Corrosion-like Defect Severity Estimation in Pipelines Using Convolutional Neural Networks

1st Guilherme Rezende Bessa Ferreira
Department of Mechanical Engineering
Pontifical Catholic University of Rio de Janeiro
Rio de Janeiro, Brazil
Email: bessa.guilherme@aluno.puc-rio.br

2nd Paula Aida Sesini
Department of Mechanical Engineering
Pontifical Catholic University of Rio de Janeiro
Rio de Janeiro, Brazil
Email: paulaaida@esp.puc-rio.br

3rd Luis Paulo Brasil de Souza
Department of Mechanical Engineering
Pontifical Catholic University of Rio de Janeiro
Rio de Janeiro, Brazil
Email: luisbr@puc-rio.br

4th Alan Conci Kubrusly
Centre for Telecommunication Studies
Pontifical Catholic University of Rio de Janeiro
Rio de Janeiro, Brazil
Email: alan@cpti.cetuc.puc-rio.br

5th Helon Vicente Hultmann Ayala
Department of Mechanical Engineering
Pontifical Catholic University of Rio de Janeiro
Rio de Janeiro, Brazil
Email: helon@puc-rio.br

2021 IEEE Symposium Series on Computational Intelligence (SSCI) | 978-1-7281-9048-8/21/$31.00 ©2021 IEEE | DOI: 10.1109/SSCI50451.2021.9659884

***Abstract*—The study of methodologies for the effective monitoring of structural damage and leaks in oil and gas pipelines has been a relevant topic in recent years due to the importance of avoiding fatalities, environmental disasters, and economic losses. In this context, the present study aims at developing a deep learning-based framework for estimating the severity of corrosion-like defects in pipelines. The dataset used in this work was generated by finite element simulation of a simple cylinder with different defect depths. The simulation was carried out with the commercial software On-scale™. In this way, 100 samples were obtained representing diverse structural conditions. A Convolutional Neural Network (CNN) architecture based on LeNet-5 was proposed to address the problem. This architecture was trained and tested 100 times with a Monte Carlo Cross-Validation procedure. Results show that the proposed architecture achieved good performance, with mean $RMSE$ and R^2 of 0.4448 and 0.9637, respectively.**

***Index Terms*—structural health monitoring, corrosion, pipeline, finite element method, convolutional neural networks**

I. Introduction

Oil pipelines are considered the main mean of transporting petroleum products over long distances [1] as they have been shown to be the most economical and safest. These structures suffer various types of damage mainly caused by the effects of corrosion, which can lead to fatalities, environmental disasters and economic losses [2]. Therefore, increasing the safety of the pipelines is essential to prevent these serious problems. Thus, the study of methodologies for the effective monitoring of structural damage and leaks in oil and gas pipelines is extremely necessary [3]. Recent studies show that there are several methods that can be used and that they usually present accurate results [4]–[7]. Although these recent studies introduce effective solutions for monitoring oil pipelines, remains a need to improve these systems in several aspects. It is of great importance that these systems indicate the severity of both the leakage and the structural damage, reliably and with high precision of the results. It is also important to invest in numerical simulation studies to generate data without the necessity of experiments to reduce costs.

Liu et al. [4] propose an acoustic leak location system for gas pipelines through experiments, using four methods proposed for different situations. Based on these results, an experimental apparatus on a laboratory scale was built and experiments were carried out for the same leak point. Finally the methods were verified and applied to find leaks. The maximum leak location errors for the four methods were: -0.59%, -2.44%, 1.83%, and -11.68%. Using these new methods, the presented system can be applied for protection and monitoring of natural gas pipelines. This study presents precision in the results but uses experimental studies that mean a high cost compared to numerical simulations and does not present studies on the severity of leakage.

A study that considers the analysis of leak detection signals is the one by Xiao et al. [5]. They feature an integrated leak detection method using acoustic signals combined with wave transformation and support vector machine (SVM). For leak detection and severity classification the Relief-F algorithm is applied. This selects the best ranked settings that will be used as input to the SVM classifiers. The method is validated from laboratory experiments. The results allow us to conclude that the methodology presents an accuracy of 99.4% to discern between a leaky and non-leakage status and 95.6% to classify the leak status as normal or severe. Therefore, the authors suggest that this methodology shows promise for the development of a real-time monitoring system. This study proposes methods for analyzing signals for leak detection, but does not consider structural damage detection.

Ren et al. [7] introduce a new application of the optical frequency domain reflectometry (OFDR) technique to monitor both corrosion and leakage. In order to verify this method, corrosion and leakage simulation tests are carried out. For the corrosion test, several optical fiber sensors were adhered to the surface of the duct, maintaining the same distance interval between them, forming a sensor vector. From this vector, a stress distribution diagram is created (hoop strain nephogram) that shows the corrosion level for each localized corrosion point. In the case of the leak test, the results indicated that the distributed optical fiber sensor (DOFS) can detect the duct leaks. Therefore, it is possible to monitor the corrosion and leakage of the pipeline from the theory of stress distribution and DOFS. This study considers both leaks and corrosion, but does not consider structural damage caused by other reasons.

Yaacoubi et al. [6] use the Ultrasonic Guided Waves (UGW) technique for the safe monitoring of tubular structures, mainly studying the stability of measurements. Defects produced by corrosion are mapped onto a full scale pipe. Several aspects that influence the detection of defects are studied: quality of adhesion of the probe to the pipe, the type of propagation mode and the central frequency, and variations in ambient and operating conditions. From the results obtained, it can be concluded that ultrasonic waveguides are an efficient technique for monitoring pipes. However, to increase the level of efficiency, statistical algorithms that indicate false alarms are needed.

In the work of Zhang et al. [8] it is presented the combination of a DOFS with the conjugate beam method to solve the deformation monitoring of pipelines subjected to sudden temperature changes. To validate the deformation method, a finite element model of a 50 meter long pipe was used and a 4 meter long Polyvinyk Chloride (PVC) pipe was constructed. In both tests, distributed and discrete stress data were used to calculate the pipe deformation using the conjugate beam method and the displacement curves of the two cases were compared. The results of the two tests indicated that the pipe deformation can be well monitored and that the proposed method can be applied. However, the studied method does not detect leaks and does not indicate the severity of the pipe deformation.

A method that uses decision schemes and algorithms to analyze the detected signals is presented by Liu et al. [9]. They propose a new leak detection method based on Markov resource extraction and a two-stage decision scheme. The Markov feature is introduced to extract information from the leak. Through a transformation the pressure can be transformed into a Markov chain. By extracting the dynamic properties, pressure can be effectively represented. Using a switching rule, short-term and long-term detection models can be correctly selected to identify the pipe status quickly and accurately. The proposed method is verified using pressure data collected from industry and experimental results, indicating a high accuracy and low rate of false positive results. This method does not consider the detection of structural damage.

In [10] the authors propose a new method for detecting leaks in gas pipelines. The new method is based on non-isothermal process modeling. The new software-based method is developed by designing an unknown input observer. It treats the disturbance produced by changes in temperature and pressure drop, which comes from the pumping station, and estimates the limiting flow of the pipeline. A new adaptive model updates the temperature of pipe boundary pressure changes to estimate the location of the leak. A simulation of a pipeline with connection to the consumer was demonstrated. This method uses numerical modeling but does not consider algorithms for analyzing the severity of leakage.

Although these works present effective solutions for monitoring oil pipelines, several aspects still need further study. It can be seen that many authors use experiments to validate the proposed methods [4]–[8]. The use of numerical simulation to generate data and thus avoid the need for experiments that require a higher cost is one of the aspects that need further research. In studies presented in the literature is also observed that some authors consider the detection of structural damage [6], [8] and others of leaks [4], [5], [9], [10], but these works do not present techniques for indicating the severity of failures. Therefore, it is important to develop detection methods that, besides detecting structural damage, indicate its severity.

Given the shortcomings previously mentioned, it can be concluded that the main gaps are: lack of studies using numerical simulations to generate data and absence of tools that provide information about the severity of the structural damage. The major contribution of this work is to develop a deep learning-based framework for corrosion-like defect estimation in oil pipelines, indicating not only the presence of defect but its severity. For that purpose, numerical simulation experiments were developed, resulting in 100 different structural conditions of a pipe. A Convolutional Neural Network (CNN) architecture is proposed, and its performance is assessed through different regression metrics.

This work is organized as follows: Section II presents a description of the problem herein addressed; Section III is dedicated to the methods ; Section IV describes the results and, finally, Section V presents the conclusions.

II. Problem Description

Data used to evaluate the machine learning technique introduced here, were obtained using numerical simulation of a case of study. This consists of a cylindrical structure, mimicking the geometry of an oil and gas pipeline. The pipe presents a defect in the upper region that simulates a damage produced by corrosion. It was simulated the propagation of waves in the z-axis direction. The excitation signal is applied as an external cylindrical source in the central region of the pipe to represent the effect of a transducer. The simulation

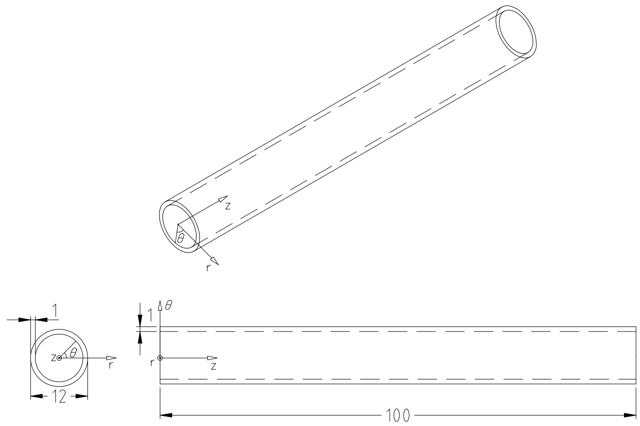


Fig. 1. Geometric description of the pipe

was performed with a software named Onscale™, which uses the Finite Element Method (FEM).

A. Pipe FEM model

The model consists of a 12 mm diameter steel pipe with a thickness of 1 mm and length of 100 mm, see Fig. 1. The pipe presents a defect in the upper region, located 40 mm from the center of the cylinder. The length of the defect in the z-axis direction (Ld) is 4 mm and the width of the defect in the theta direction (Thd) is 90 degrees. To discretize the domain, a mesh with a square element of size equal to 0.1 mm was used. The excitation signal consists of a ten cycle sine function with a frequency of 500 kHz. This signal is applied as an external cylindrical source in the central region of the pipe, in the direction normal to the pipe circumference. The source thickness in the z-axis direction is 1 mm, which is about the size of the half wavelength of one of the modes being excited by the 500 kHz frequency. The boundary conditions are set as absorber at the ends of the pipe and free in the rest of the cylinder.

B. Defect modeling

Simulations were performed for 100 different defect depth values between 0 mm and 1 mm. The objective of these simulations was to obtain results for different cross-sectional areas (see Fig. 2) of the defect.

C. Simulation description

The numerical simulation computed the z component of the particle velocity wave at the nodes along a line in the cylinder in the z-axis direction passing through the defect. This line starts at the end of the source and ends at the upper end of the pipe. To show the results three points were chosen. The points are located at 1 mm (end of the source), 20.5 mm (about half of the upper part of the pipe), and 40 mm (beginning of the defect). All the distances are measured from the center of the cylinder. The responses acquired at each one of the above

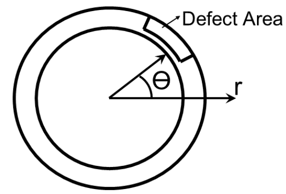


Fig. 2. Schematic representation of the defect area.

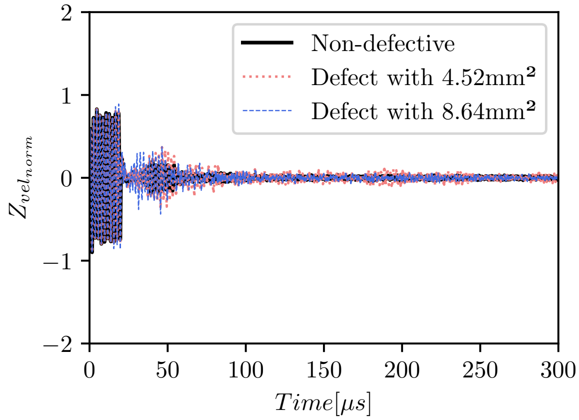
mentioned points are depicted in Fig. 3. In all figures, three different simulation cases were plotted. Therefore, the black line corresponds to the non-defective case, while the red and the blue lines correspond to defective cases with respective areas equal to 4.52mm² and 8.64mm².

III. Methods

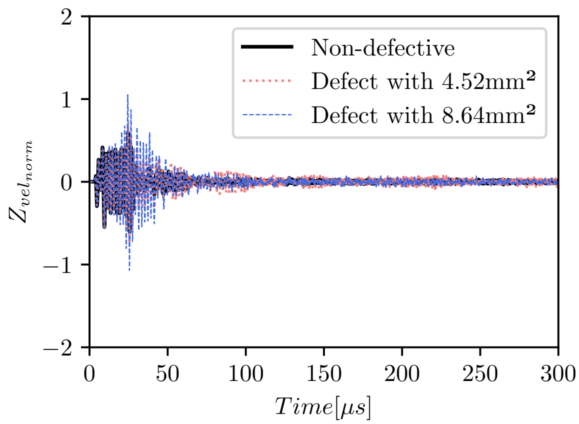
A. Convolutional Neural Network (CNN)

CNNs are a robust deep learning algorithm capable of dealing with data of different dimensions like one-dimensional (1D) signals and sequences; two-dimensional (2D) images or spectrograms; and three-dimensional (3D) data such as videos or RGB images [11]. Given the flexibility of dealing with input data of different dimensions and the capacity of processing data in its raw state, without the need for handcrafted feature extraction, CNNs have been widely employed in diverse fields such as computer vision [12], natural language processing [13], time series classification [14], time series forecasting [15] and structural health monitoring [16].

A typical CNN can be divided into two main blocks. The first part, composed of convolutional and pooling layers, functions as a features extractor, while the second part, composed of fully connected layers, builds a relationship between the extracted features and the target variable. In synthesis, the convolutional layer generates a feature map by applying convolutional filtering operations, with small sliding windows, to an entity. The output of this layer is then reduced by a pooling layer while preserving the relevant information. Traditionally, the pooling operations consist in calculating the maximum (max pooling) or the average (average pooling) value of a subarray. These convolution and pooling operations can be repeated several times before concatenating the last feature map into a 1D vector provided to the fully connected layers. The dense layers, another name for fully connected layers, are composed of artificial neurons and activation functions. They are the same as the layers that compound shallow learning neural networks. The activation function is the source of non-linearity of the models, and it can be of many types being the rectifier linear unit (ReLu) commonly used in deep learning applications [17].



(a)



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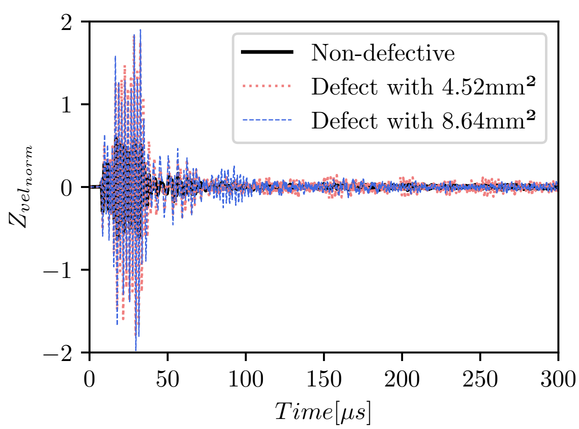


(c)

Fig. 3. Axial component of the particle velocity wave for different positions along pipe length: at 1mm (a), at 20.5mm (b), and at 40mm (c).

B. LeNet-5

The LeNet-5 is a type of CNN proposed by LeCun et al. [18] in the late 1990s, and it is one of the several widespread architectures developed to date [19]–[23]. The LeNet-5 was designed to solve the problem of handwritten digits recognition, for which it achieved great success. The structure is comprised of seven layers, including convolutional, pooling, and fully connected ones as depicted in Fig 4. In this architecture, the convolutions are done with 5x5 sliding windows, while the subsampling operations are performed with a pool size equal to 2x2. It is also worth noticing that the first set of convolutional and subsampling layers are composed of 6 filters, and this value increases to 16 in the subsequent layers. The dense layers have 120 and 84 nodes, respectively. Finally, the output layer has 10 nodes with Euclidean Radial Basis Function as an activation function.

Despite being firstly employed to solve handwritten digits recognition problems, for which they were very successful, several works have adapted or improved the LeNet-5 architecture aiming at addressing different tasks [24]–[26]. Therefore, it has shown to be a flexible algorithm capable of dealing with problems of varied nature after some adaptations.

C. Proposed CNN architecture

In this work, a CNN architecture based on LeNet-5 is proposed as means of estimating the area of corrosion-like defects in pipelines. The structure of the CNN consisted of two convolutional layers, two average pooling layers, two fully connected layers, and one output layer, as depicted in Fig 5 .

The proposed CNN requires 2D input data. Therefore, the 1D ultrasonic signals need to be preprocessed before being fed to the CNN. The 1D signals were interpolated, moving from 44,120 to 65,536 data points, and the new signals were converted into 2D grayscale images with a resolution of 256x256 pixels. Fig. 6 depicts some examples of images generated from the ultrasonic signals. In the CNN, the automatic feature extraction was performed by two sets of convolutional layers followed by average pooling layers. The structure of the convolutional layers consisted of 30 filters with a 3x3 sliding window (stride of 1) and ReLu activation function, and the shape of the sliding window for the pooling layers was 2x2 (stride of 2). The automatically extracted features were then connected to three dense layers with ReLu activation function. The first dense layer had 56 nodes connected to a second layer with 28 nodes followed by a single node output layer, used to estimate the area of the defect.

IV. Results

This section is dedicated to evaluating the performance of the proposed CNN architecture. For this purpose, different regression metrics, namely, Root Mean Squared Error ($RMSE$), R-Squared (R^2), Mean Absolute Error (MAE), and Maximum Error ($MAXE$), are addressed. A Monte Carlo Cross-Validation approach was adopted to split the data into training and test 100 times. This procedure provides a robust performance estimate, indicating how the model generated

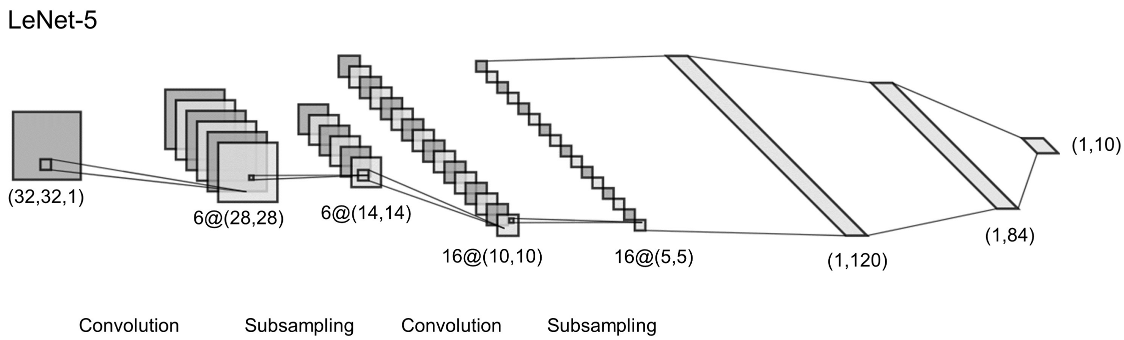


Fig. 4. Architecture of the LeNet-5 [18].

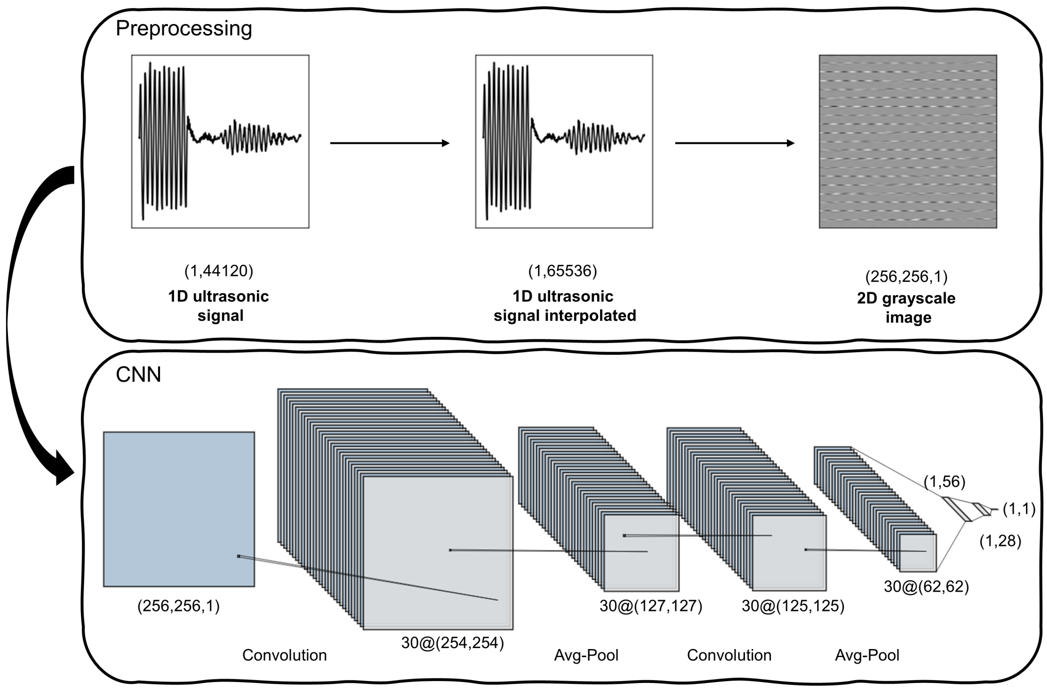


Fig. 5. Schematic drawing showing the preprocessing procedure and the structure of the proposed CNN architecture for defect estimation.

from the proposed algorithm is affected by different data partitions.

Table I summarizes the results obtained throughout the test phase for all data resamples. Both the $RMSE$ and MAE are metrics that measure the average magnitude of the error between the actual and predicted values. The difference is that the $RMSE$ is a quadratic rule that gives high weight to higher errors. The results show that the mean $RMSE$ was higher than the mean MAE indicating variations in the magnitude of the errors. Despite that, both metrics were close to the ideal value of 0.0. The $MAXE$ represents the maximum error for a set of test samples. The fact that the mean $MAXE$ value was higher than 1.0 indicates that some of the models committed relatively large errors. The R^2 is a measure that represents the goodness of fit of a regression model, and its ideal value of 1.0 is achieved when the predictions are equal to the real values. One can see that the models achieved a mean R^2 value of 0.9637, which is relatively close to the ideal. Therefore, the results presented in Table I indicate that the proposed architecture is suitable for estimating the area of corrosion-like defects in pipelines.

TABLE I
SUMMARY STATISTICS OF THE REGRESSION METRICS OBTAINED FOR ALL THE 100 TESTS.

	$\boldsymbol{RMSE}$	$\boldsymbol{MAE}$	$\boldsymbol{MAXE}$	$\boldsymbol{R^2}$
Mean	0.4448	0.2719	1.6659	0.9637
Stdev	0.1740	0.0890	0.8160	0.0317

Further analysis of the results is provided by the raincloud

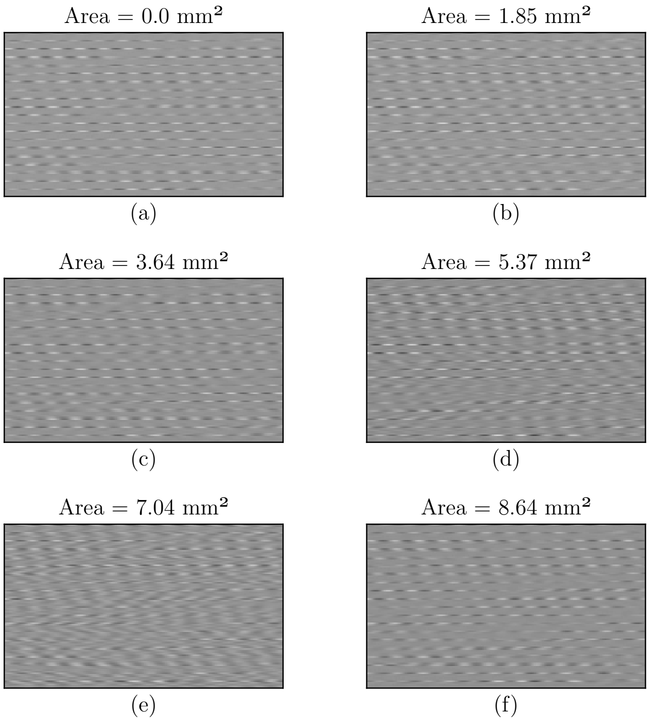
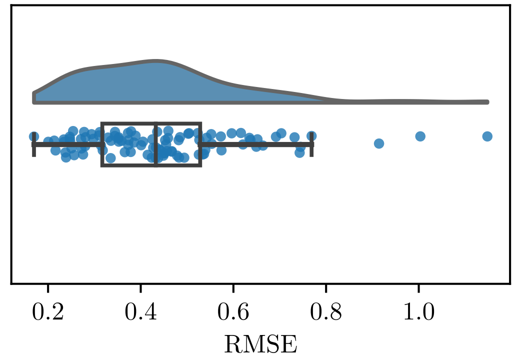


Fig. 6. Examples of 2D grayscale images generated from the ultrasonic signals. (a) depictsa non-defective sample, and (b) to (f) depicts defective samples with increasing defect area.



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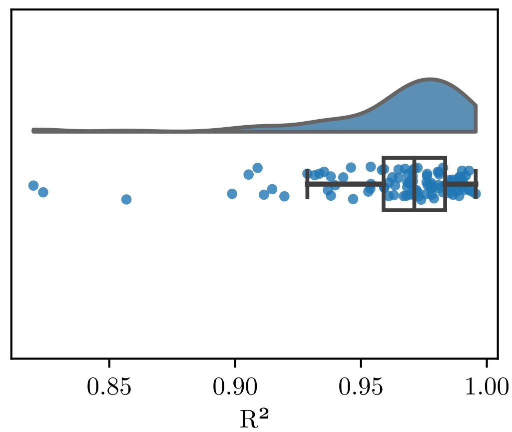

(b)

Fig. 7. Raincloud plots of the $RMSE$ (a), and the R^2 (b).

plots [27] depicted in Fig. 7. These plots comprise information about all the 100 test procedures, providing an overview of the results. Analyzing Fig. 7a, one can see that, despite three outliers, $RMSE$ values ranged between 0.2 and 0.8, which represents good results. Regarding the R^2, the scenario is even better. Fig. 7b shows that, for most cases, the R^2 value was higher than 0.95 and sometimes even reached values very close to the ideal value of 1.00.

The results of the model with the best performance are depicted in Fig. 8. For this case, the $RMSE$, R^2, MAE, and $MAXE$ were equal to 0.1697, 0.9956, 0.1172, and 0.7640, respectively. As seen in the figure, the model provided an excellent approximation between the predicted and actual values. Moreover, the maximum error occurred for a sample where the predicted value was higher than the actual one.

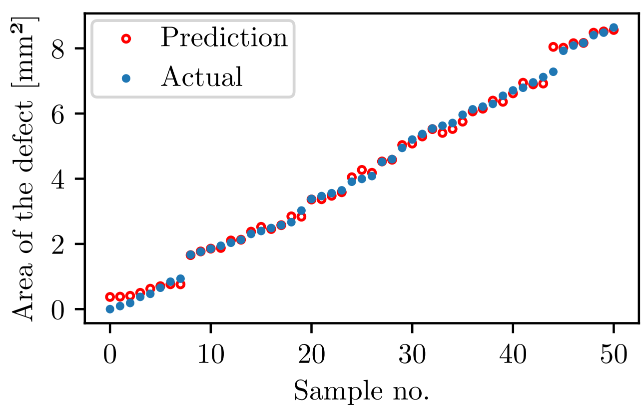

Fig. 8. Actual and predicted values for the best case amongst all models. The model was capable of predicting the area of the defect with good approximation. It is valuable to notice that, for the case that the error was maximum, the value predicted was higher than the actual area of the defect.

V. Conclusion

The present paper addressed a deep learning-based framework for corrosion-like defect estimation in oil pipelines using data obtained through finite element simulations. In total, 100 cases representing different levels of corrosion severity were simulated to enable the evaluation of the deep learning framework. The CNN was trained and tested 100 times, providing rich information about the performance of the proposed architecture. Results indicate the suitability of the developed CNN to the problem at hand.

Despite the promising results, further developments are necessary. Adding new simulation cases varying the position of the defect must be considered as an indication of future work. Another improvement to be considered is the development of an experimental procedure to validate the results herein obtained. Regarding the machine learning knowledge field, neural architecture search (NAS) [28]–[30] algorithms can be used to enhance the results.

ACKNOWLEDGMENT

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001. In addition, the authors would like to thank the financial support from the Brazilian National Agency for Petroleum, Natural Gas and Biofuels (ANP) through the Human Resources Program for the Petroleum, Natural Gas and Biofuels sector - PRH-ANP.

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