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COB-2023-0363: A NOVEL APPROACH FOR ANOMALY DETECTION IN EDGE ANALYTICS OF VIBRATION DATA IN ROTATING MACHINERY

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Abstract. *Due to the increasing use of Edge analytics techniques, made possible by the development and lower cost of IoT (Internet of Things) sensors, together with the assumptions of Industry 4.0, real-time vibration monitoring of rotating machinery has become a reality in modern industry. In order to be able to manage a large volume of data and information, in addition to reducing high storage costs, new monitoring tools have been seeking to offer integrated anomaly detection. However, it is noted that these tools still generate many false negative results, leading to breaks or storage of undesirable data. In this paper a new approach based on Autoencoder neural networks and statistical histogram comparison techniques for detecting anomalies in dynamic data streams is presented. Validation in five synthetic and real datasets demonstrate the viability of the approach, with Recall results superior to 90%.*

Keywords: *Vibration Analysis, Real-time Monitoring, Rotating Machinery, Anomaly Detection, Edge Analysis*

1. INTRODUCTION

The monitoring of industrial assets plays a big role in industry nowadays driven by predictive maintenance concepts and is present in the most diverse sectors, from manufacturing processes Brito et al. (2023a) to rotating machinery, Lei et al. (2020).

Due to their great industrial importance (high costs and direct impact on production) several sensors are used to monitor the operating condition, in order to guarantee the reliability and availability of assets, among which the following stand out: temperature, pressure, vibration sensors etc. Despite helping to avoid unexpected stops and breakdowns, the volume of data generated by the sensors, especially when used in real-time, is extremely high, which makes manual analysis and storage a complicated and costly process.

The study of artificial intelligence techniques for fault diagnosis is being consolidated every day with several works that show recent contributions (Lei et al., 2020, Liu et al., 2018 and Brito et al., 2023b). Despite recent advances, most techniques consider the supervised training scenario, which is not always available for industrial data. Thus, the use of an unsupervised approach becomes essential to enable the application of studies developed in an industrial environment. Although there is a high number of research related to artificial intelligence in the field of monitoring rotating machinery, a small number of approaches have been presented based on unsupervised detection of anomalies, most of which are related to classification and prognosis, as shown in the review works (Kumar and Hati, 2020, Lei et al., 2020, Liu et al., 2018 and Stetco et al. 2019)

Among the unsupervised approaches, anomaly detection techniques stand out. The main objective is to identify unusual, outliers or anomalous patterns in relation to the dataset used for training. For rotating machinery, anomalies can indicate both variations in the dynamic behavior of the equipment due to process changes (example: variation in rotation, load etc.), as well as failures due to component wear. Both variations generate changes in the monitored signals and therefore are objects of interest to analyst engineers.

Due to the consolidation of Industry 4.0 and the lower cost of IoT (Internet of Things) sensors, the detection of anomalies in real-time signals has become a necessity, and also a priority, for modern industrial applications. Aiming to overcome these challenges, researchers have been studying the application of artificial intelligence techniques for detecting anomalies, seeking to identify when there is some variation in the machine's behavior in an unsupervised approach. Through new integrated anomaly detection tools, it is possible to manage large volume of data and information, in addition to reducing high storage costs. In other words, the variation when identified is saved in the database allowing analysis by the specialist. On the other hand, if the method does not detect any anomaly or variation in the signal, it is discarded, avoiding storing similar signals in the database, which in turn contains the same information.

In the references found, there are very few studies involving anomaly detection with unsupervised approaches in the monitoring of rotating machinery. Ogata and Murakawa (2016) used Fourier local autocorrelation (FLAC) and Gaussian Mixture Model (GMM) approach to fault detection. Von Birgelen et al. (2018) applied SOM (Self Organizing Maps) for anomaly detection in cyber-physical system components. Zhang et al. (2019), Hasegawa et al. (2017) and Hasegawa et al. (2018) worked with different combinations of GMM for anomaly detection.

Among recent studies on unsupervised anomaly detection, the following stand out: Brito et al. (2022) studied the behavior of different state-of-the-art models for anomaly detection in rotating machinery, showing their feasibility of use, in addition to presenting a study on XAI (Explainable Artificial Intelligence). Among all the different ML (Machine Learning) models tested (Clustering Based Local Outlier Factor (CBLOF), Local Outlier Factor (LOF), Isolation Forest (IF), Lightweight on-line detector of anomalies (LODA), Histogram-based Outlier Detection (HBOS), k-Nearest Neighbors (kNN), Fast - Angle-based Outlier Detector (FastABOD), Outlier Detection with Minimum Covariance Determinant (MCD), One-Class Support Vector Machine (OCSVM), Feature Bagging (FB) and Ensemble (combination of all models), those that obtained the best responses were IF, HBOS, kNN and MCD, being IF present among the best for all datasets. Chuya-Sumba et al. (2022) present a method based on Deep-Learning, using Convolutional Neural Networks (CNN) to identify anomalies in vibration signals from rotating machinery. Three databases of vibration signals with bearing faults and three different configurations were used. The technique resulted in an accuracy of 99% and a great adaptability. Audibert et al. (2022) carried out a study to verify the contribution of deep neural networks in the anomaly detection of multivariate time series, comparing sixteen different methods, including conventional statistical techniques, machine learning-based and, deep neural network approaches on five real-world open datasets. Dimoudis et al. (2023) developed an algorithm for detecting anomalies with an adaptive sliding window, which uses F1 Score and T-test as a basis for changes in the window. In Brito et al. (2021) the authors used the Isolation Forest (IF) model associated with feature extraction and dimensionality reduction techniques to detect anomalies in bearings, showing the feasibility of the technique.

Despite the recent works presented, anomaly detection is an extremely complex task, considering that there are no labels available for training the models, and most of the time, little or no knowledge about the characteristic/behavior of normal and anomalous signals. These factors generate great difficulty in developing models and choosing evaluation metrics that are sensitive enough to detect anomalies. To overcome these problems, this work aims to develop an approach based on Autoencoder Neural Networks and Histogram comparison statistical techniques for detecting anomalies in dynamic data streams in which the result is not highly affected by the choice of threshold and evaluation metric.

2. METHODOLOGY

The criteria normally used to classify a time series as an anomaly are based on an error metric (RMSE - root mean square error or MAE - Mean Absolut Error, for example) and a threshold chosen from basic statistics (mean and standard deviation) of the errors of the training dataset defined as 'normal' a priori.

The proposed methodology consists of using classical statistical techniques to define whether or not two random samples belong to the same population by statistically comparing their histograms and using the p-value as an anomaly evaluation metric.

Given a basic time series, considered normal, the proposed methodology consists of:

1. Build a Deep Autoencoder Neural Network with the number of input/output neurons smaller than the length of the time series.
2. Construct a set of instances for training the network using segments of the basic time series. In the construction of instances, a vector of white noise with zero mean and constant variance is added. The addition of noise has two purposes: to increase the diversity of the training data and to ensure that the difference between a normal time series and the series reconstituted by the network belongs to a population with normal distribution of zero mean and constant variance. The number of instances must be greater than the number of net trainable parameters to prevent overfitting.
3. Train the Deep Autoencoder Neural Network.
4. Difference between the base signal and the reconstructed base signal and create a base reconstruction error signal.
5. Estimate the base histogram using the reconstruction error signal and a number of bins (*n_bins*).
6. Given a test signal: to be classified as normal or an anomaly, in relation to the base signal, the reconstruction error of the test signal and its histogram are calculated using the same bin intervals as the base signal.
7. To verify whether the two histograms come from the same distribution, among the various possibilities, the two-sample KS test is used due to speed of estimation criterion.
8. Compare the p-value of the test statistic with the threshold value.
9. If the estimated p-value is greater than the threshold, the test signal is considered normal and goes back to step 5 with a new test signal.

10. If the p-value of the test is less than the threshold, the signal is considered an anomaly. In this case, the test signal becomes the base signal and goes to step 3.

It is observed that the deep autoencoder is only trained once in the proposed anomaly detection procedure.

3. EXPERIMENTAL PROCEDURE

To evaluate the effectiveness of the methodology for anomaly detection in vibration signals from rotating machinery, time series of five datasets and four approaches for detecting anomalies in time series were used. The datasets are composed of blocks of data classified as normal or anomalous, with variations in the amplitude of the signals, variations in the rotor rotation frequency and short-term impacts being classified as anomalies.

The anomaly detection methods used for comparison with the proposed methodology were:

- Histogram: the proposed methodology.
- Wavenet: methodology using wavenets for signal reconstruction without anomaly based on the article by Hayashi et al. (2018).
- Clustering: based on the article by Li et al. (2021).
- Ocsvm: methodology using the machine learning approach One Class SVM (Ma et al., 2003).
- Deepant: methodology based on the article by Amarbayasgalan et al. (2020).

The five datasets used refer to synthetic signals (Test 1) and real signals from rotating machinery (Test 2-5). Figure 1 shows the experimental bench used to develop the tests 2, 3 and 5, consisting of: motor, two magnetic bearings, rotor, speed controller, operating range 0-12000 rpm.

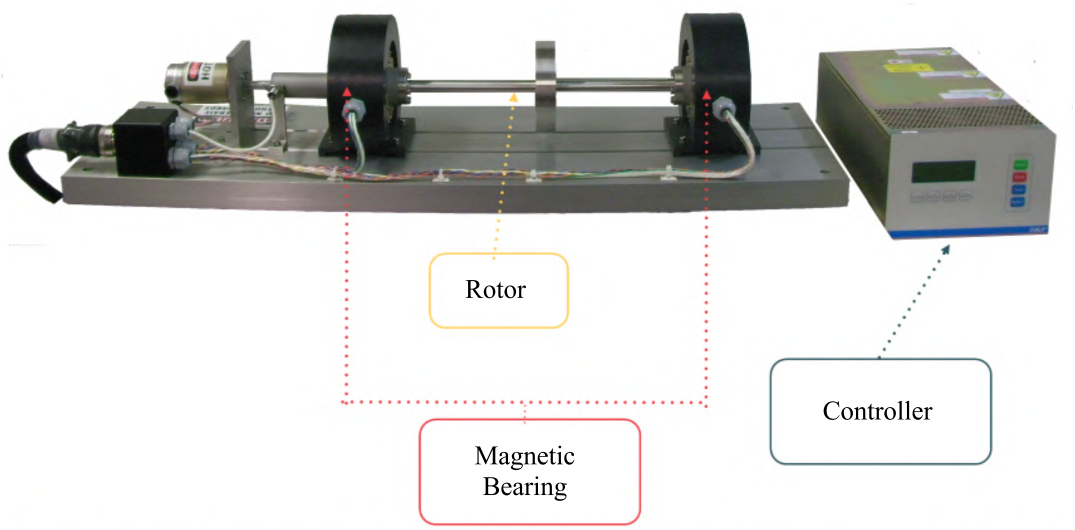


Figure 1. Experimental bench.

Figure 2 shows the experimental bench (industrial fan) used to develop the test 4, consisting of: motor, pulley, rotor and two bearings. Motor speed of 1720 rpm and rotor speed 2160 rpm,

Figure 2. Experimental bench (Industrial Fan).

Figures 3-7 show the time signals and targets for each dataset. It is noteworthy that the targets were not used in the training process and are used here only to assess the efficiency of the techniques. The respective targets were defined by the variations applied and by the analysis of the signals carried out by specialists. Values less than or equal to 0.2 represent normal signals and values equal to 0.8, anomalies, being:

1. Test 1, Figure 3: Synthetic signal composed of a base frequency of 3540 rpm and the second harmonic added a white noise with zero mean and rms value (Root Mean Square) of the order of 0.5% of the energy of the harmonics. Each data block is composed of 2048 points with an acquisition frequency of 2048 Hz resulting in one second of data. The existing anomalies in the test are: 3 increases of 2 dB in the signal energy and a variation of 20 rpm in the harmonics. As the test was generated using analytical forms, this test is the only test that has 100% certainty on the targets (normal, anomaly).

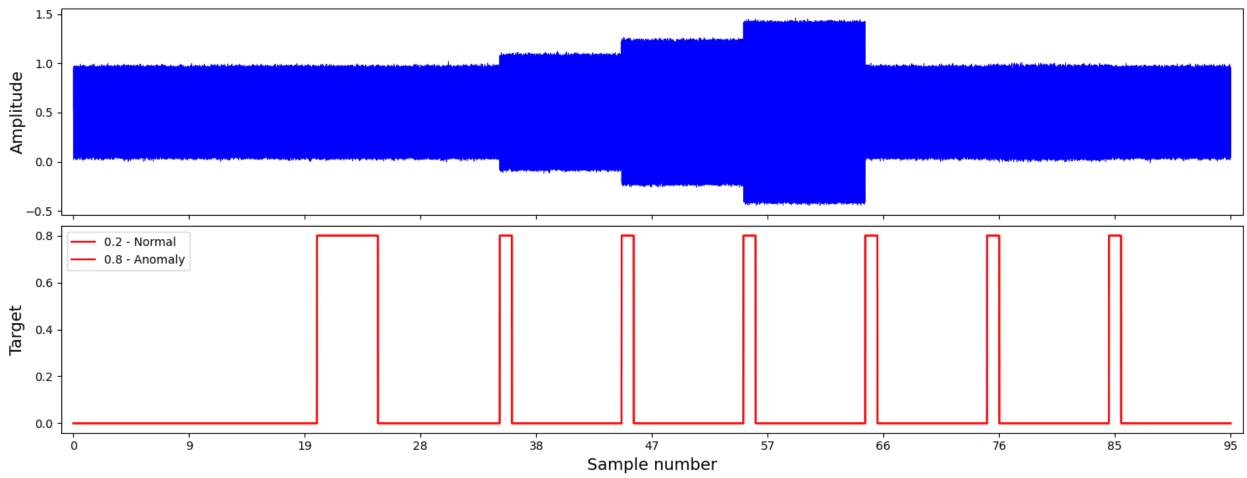


Figure 3. Time domain signal and target for Test 01.

2. Test 2, Figure 4: Displacement signals from a rotor rotating at 1800 rpm. Each data block is composed of 400 points acquired with a frequency of 1000 Hz. The anomalies introduced were increases in unbalance and impacts on the rotor.

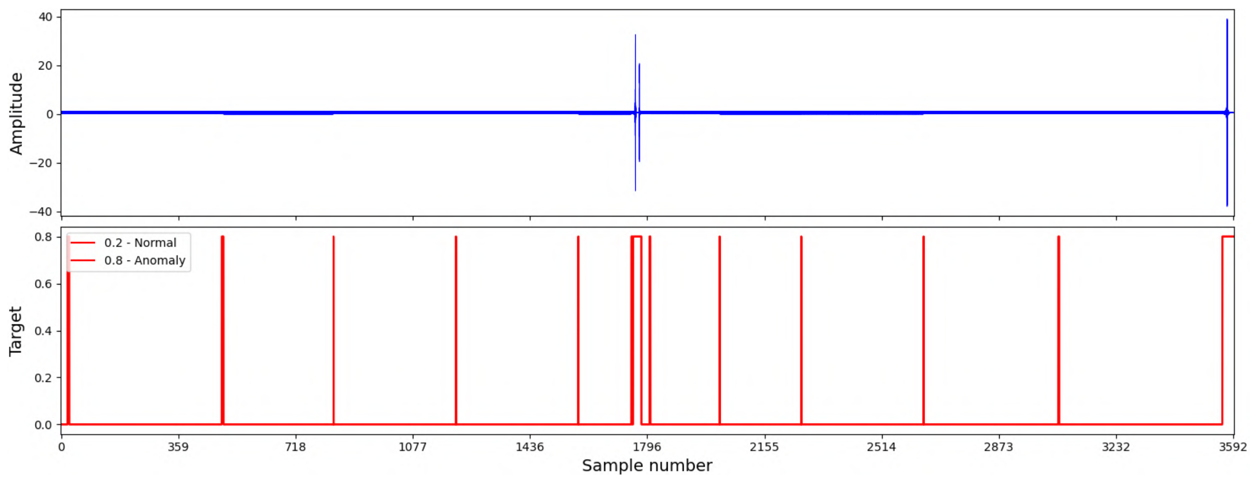


Figure 4. Time domain signal and target for Test 02.

3. Test 3, Figure 5: Displacement signals from a rotor rotating at 2244 rpm where external forces were applied simulating unbalance and misalignment.

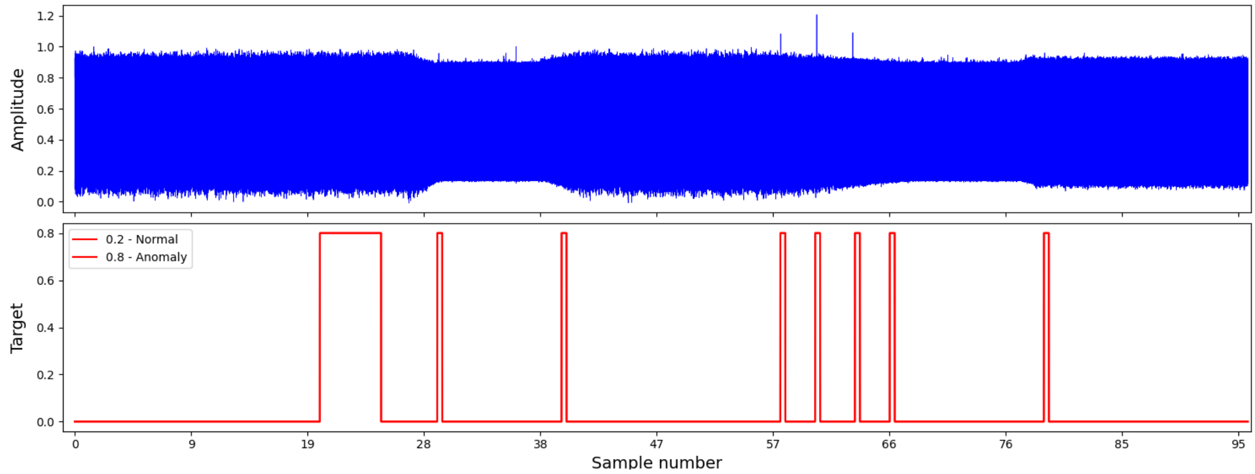


Figure 5. Time domain signal and target for Test 03.

4. Test 4, Figure 6: Acceleration signals from a rotor at a nominal frequency of 2160 rpm where anomalies were introduced by light impacts on the rotor structure and run-up and run-down. Each data block has 20000 points acquired with a frequency of 19638.8 Hz.

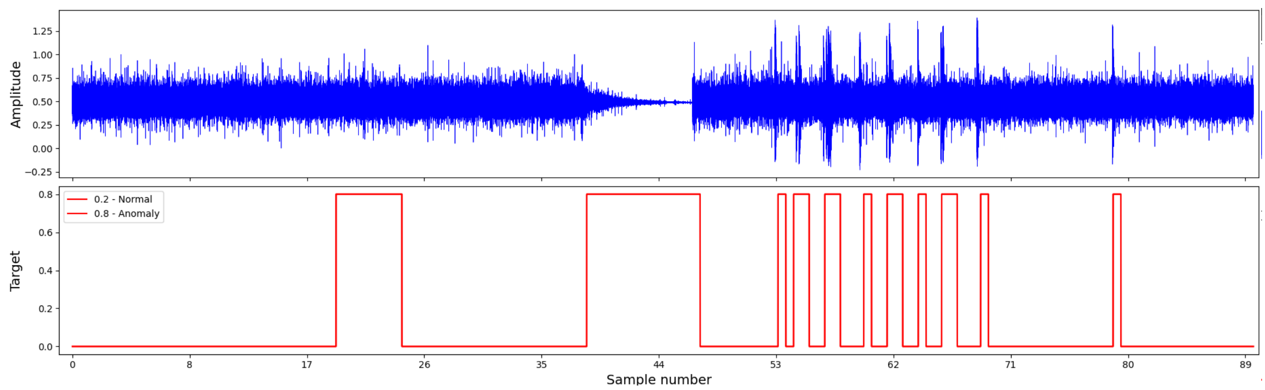


Figure 6. Time domain signal and target for Test 04.

5. Test 5, Figure 7: Signals of displacement being the anomalies: impacts, variations in speed and performing run-up and run-down.

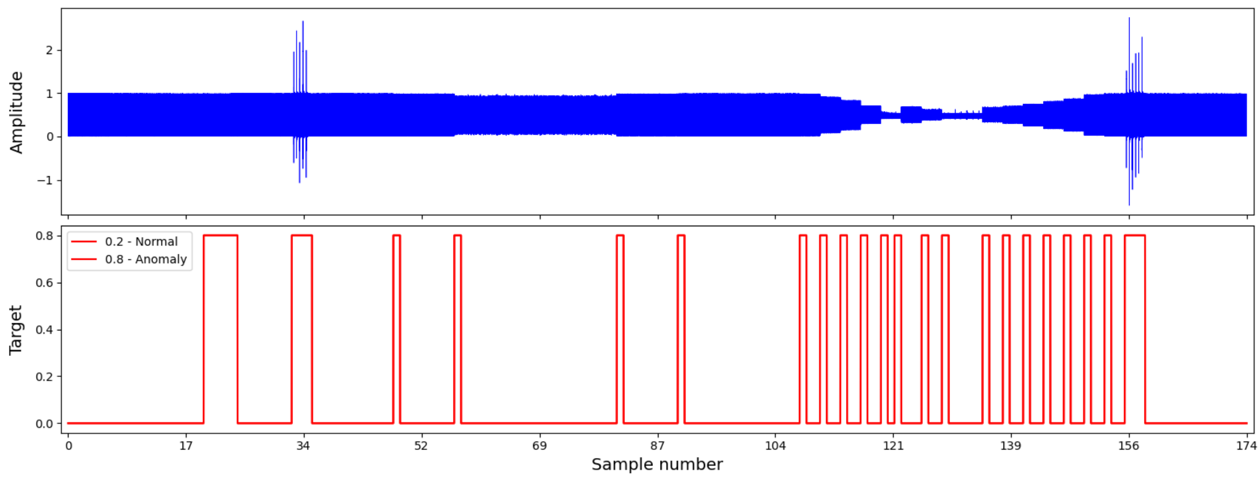


Figure 7. Time domain signal and target for Test 05.

The hyperparameters for the proposed deep autoencoder structure were:

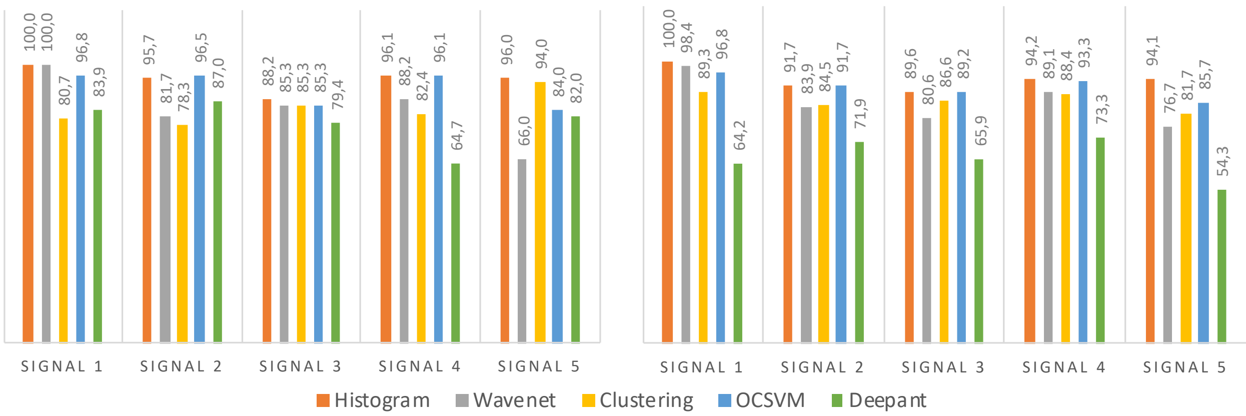
- Input: 256 neurons.
- Input: 128 neurons and relu activation function.
- Layer 1: 64 neurons and relu activation function.
- Layer 2: 32 neurons and relu activation function.
- Layer 3: 16 neurons and relu activation function.
- Layer 4: 32 neurons and relu activation function.
- Layer 5: 64 neurons and relu activation function.
- Layer 6: 128 neurons and relu activation function.
- Layer 7: 256 neurons and sigmoid activation function.

As the number of parameters to be adjusted in the training is equal to 153552 weights and bias, 150000 instances composed of data blocks with 256 points were generated from random points of the base signal where a white noise of mean zero common to the energy of 2.5% of base signal power was added. The optimizer was Adam minimizing the means squared error at 20 epoch and a batch size of 120. All histograms were estimated using n_bins = 20.

To evaluate the results, two metrics were used: Recall and F1-Score. Since it is a scenario where the machine is predominantly in a stable and normal operating condition, it is expected that there will be few anomalies. Therefore, using metrics such as accuracy could lead to an error in the evaluation of the models due to the imbalance of data between normals and anomalies. To overcome this problem, F1-Score was used, a state-of-the-art metric for evaluating anomaly detection. In addition, to assess the model's ability to correctly detect the present anomalies, the Recall was measured.

4. RESULTS AND DISCUSSIONS

The results obtained by the proposed methodology, namely Histogram, and the other methods are presented in Figures 8a and 8b, for Recall and F1-Score respectively.



(a) Recall (b) F1-Score

Figure 8. Results obtained in each test.

Analyzing the figures, it is noted that the proposed methodology has the higher metrics in all tests. Considering the Figure 8b, F1-Score obtained for all methods, in all cases the proposed methodology obtained values greater than 89%. Considering all tests, the worst result was obtained for Deepant methodology, never above 75%. The other methodologies had little variation in the metric considered, varying between 80 and 90%, with OCSVM obtaining slightly better results than other methods.

Considering the Figure 8, Recall, except for test (signal) 02, where the OCSVM technique was able to better detect the present anomalies (but with only a small difference), the Histogram obtained the best results, greater than 88% for all tests. The worst methodologies for Recall metric were Clustering (Signal 1 and 2), Deepant (Signal 3 and 4) and Wavenet (Signal 5). The constant results obtained with the proposed methodology also show that it is robust enough to perform in different scenarios.

To exemplify the reconstruction quality of the methodology, as well as the variations in the histograms and pdf, Test 01 was selected (bearing in mind that the analysis is repeated for the others). Figure 9 shows the reconstruction quality of the deep autoencoder. It can be seen the histogram of the reconstruction errors of a normal sample of test signal 1 and the probability density function (pdf) of the normal distribution with zero mean and variance equal to that of the white noise added to the training datasets of the deep autoencoder are almost the same. In other words, the pdf is the random error probability distribution function, which constitutes an excellent result. For comparison purposes, the pdf was normalized so that its maximum was equal to the histogram maximum.

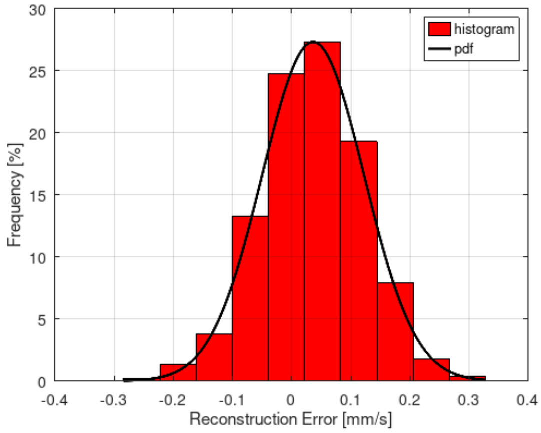


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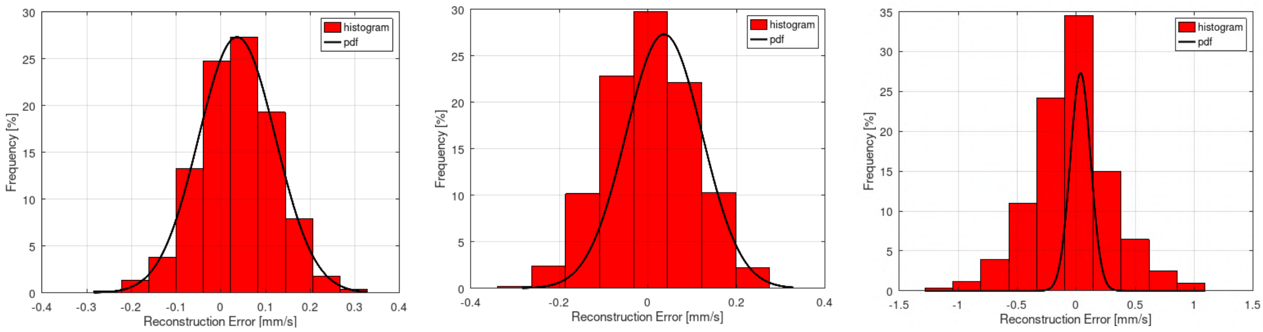
Figure 9. Histogram of reconstruction errors and probability density function.

Figure 10a, Figure 10b and Figure 10c show the histograms, and random error pdf, for three test signal samples. Figure 10a is a normal signal, Figure 10b is a signal whose amplitude has increased by 2 dB and Figure 10c is a signal where there has been a variation of 20 rpm. The purpose is to show the influence of anomalies in changing the amplitude and variation in rotation on the histogram of reconstruction errors.

Analyzing the figures, it can be observed that when presenting a variation in the signal, consequently the modification of the histograms and pdf occurs. In Figure 10a the histogram and pdf had great similarity, while in Figure 10c it can be seen that the histogram and the pdf have greater differences and the pdf already has high kurtosis, which allows the correct identification by the proposed methodology.



(a) (b) (c)

Figure 10. Histogram of reconstruction errors and probability density function for different samples.

Figure 11 shows the graph with the 95 blocks of data and the respective values of p-value and MAE using the reconstruction errors of each block.

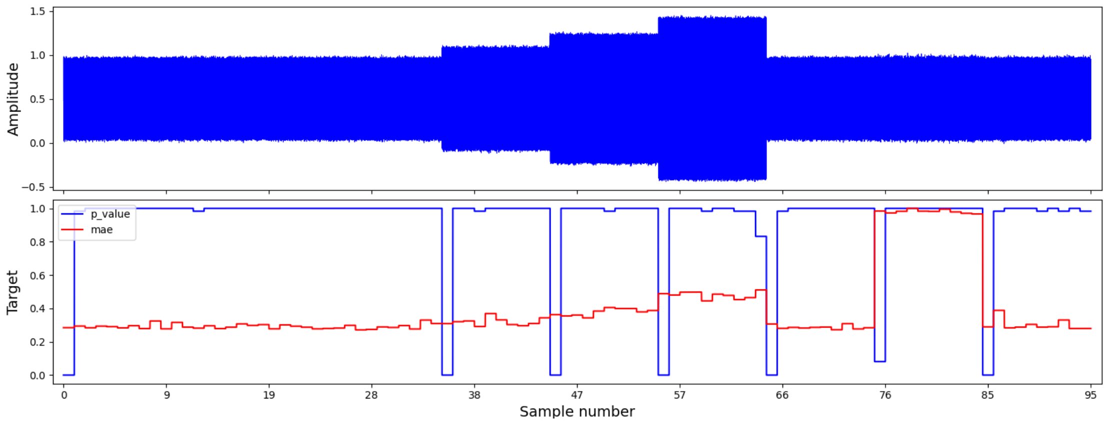


Figure 11. Complete temporal signal and target variation according to the metric used.

Analyzing Figure 11 it is observed that the p-values are much more sensitive to anomalies than a classic reconstruction error metric, which allows the correct identification of anomalies with the least possible interference from threshold adjustments. It can be noted that using the MAE and a static threshold, several anomalies would not be identified, as well as normal signals would be identified as anomalies.

5. CONCLUSIONS

This work presents a new methodology for detecting anomalies in Edge Analytics applications in rotating machinery using vibration signals. The combination of the Deep Autoencoder artificial intelligence model with the Histogram statistical model allows the use of an evaluation metric that is more sensitive to variations in the signal, avoiding threshold adjustment problems as in other metrics. The proposed methodology was able to achieve F1-Score and Recall results greater than 88% in all cases, better than other analyzed methodologies.

Considering the analysis of the reconstruction quality of the methodology, as well as the variations in the histograms and pdf, it can be noted that when presenting a variation in the signal, consequently the modification of the histograms and pdf occurs, which allows the correct identification by the proposed methodology.

The p-values of the proposed methodology are much more sensitive to anomalies than a classic reconstruction error metric, which allows the correct identification of anomalies with the least possible interference from threshold adjustments.

The results show that the methodology is able to identify significant variations in the signal, preventing possible failures from being detected, and reducing the cost of storing similar data. Furthermore, the unsupervised nature of the methodology allows for dissemination in industrial settings, where labeled data is rarely present.

6. ACKNOWLEDGEMENTS

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8. RESPONSIBILITY NOTICE

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