FAILURE DETECTION IN THREE-PHASE MOTORS USING DEEP LEARNING IN VIBRATION ANALYSIS

DETECÇÃO DE FALHAS EM MOTORES TRIFÁSICOS UTILIZANDO DEEP LEARNING NA ANÁLISE DE VIBRAÇÕES

DETECCIÓN DE FALLOS EN MOTORES TRIFÁSICOS MEDIANTE APRENDIZAJE PROFUNDO EN ANÁLISIS DE VIBRACIONES

10.56238/edimpacto2025.041-003

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ABSTRACT

Induction motors play a fundamental role in the industrial sector and require proper monitoring to avoid unscheduled production downtime. Vibration monitoring stands out in the condition diagnosis of these motors due to its effectiveness in detecting faults, especially in bearings. This work proposes the use of Deep Learning techniques to automate bearing fault detection through a comparative analysis between Long Short Memory (LSTM) and Convolutional Neural Network (CNN) models. Using the University of Cincinnati's Intelligent Maintenance System (IMS) dataset, the LSTM model was trained with statistical descriptors extracted from

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the vibration signals, while the CNN operated directly on the raw data. The results demonstrate the superiority of the LSTM model, which achieved 98% accuracy, compared to the CNN, which achieved 86%.

Keywords: Vibration Analysis. Induction Motor. Bearing Faults.

RESUMO

Os motores de indução desempenham um papel fundamental no setor industrial, sendo necessário que sejam devidamente monitorados a fim de evitar paradas não programadas na produção. O monitoramento por vibração destaca-se no diagnóstico de condição desses motores, por sua eficácia na detecção de falhas, especialmente em rolamentos. Nesse trabalho, propõe-se o uso de técnicas Deep Learning para automatizar a detecção de falhas em rolamentos, por meio de uma análise comparativa entre modelos Long Short Memory (LSTM) e Convolutional Neural Network (CNN). Utilizando o conjunto de dados da Intelligent Maintenance System da universidade de Cincinnati (IMS), o modelo LSTM foi treinado com descritores estatísticos extraídos dos sinais de vibração, enquanto a CNN operou diretamente sobre os dados brutos. Os resultados demonstram a superioridade do modelo LSTM, que obteve 98% de acurácia, em comparação com a CNN, que alcançou 86%.

Palavras-chave: Análise de Vibração. Motor de Indução. Falhas em Rolamento.

RESUMEN

Los motores de inducción desempeñan un papel fundamental en el sector industrial y requieren una monitorización adecuada para evitar paradas de producción no programadas. La monitorización de vibraciones destaca en el diagnóstico del estado de estos motores debido a su eficacia en la detección de fallos, especialmente en rodamientos. Este trabajo propone el uso de técnicas de aprendizaje profundo para automatizar la detección de fallos en rodamientos mediante un análisis comparativo entre los modelos de memoria de larga duración (LSTM) y redes neuronales convolucionales (CNN). Utilizando el conjunto de datos del Sistema de Mantenimiento Inteligente (IMS) de la Universidad de Cincinnati, el modelo LSTM se entrenó con descriptores estadísticos extraídos de las señales de vibración, mientras que la CNN operó directamente con los datos brutos. Los resultados demuestran la superioridad del modelo LSTM, que alcanzó una precisión del 98 %, en comparación con la CNN, que alcanzó el 86 %.

Palabras clave: Análisis de Vibraciones. Motor de Inducción. Fallos en Rodamientos.

1 INTRODUCTION

Induction motors play a key role in various sectors, being widely used in industry, commercial environments, and even homes. This popularity is due to characteristics such as robustness, reduced cost, and long lifespan (Bahgat, 2024). However, despite their reliability, these engines are not immune to failures, which can generate significant losses, especially when they result in unplanned production stoppages, directly impacting productivity and profit (Garcia-Calva *et al*., 2022).

Given this scenario, predictive maintenance measures have been increasingly adopted, with the aim of avoiding catastrophic failures and allowing the correction of anomalies before they compromise the operation of the equipment. Continuous monitoring, for example, makes it possible to identify degradation patterns and anticipate failures, enabling planned corrective actions and reducing the impact of downtime (Junior *et al*., 2023).

In general, failures in induction motors can be classified into three stages: incipient failure, when there is internal degradation without noticeable symptoms; Developed failure, when the performance of the engine is affected, catastrophic failure, is when the engine becomes unable to operate (Garcia-Calva *et al*., 2022).

Among the monitoring techniques, vibration analysis stands out for its effectiveness in identifying failures in electric motors. However, this type of analysis often depends on human interpretation, which can become unfeasible in the face of the large volume of data and the subtlety of signals associated with incipient failures, often masked by noise (Ahmed; Nandi, 2020).

Among the types of failures, those that occur in bearings represent 40% of the total in electric motors. Such failures are usually progressive and can be avoided with appropriate vibration techniques (Immovilli, F et al. 2012; Frosini, L 2020). In this context, machine learning techniques, such as convolutional neural networks (CNN) and recurrent neural networks with long- and short-term memory (LSTM), have shown promising results in automating diagnosis, with high accuracy and the ability to identify anomalies in an unsupervised manner (SUN *et al*., 2025).

Bearing fault diagnosis is therefore a field widely explored in the literature, with a focus on signal processing methods and machine learning algorithms. Proper analysis of vibration data allows for the early identification of failures, significantly reducing the risk of unexpected downtime (CERRADA et al, 2018).

In this context, the present work aims to compare the performance of two models, based on *Deep learning* - one using LSTM and the other CNN applied to the detection of failures in bearings of electric motors. To do this, vibration signals from the *Intelligent Maintenance Systems* (IMS) dataset are used.

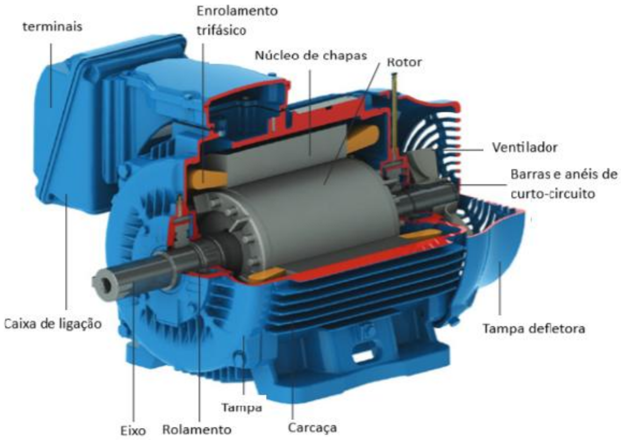
2 FAILURES AND WORKING PRINCIPLE OF INDUCTION MOTOR

In induction motors, when energizing the stator with a three-phase current, a rotating magnetic field of constant intensity is generated inside the coils. The rotor, which is therefore immersed in a rotating field, generates induced currents. These currents, in turn, produce a magnetic field that will try to align with the rotating magnetic field of the stator, producing torque and causing the rotor to rotate (Martignoni, 1978).

The basic constitution of the induction motor is the stator and rotor. The stator is the static part composed of thin sheets of magnetic steel where the coils are housed. And the rotor is the moving part also composed of thin sheets of magnetic steel and with winding housed longitudinally (Silva, 2008). Figure 1 represents the parts that make up a three-phase squirrel cage motor.

Figure 1

Schematic of a squirrel cage type induction motor

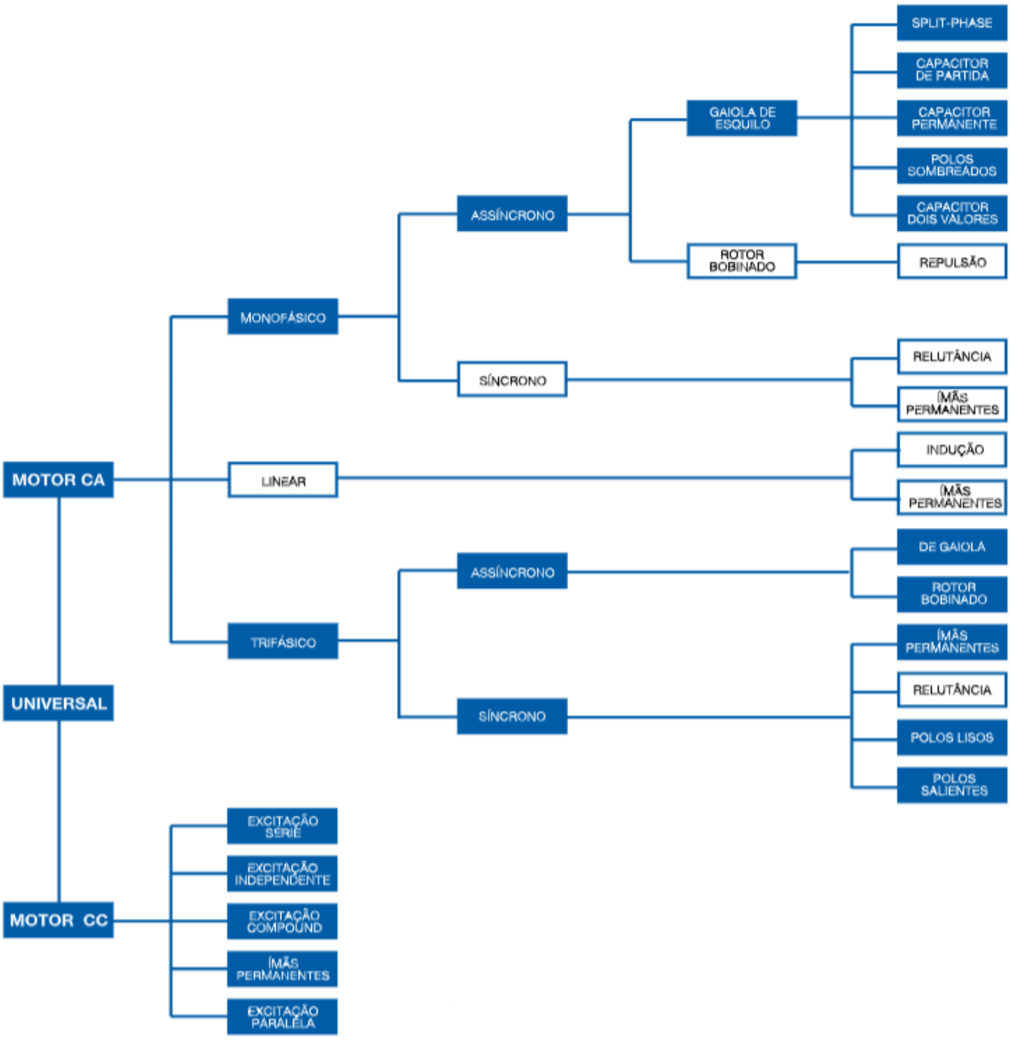


Source. Adapted from Weg (2024).

They can be divided into two main types: Single-phase and three-phase. Single-phase motors are generally used in commercial or residential environments where they are used in lower power situations, such as small industrial equipment and household appliances. Three-phase motors are common in industrial settings, where they operate in high-power systems (Cabrera, 2013). Figure 2 illustrates the classification of electric motors.

Figure 2

Engine Classification



Source. Weg, 2024.

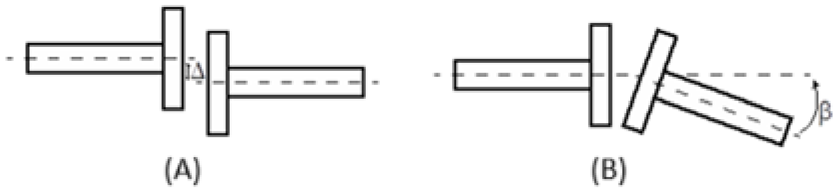
The most common failures in induction motors that cause vibration include: Unbalance; Misalignment; Eccentricity; Resonance; Mechanical clearances; Bearing defects (Spamer, 2009).

Unbalance occurs when there is an imbalance of mass with respect to the axis of rotation, often caused by asymmetries in the rotor or rotor-stator assembly. This imbalance generates a stationary force relative to the rotor that induces a sinusoidal vibration at the rotational frequency. This vibration can present high amplitude in the radial directions (horizontal and vertical) (Baccarini, 2005).

Following the same line of reasoning as Baccarini (2005), misalignment occurs when the components of two coupled machines show wear. It occurs in two main ways: parallel or angular. Parallel misalignment can be subcategorized as vertical or horizontal misalignment. It happens when there is both vertical and horizontal displacement of the axes that are in parallel. Angular misalignment occurs when an angle is formed in the centerline of two axes, which can also be both vertical and horizontal. Figure 3 represents in a simplified way the parallel and angular misalignments and Figure 4 represents the axial and radial vibrations associated with misalignments in induction motors.

Figure 3

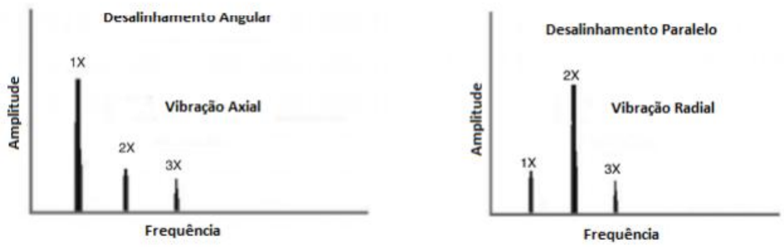
Schematic representation of misalignment types: (a) parallel and (b) angular



Source. Silva, 2013.

Figure 4

Representation of axial and radial vibrations associated, respectively, with angular and parallel misalignments in induction motors



Source. Silva, 2013.

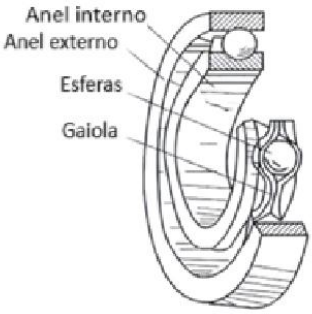
Mechanical clearances in induction motors can be classified into three distinct types:

- Type A: associated structural problems, such as lack of rigidity in the foundation or base of the machine.
- Type B: related to loose or damaged components, such as gaps in screws or cracks in the feet.
- Type C: Associated with inadequate fixation between machine parts such as clearance between the bushing and the bearing cover, between the inner ring of the bearing and the shaft, or between the outer ring and the bearing cover (Spamer, 2009).

Bearings are fundamental elements in the support of the rotor shaft in induction motors, with the function of reducing friction between moving parts. A typical bearing is composed of four elements: inner raceway, outer race, ball, and a cage that keeps the balls equidistant and correctly positioned (Garcia-Calva *et al.,* 2022). It is represented in Figure 5.

Figure 5

Ball Bearing Components



Source: Adapted from SUN et al, 2025.

Bearing failures can be classified into two main categories:

- Pre-operational, which originate from installation problem or improper handling.
- Operational, which occur during the operation of the bearing.

Within the operational category, the most common failures are related to fatigue, insufficient lubrication, wear, and other degradation mechanisms (Luciano, 2020).

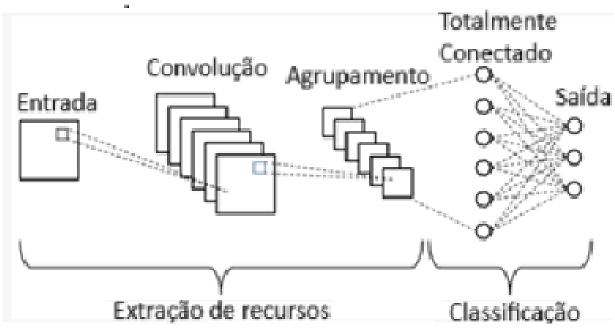
3 NEURAL NETWORKS

Artificial neural networks (ANNs) are computational systems inspired by the functioning of the human brain. According to Haykin (2007, p28) "an ANN is a massively parallel and distributed processor, made up of simple processing units, which has a natural propensity to store experimental knowledge and make it available for use."

Among the various types of ANNs, the *Convolutional Neural Network* (CNN) stands out, which is widely used in the recognition of patterns in images. CNNs are designed to automatically and adaptively learn spatial hierarchies of features – from low-level to high-level patterns. Its architecture is mainly composed of three types of layers: convolution layers, pooling layers, and fully connected layers. The first two are responsible for the extraction of features, while the last maps the extracted features to the final output, such as the classification (Yamashita, 2018), Figure 6, depicts the architecture of a CNN.

Figure 6

CNN's three-tier architecture



Source. Cha et al, 2024.

In the CNN architecture, the most significant component is the convolution layer, whose primary function is feature extraction. This layer is composed of a set of filters (or kernels) that slides over the entire input, making the product scale between its weights and the input values in each position. This process allows the network to learn relevant spatial and temporal patterns (Mishra, 2020).

To introduce nonlinearity to the model, activation functions are applied, the most common being the Rectified Linear Unit (ReLU), which accelerates training and avoids the problem of descending gradient. Then, the clustering layer is used to reduce the spatial dimensionality of the feature maps, which contributes to the decrease in computational load and the number of parameters. In addition to avoiding *overfitting* (Alzubaidi *et al*, 2021; Mishra, 2020).

At the end of the architecture, there is the Fully Connected Layer responsible for receiving the extracted features, which are flattened into a one-dimensional vector, and performing the final classification based on this processed data (Mishra, 2020).

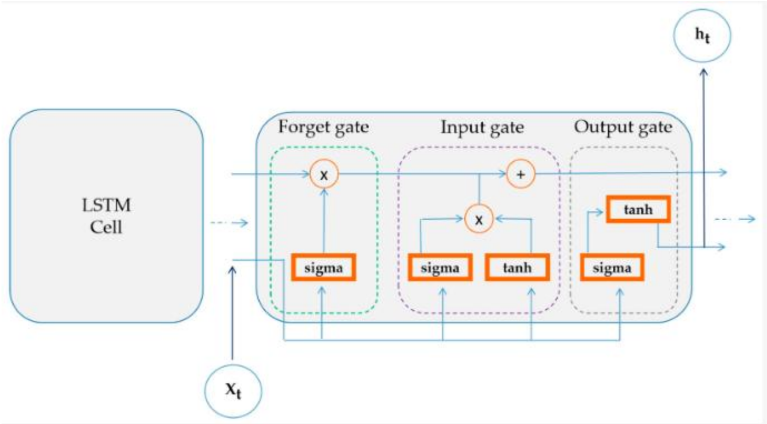
These layers, when combined, allow CNN to process raw data, such as vibration signals, from sensors attached to the motors, extract relevant hierarchical characteristics, and ultimately perform classification with high accuracy, making it a promising solution for automatic fault detection in induction motors.

Another prominent architecture in the context of fault diagnosis is LSTM, a type of Recurrent Neural Network (RNN) designed to store information over time, being especially effective for tasks involving time series, such as the analysis of vibration signals.

Each LSTM Cell is composed of three basic components that regulate the flow of information: Input port that controls the data that must be added to memory, the oblivion gate, responsible for deciding what information should be discarded; and the output port, which determines what information from memory will be used as output at that instant. This framework allows LSTM to learn long-term dependencies in the data, overcoming common limitations of traditional RNNs (Rafi *et al.*, 2021; Calzone. 2022; Conte, 2024). As illustrated in Figure 7

Figure 7

Architecture of an LSTM Unit



Source. Conte, 2024.

4 TIME DOMAIN ANALYSIS

To analyse vibrations, it consists of evalu ating the raw data from the vibration sensors acquired in the time domain. This temporal analysis allows you to observe the evolution of the machine's behavior and serves as a basis for the extraction of statistical metrics. These statistical indicators can form a signature that helps diagnose the operating condition of the equipment (Lobão, 2020).

Statistical parameters such as the mean value (Xm), the root amplitude (Xroot), the root mean square (Xrms), the peak value (Xpeak), the standard deviation (Xstd), skewness (asymmetry - Xskewness), kurtosis (Xkurtosis), crest factor (Xcrest), backlash factor (Xclearance), form factor (Xshape) and impulse factor (Ximpulse), can represent the behavior of faults, which are shown by the vibration signals (Wolf, 2020). Figure 8 shows the descriptors extracted from the signal in the time domain.

Figure 8

Statistical descriptors extracted from the time domain signal

Parâmetro	Descrição Matemática
Valor médio	$X_m = \frac{\sum_{n=1}^{N} x(n)}{N}$
Valor de pico	$X_{peak} = max\|x(n)\|$
Fator de folga	$X_{clearance} = \frac{X_{peak}}{X_{root}}$
Amplitude da raiz	$X_{root} = \left(\frac{\sum_{n=1}^{N} \sqrt{\|x(n)\|}}{N}\right)^2$
Curtose	$X_{kurtosis} = \frac{\sum_{n=1}^{N}(x(n)-X_m)^4}{(N-1)X_{std}^4}$
Fator de impulso	$X_{impulse} = \frac{X_{peak}}{\frac{1}{N}\sum_{n=1}^{N}\|x(n)\|}$
Desvio padrão	$X_{std} = \sqrt{\frac{\sum_{n=1}^{N}(x(n)-X_m)^2}{N-1}}$
Skewness	$X_{skewness} = \frac{\sum_{n=1}^{N}(x(n)-X_m)^3}{(N-1)X_{std}^3}$
Fator de forma	$X_{shape} = \frac{X_{rms}}{\frac{1}{N}\sum_{n=1}^{N}\|x(n)\|}$
Raiz quadrada média	$X_{rms} = \sqrt{\frac{\sum_{n=1}^{N}(x(n))^2}{N}}$
Fator de crista	$X_{crest} = \frac{X_{peak}}{X_{rms}}$

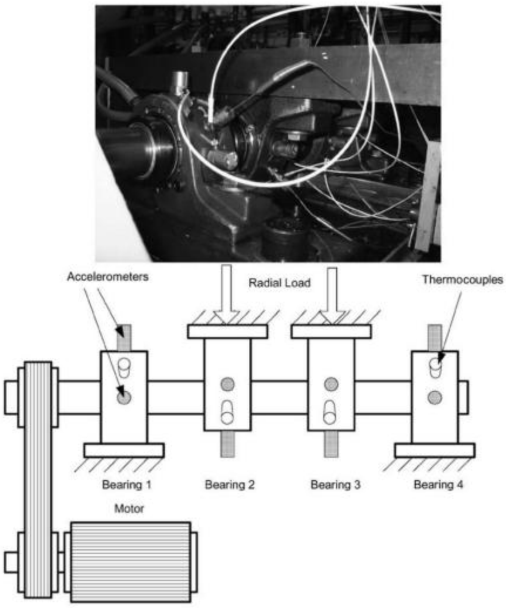
Source: Lobão, 2020.

5 VIBRATION DATA COLLECTION

The vibration data used in this study were from *the Intelligent maintenance system of the University of Cincinnati* (IMS). According to the document present in the file in which the vibration data consists of, the experiment was carried out using four Rexnord ZA-2115 bearings that were installed on a shaft that was at a speed of 2000 rpm, these bearings were forcibly lubricated. A spring mechanism applies a radial load of 2700 kg to the shaft and bearing. Figure 9 represents the bench used to collect the signals. To collect the vibration signals from data set 1, two high-sensitivity quartz ICP accelerometers were placed in the bearing housing for each bearing and one accelerometer for sets 2 and 3. All bearings have failed after exceeding their service life.

Figure 9

Experimental bench of the IMS research center



Source: IMS

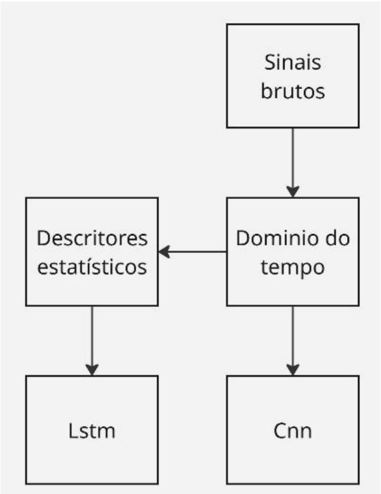
In all, it has three sets of IMS tests. And all the tests were finished when the bearings failed and each file in the dataset presents a snapshot of the vibration signals of 1 second and each file consists of 20,480 points with the sampling rate set at 20 khz.

In the present study, set 1 will be used, which lasted 35 days, and at the end of the test, presented failures in the inner raceway of bearing 3 and a defect in the roller in bearing 4 and 2156 vibration signals were produced. In set 2, the experiment lasted 7 days, had a failure in the raceway of bearing 1 and 984 vibration signals were produced and in set 3 of the IMS experiment, it lasted 30 days, 4448 vibration signals were produced and the experiment had a failure in the outer raceway of bearing 3.

The model ratings were carried out by a CNN and an LSTM. The model has a vibration signal domain (time domain) and a characteristic extractor (statistical descriptors) as shown in Figure 10. below he presents.

Figure 10

Flowchart of the comparative modeling between LSTM and CNN



Source. Authors 2025

6 PRE-PROCESSING AND ORGANIZATION OF DATA.

The signals used in this study were obtained from the IMS data set, which had already gone through a previous normalization process carried out by those responsible for the collection. Thus, it was not necessary to apply additional normalization techniques for the modeling proposed in this research.

The set analyzed, known as *IMS Bearing Dataset – Set 1*, is composed of signals with 20,480 samples per file. Each of these signals was segmented into windows of 1,024 samples, with 50% overlap between consecutive segments (512 samples). For each segment, a vector containing 10 statistical descriptors in the time domain was extracted, representing relevant characteristics of vibrational behavior.

As the signals were captured by two different accelerometers, the extraction process was performed separately for each channel, resulting in vectors of 20 characteristics per segment (10 per channel).

For the purposes of supervised classification, the data were labeled into three distinct classes, based on the life cycle of the monitored bearing:

- *Healthy*
- *Developing Fault*
- *Imminent Failure*

The extracted trait vectors were organized in sequences of 20 consecutive segments, in order to preserve the temporal evolution of the statistical descriptors over time. This approach allows models to consider the dynamics of vibrational behavior rather than just isolated snapshots.

In the case of modeling using convolutional neural networks (CNNs), it was not necessary to perform additional pre-processing, since this type of architecture is able to automatically extract the relevant features directly from the raw signals.

Considering that the signals from set 1 were captured by two accelerometers positioned at different points in the bearing, the data were organized in such a way as to allow CNN to process them as a two-dimensional (2D) image. To do this, the two one-dimensional (1D) time signals were combined into a 2D matrix, where each line represents the signal of an accelerometer and each column corresponds to a sample in time. This matrix representation enables the application of convolutional filters that explore spatial and temporal correlations between channels, simulating the structure of an image.

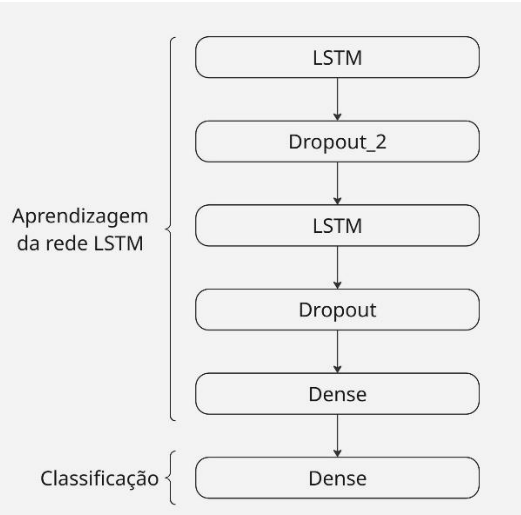
7 NETWORK ARCHITECTURE USED FOR CLASSIFICATION

The architecture of the proposed network is composed of six stacked layers. The first two are LSTM layers, containing, respectively, 64 and 32 neurons. The first LSTM layer was configured with the return_sequences=*True parameter*, allowing the full sequence to be passed on to the next layer, which is required for networks with multiple LSTM layers.

Then, two Dropout layers are inserted: the first aims to reduce *overfitting*, while the second acts on the regularization of the exit of the second LSTM layer. Finally, the network has two dense layers (*fully connected*). The first has 32 neurons and uses the ReLU activation function, and the second contains 3 neurons with *Softmax* activation function, suitable for the multiclass sorting task. Figure 11 shows the flowchart of the architecture used.

Figure 11

Model construction flow chart



Source. Authors 2025

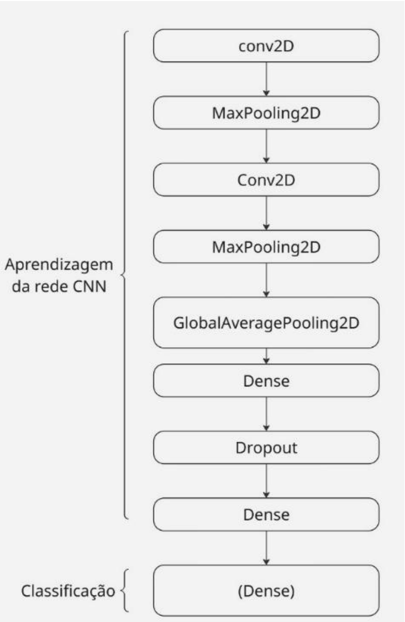
The CNN architecture used in this study is composed of 8 layers. The first two are convolutional layers with ReLU activation. The first convolutional layer has 32 filters with a *kernel* size of (2, 8), while the second contains 64 filters with a size of (1.8). Then, two *pooling* layers were applied, both with size window (1, 2). The first layer of *pooling* aims to reduce the dimensionality of the data while preserving the most relevant characteristics.

Subsequently, a *global average pooling* layer is used to transform the two-dimensional representations extracted by the convolutional layers into a one-dimensional vector, preparing the data for the classification step.

The network ends with three dense layers. The first contains 128 neurons with ReLU activation, the second has 64 neurons, also with ReLU, and the last layer has 3 neurons with *Softmax activation function*, suitable for classification into three classes. Figure 12 shows the flowchart of the architecture used.

Figure 12

CNN Network Architecture



Source: Authors 2025

8 TRAINING AND VALIDATION SETUP

For the training of the models, the data were divided into 70% for training and 30% for testing. Of the total allocated to training, 20% was used for validation during each season.

All models have been trained for up to 30 times. To avoid *overfitting,* the early to-do *technique was used*, which was configured to interrupt training if the validation loss did not improve after 10 consecutive seasons.

The experiments were conducted on the Google Colab platform.

9 RESULTS

The results obtained demonstrate a satisfactory performance of the LSTM model in the task of fault detection. As shown in Figure 13, after 30 training periods, the model achieved a loss of approximately 0.03% and an accuracy of 98%.

The analysis of Table 1 reveals a sensitivity of 99%, indicating that the model is highly effective in identifying the normal condition of the bearings. These results highlight the robustness of the model proposed for predictive diagnostic applications in rotary systems.

Table 1

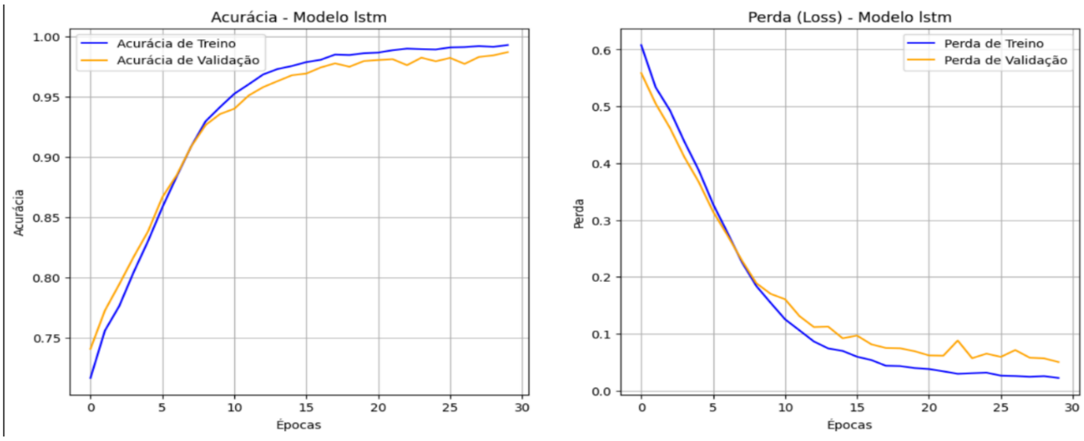
LSTM results as a classifier

	Precision	Sensitivity	F1-score
Developing_fault	0.98	0.98	0.98
Healthy	0.99	0.99	0.99
Imminent_Failure	0.98	0.99	0.98
Accuracy			0.98
avg macro	0.98	0.99	0.98
Weighted avg	0.98	0.98	0.98

Source. Authors 2025

Figure 13

Graph of LSTM training



Source. Authors 2025

The CNN-based model test was conducted with the same epoch number (30) used in the LSTM model. However, it showed significantly lower performance, with an accuracy of 86% and a higher loss of 0.35%.

In addition, the sensitivity value was 86%, which indicates a higher probability of false positives occurring during fault detection. As shown in Figure 14 and Table 2.

Table 2

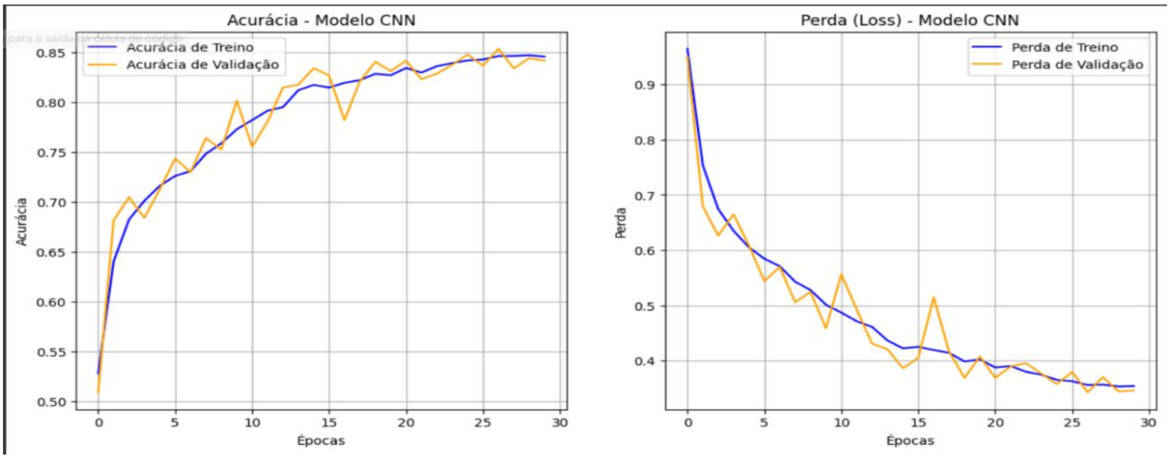
CNN result as a classifier

	Precision	Sensitivity	F1-score
Developing_fault	0.75	0.80	0.77
Healthy	0.90	0.88	0.89
Imminent_Failure	0.92	0.89	0.90
Accuracy			0.86
avg macro	0.86	0.86	0.86
Weighted avg	0.86	0.86	0.86

Source. Authors 2025.

Figure 14

CNN Training Chart



Source. Authors 2025

10 CONCLUSION

The present work was based on the observation that unplanned engine shutdowns in industrial production can generate significant financial impacts. In addition, it was observed that traditional vibration analysis requires the performance of trained specialists to interpret the data. In this context, in order to automate fault diagnosis, applications of Deep Learning models were investigated .

The objective of performing a comparative analysis between the LSTM and CNN models was successfully achieved. For this, a study was carried out on the main defects that occurred in electric motors and applied metrics to compare the performance of the models.

The LSTM model outperformed CNN. The LSTM was trained with statistical descriptors extracted from the vibration signals and presented an accuracy of 98% and 99% sensitivity. This indicates a high accuracy in the detection of bearing anomalies. While the CNN model, although functional, presented an accuracy of 86% and the values of sensitivity and F1 score (86%, respectively), this indicates that the use of this architecture to implement fault diagnosis systems can be problematic for industrial use. This result, solving the problem of this research, points to LSTM as the most effective in the classification of bearing vibration anomalies.

Data were obtained from a dataset (IMS), collected in an experimental benchtop setting. As a limitation, the performance of the models may vary in real industrial environments, which have greater complexity and distinct noise sources. In addition, it is essential to consider that CNN carried out an end-to-end learning process, responsible for both the extraction of characteristics from raw data and the classification, while LSTM operated on statistical descriptors already consolidated in the literature. This difference means that CNN's work was much larger and more difficult, which helps explain its lower performance compared to the approach taken with LSTM.

As a proposal for future work, it is suggested the development of a hybrid CNN-LSTM model, combining the potential of CNN in the extraction of spatial features with the ability of LSTM to interpret temporal dependencies. Additionally, the use of Fast Fourier Transform (FFT) is recommended for approaches in the time-frequency domain.

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