that allow for continued specialized training. In this work, we employed the SqueezeNet model [33], an 18-layer convolutional neural network. The network received more than a million photos from the ImageNet database [34]. A collection of images named ImageNet is structured according to the WordNet model [35], with thousands of images serving as representations for each central point of this hierarchical model. This database has fostered the development of research on deep learning and machine vision. In the case of a non-profit application, the information is offered free of charge to researchers [36]. The pre-trained network has obtained a detailed description of the characteristics of various photos and is capable of dividing the photos into 1000 distinct groups. The images in the network have dimensions 227×227. To solve our problem, we adjusted the settings of the input layer to receive images of size 800 × 800. In the network's waiting process, we modified the classification layer to produce only two categories (No-Fault and Fault).

Table 2. Pre-trained CNN Training Option.

Solver	Basic	Advanced
ADAM	Maximum epochs = 100	L2Reg = 0,0001
Initial learning rate = 0,01	Mini Batchsize = 1	Grad Threshold Methods = 12norm

Thanks to the use of a previously trained network, we were able to adjust and shift the network's weights based on new information regarding the sound emissions detected under various engine operating conditions. The spectrograms served as the basis for creating the training and test sets. The sound sensor recordings were extracted following appropriate enhancement. The training set was used to design the classification model, while the test set was used to evaluate its results. 70% of the available samples (588 spectrograms) were reserved for the training phase. These were also distributed between defect-free incidents and those with defects. Regarding the training phase. We evaluated the model's performance based on the 30% available, which is 252 spectrograms, that were also distributed between defect cases and non-defect cases. Table 2 presents all the learning features.

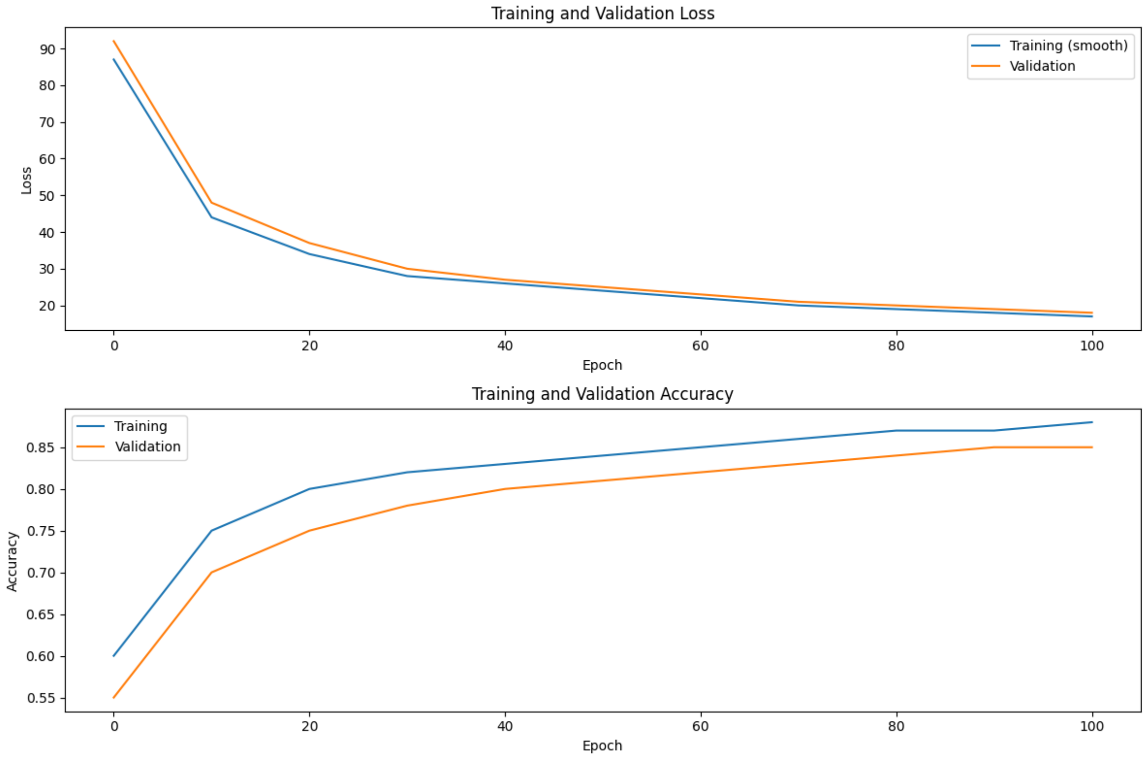

Figure 11. Accuracy and loss during the training and validation phases.

The learning phase first requires the activation of filters, parameters, and weights; during this process, all learning possibilities are determined based on the characteristics of the existing GPU [37]. Subsequently, we will be able to start preparing the network using the selected training program. It is an extremely costly operation in terms of computing: In reality, it is possible to avoid costly network training by using a transfer learning process and utilizing a pre-trained network [38;39]. Thanks to the use of weights adjusted during previous training and transferred to examine a visible model, the previously trained network is leveraged for the next task. When it served as a feature extractor on all the information collected from the fan's sound records, the pre-trained network (Squeeze Net) was reused after the final layer (fully connected) was removed. Figure 11 shows the accuracy and loss patterns of the network during training and validation.

In order to prevent overfitting issues, the model was tested based on the remaining 30%. Information obtained from the training of the network, constituting 70% of all available data. This ensured that, during the testing phase, the model had never seen the data used before. The effectiveness of our model was evaluated using precision, as it is an indicator of its efficiency. If our model is accurate, it should be around one. The accuracy of the convolutional neural network model reached 0.987, thus demonstrating the validity of this technique for determining the functional settings of the engine.
Precision allows us to evaluate the relationship between a predicted value and an actual one. An exact result, a real value, indicates fewer errors in the prediction. Therefore, the accuracy of a prediction shows us how close the predicted value is to the actual value of this volume. Table 3 presents a comparison between the results of this research and those published by other authors.

Table 3. Diagnostic Methods for Defects Based on Machine Learning

Authors	Models	Accuracy (%)	Rappel (%)	F1-Score (%)
Proposed	CNN	98,7	95.0	96.8
[27]	Deep Learning	95	92.0	93.5
[28]	Deep Learning	98	91.5	93.5
[34]	CS-ELM	97	90.0	92.6

The results presented in Table 3 show that our model based on a convolutional neural network (CNN) achieved an accuracy of 98.7%, a recall of 95.0%, and an F1-score of 96.8%. Compared to the results of previous studies, our method stands out for its superior performance. For example, the model in [27] achieved an accuracy of 95.0% and a recall of 92.0%, while the model in [28] achieved an accuracy of 98.0% with a recall of 91.5%. Even the CS-ELM model in [34] had an accuracy of 97.0% and a recall of 90.0%. These metrics reveal that our method is not only accurate, but also excels at detecting anomalies, as evidenced by our high recall of 95.0%. This suggests an enhanced ability to identify existing defects, which is essential in a proactive maintenance context.

The results of our study have significant implications for the maintenance practice of rotating machine fans. A high recall, such as the 95.0% achieved by our model, indicates a better ability to detect anomalies before they turn into critical failures. In industrial environments, where unplanned downtime can lead to significant financial losses and safety risks, such detection capabilities are crucial.

By integrating our high-performance model into maintenance strategies, operators can take a more proactive approach, enabling them to plan preventive maintenance interventions based on accurate data. This can not only reduce the costs associated with emergency repairs, but also improve machine availability, thereby increasing overall operational efficiency. Our method represents a breakthrough in fan maintenance, providing tools for more effective anomaly detection, which is essential for ensuring the reliability and durability of industrial systems.

3.4. Discussion on Operating Environments

The tests conducted in this study took place in an industrial environment, which made it possible to evaluate the performance of the diagnostic method under real-world conditions. Operating conditions include temperature variations, ambient noise levels, and load fluctuations on the machines. These factors can influence the acoustic emissions of fans and, consequently, the accuracy of diagnostics.

In addition, several challenges were encountered during the evaluation. For example, variations in the power supply, such as voltage or current spikes, impacted machine operation and generated background noise that made signal interpretation more complex. The interaction between different pieces of equipment in the industrial environment also added a layer of complexity, requiring adaptation of data collection and analysis methodologies.

These variations and challenges must be taken into account when interpreting the results, as they reflect the reality of industrial operations. The robustness of the proposed diagnostic model, capable of adapting to these conditions, is essential to ensure proactive and effective maintenance of rotating machines.

4. Conclusion

This work has established a novel approach to automate fan maintenance procedures. It has been formulated. A method that uses data collecting and deep learning for problem identification is used to find dust accumulations on an axial fan's blades. A test was conducted on the auditory emission. First,

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data on the different operating circumstances was gathered. We determined that there were two operational conditions: Defect, defect. The fan blades are immaculate, with no material on the surface and a spotless finish. Conversely, in the event of a malfunction, material deposits were fabricated on the fan blades to mimic those often seen while the apparatus was operating normally. The apparatus is operating normally. The sound emission data of the machine's cooling fan 660 were correctly detected under different functional situations (no problem, no problem) using a dichotomous classification. To automatically identify the fan's functional features, a convolutional neural network (CNN) algorithm was programmed using the data gathered. specifics about how the fan works.

Based on the ImageNet database, the network was previously trained (Squeeze Net) to classify up to 1000 different categories. Among the total data, ImageNet can classify objects into as many as 1000 different groups. Excellent results were obtained by applying transfer learning to the visuals of the spectrograms produced from image capture. The noises produced by the fan under both operating situations were recorded to form spectrograms. On the test set, the model's values were extremely similar to the unit's (0.987). An impressive closeness to unity (0.987) indicates how well the methodology works. The maintenance procedures for fans used in industrial processes handling saline flows could be automated with this technology. Direct access problems are present in industrial procedures that handle contaminated fluids.

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