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# A Hybrid FEM-CNN for Image-Based Severity Prediction of Corroded Offshore Pipelines

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**Abstract.** The combination of the Finite Element Method (FEM) with Convolutional Neural Networks (CNNs) presents a key breakthrough in the assessment of the structural integrity of offshore pipelines. The advantage of the standard FEM is in stress visualization, but it is time-consuming due to high computational analysis. This research aims to quickly and accurately determine the severity of pipeline corrosion categorized as high, intermediate, or low through stress images generated from FEM. A transfer-learning algorithm was applied to refine and validate the model using a diverse image dataset of uniformly corroded pipelines (200x200 mm, 100x100 mm, 75x75 mm, 50x50 mm, and 10x10 mm), annotated with corresponding severity levels. Moreover, the model was validated for prediction with irregular-sized corroded pipelines (50x100 mm and 10x100 mm). Both samples are modeled for degrees of corrosion, 30%, 50%, and 70% of the corrosion depth, with API 5L X42 specifications. An exceptional predictive accuracy was observed, attaining average confidence levels between 97% and 100%. This work substantially augments the effectiveness of structural analyses that provide a better safety feature for critical infrastructural assets within the oil and gas industry and has great advantages to engineers, researchers, and academicians working on pipeline integrity management.

## 1 Introduction

Offshore pipelines have a significant role in the global energy infrastructure, allowing the movement of oil and gas from underwater fields to processing plants and markets. However, these pipelines are subject to constant threats to their integrity for a variety of environmental and operational reasons; corrosion has emerged as one of the major issues associated with these pipelines [1], [2]. Corrosion is a phenomenon that transpires naturally, exacerbated by

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the harsh marine surroundings and highly reactive chemical processes, resulting in the deterioration of materials by inducing thinning of the pipeline wall and compromising structural stability. Decreased structural reliability significantly increases the risk of major failures in pipelines, such as leaks or ruptures, that will lead to serious consequences environmentally and economically [3], [4].

Indeed, there is a significant relationship between the phenomenon of corrosion and the mechanical reliability of offshore pipelines, which is quite relevant to the burst pressure analysis. Burst pressure is the definition of the highest internal pressure that a pipeline can withstand without failing, and it has enormous implications for structural integrity and operational life. This could reduce the mechanical strength of the pipeline and lower its burst pressure capacity. As such, corrosion requires comprehensive monitoring and predictive evaluation to avert the possible failure of a pipeline [5], [6]. Current approaches for evaluating the burst pressure capacity and the effects of corrosion rely on extensive FEM simulations. Although such an approach is accurate, it requires extremely high computational effort and time, especially when assessing complex patterns of corrosion and their impact on the integrity of pipelines [7], [8].

Given these challenges, there is an emergent reliance on advanced technologies for assessing and monitoring the degradation of offshore pipelines [9], [10]. This paper proposes the application of FEM coupled with convolutional neural networks (CNNs) for corrosion severity prediction based on burst pressure. By creating and analyzing stress-based images of corroded pipelines, the approach greatly improves the accuracy of its predictions and significantly reduces the time taken to analyze these images. Hence, the integration approach of the FEM and CNNs amalgamates the intricate stress analysis capabilities of FEM with the swift and data-oriented results provided by CNNs to assess the extent of corrosion. Consequently, this aids in forecasting the consequent impacts on burst pressure. This research signifies a groundbreaking initiative that could potentially reshape the traditional practices of monitoring and upkeeping critical facilities by oil and gas stakeholders [11].

## 2 Methodology

This research utilized a stress-based image dataset generated from FEM for uniformly corroded pipelines and applied an image transfer learning algorithm using CNNs to forecast the severity level of irregular-sized corroded pipelines.

### 2.1 Image Generation using FEM

In the initial stage, FEM models were established for offshore pipelines, showcasing both uniform and irregular corrosion. The offshore pipeline dimensions, in the presence of localized corrosion, were idealized to be 1000 mm long, with a diameter of 168 mm and a thickness of 9.5 mm. Each model was characterized by specific boundary conditions and material properties mirroring the realistic service environment of API 5L X42 [12], [13]. Stress analyses were conducted to assess the impact of internal pressures on the material, simulating burst conditions until reaching the yield point, indicating potential failure. The samples of uniformly corroded pipelines are summarized in **Table 1**.

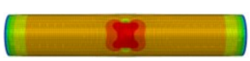
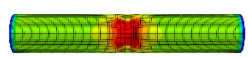
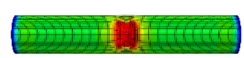
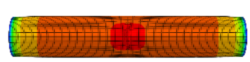
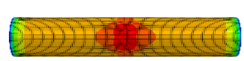
The simulations produced stress distribution images, with the corresponding corroded geometries categorized based on severity levels: high, intermediate, and low severity. The severity classification is linked to the burst pressure levels exerted on the pipeline, with high risk observed at pressures below 42 MPa, intermediate risk between 42 MPa and 55 MPa, and low risk above 55 MPa. These criteria were established considering the material failure characteristics, supported by research indicating that a bare pipe model could withstand bursts up to 58 MPa using FEM [14], [15], [16]. The samples of irregular-sized corroded pipelines are visually represented in **Table 2**.

**Table 1.** Samples of uniformly corroded offshore pipelines (for training in CNNs).

| Size of corrosion (mm) | Percentage of corrosion | Severity level |
|---|---|---|
| 200x200 | 20%<br>30%<br>40%<br>50%<br>60%<br>70%<br>80% | Low<br>Intermediate<br>High |
| 100x100 | | |
| 75x75 | | |
| 50x50 | | |
| 10x10 | | |

*Note: The 7 samples of each corrosion sizes are orientated 10 times, having a total of 350 samples in the database.

**Table 2.** Samples of irregular-sized corroded offshore pipelines (for prediction in CNNs)

| Percentage of corrosion / Size of corrosion (mm) | 30% | 50% | 70% |
|---|---|---|---|
| **50x100** |  |  |  |
| | RX42-30-6 | RX42-50-6 | RX42-70-6 |
| **10x100** |  |  |  |
| | RX42-30-7 | RX42-50-7 | RX42-70-7 |

## 2.2 Transfer Learning using CNNs

The experiment was conducted in a model training setting using the TensorFlow tool and Google Colab, employing the EfficientNetV2 architecture for efficient transfer learning. EfficientNetV2 is designed to manage the trade-off between model size, accuracy, and computational efficiency through compound scaling of three key factors: width, depth, and resolution [17]. The process is illustrated in **Figure 1**.

Phase 1 involves developing the model using an image dataset of uniformly corroded pipelines, comprising stress images and severity levels. These images are input to the CNN for feature extraction through convolutional and pooling layers, followed by classification into three severity levels. The samples of uniformly corroded pipelines are used as the database. Phase 2 predicts the severity of irregular-sized corroded pipelines using the developed CNN model. Stress images of irregularly sized corroded pipelines, without predefined severity levels, undergo similar feature extraction and classification, allowing the CNN to predict their severity levels.

EfficientNetV2 serves as the base model, featuring multiple convolutional layers for feature extraction, an input layer for stress images, and fully connected layers for classification. It balances accuracy and computational demand with 5,923,155 total parameters, including 3,843 trainable and 5,919,312 non-trainable parameters.

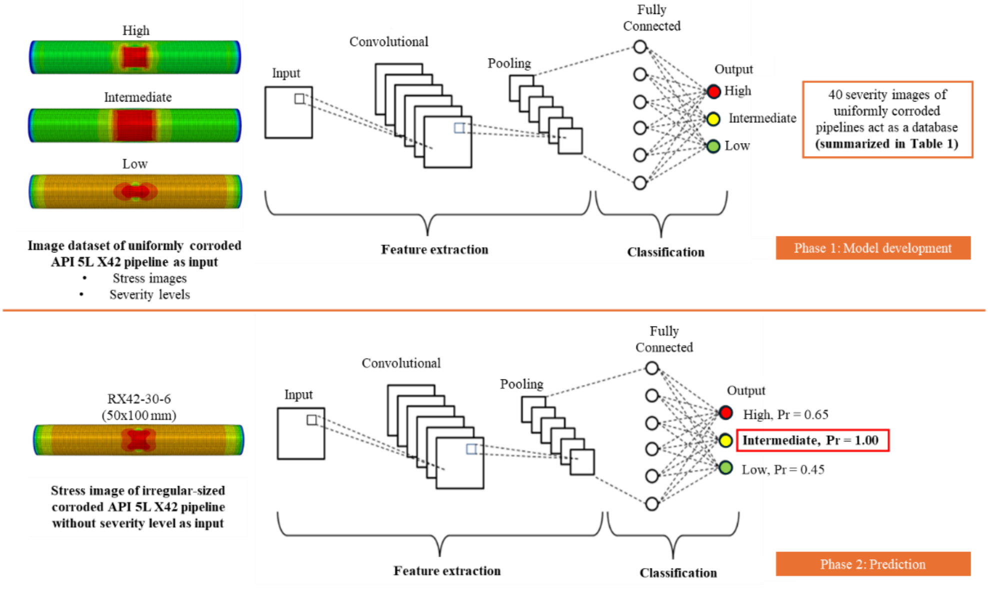



**Figure 1**. The development of the CNN model and prediction using the transfer learning process.

## 3 Results and Discussion

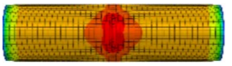
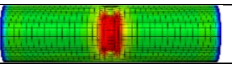
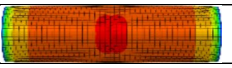
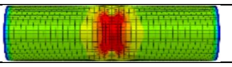
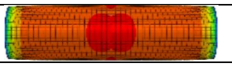
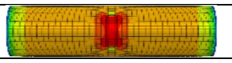
**Table 3** provides the prediction of irregular-sized corroded pipelines within variations of burst pressure based on the input learned from the uniformly corroded pipeline's severity classes. The result demonstrates high accuracy and reliability in its assessments.

*Accuracy and prediction*: The predictions from the CNNs model have remained consistently in line with the actual assessed severity levels. For example, in cases such as RX42-70-6, in which the actual and predicted severity levels are 'high', with a corresponding burst pressure of 41.3547 MPa, the ability of the model to determine severe conditions from stress images is highly accurate. This is important since it relates the high severity levels inversely to low burst pressures, meaning a high possibility of pipeline failure.

*Consistency and reliability*: The scores for prediction confidence, denoted by 'Pr', are uniformly high across almost all cases, with five out of six achieving a perfect score of 1.00 and the sixth 0.97. This seems to imply that the model is not only correct but that its analysis is also consistent, giving reliable predictions that one can trust in practical applications.

*Percentage of corrosion*: There is a significant correlation between the percentage of corrosion and the levels of severity. For example, RX42-30-6 and RX42-50-6 are both correctly predicted as intermediate severity, and RX42-70-6 is predicted as high severity. This goes in line with the understanding that higher percentages of corrosion lower burst pressures and increase severity. Yet, samples of 10x100 mm, have all been predicted as low severity since smaller corroded areas do not impact burst pressure significantly, despite the variation of the corrosion degree.

**Table 3**. Results of severity prediction by transfer learning using CNNs.

| Input (Image) | Prediction | Actual | Burst Pressure (MPa) | Image |
|---|---|---|---|---|
| RX42-30-6 (50x100 mm) | Intermediate | Intermediate | 54.7638 |  Pr: 1.00 |
| RX42-30-7 (10x100 mm) | Low | Low | 58.5665 |  Pr: 1.00 |
| RX42-50-6 (50x100 mm) | Intermediate | Intermediate | 49.1616 |  Pr: 1.00 |
| RX42-50-7 (10x100 mm) | Low | Low | 57.8761 |  Pr: 1.00 |
| RX42-70-6 (50x100 mm) | High | High | 41.3547 |  Pr: 1.00 |
| RX42-70-7 (10x100 mm) | Low | Low | 55.9357 |  Pr: 0.97 |

*Note: The images in the output may not be clear due to the reduction of resolution caused by the CNNs model's processing, reducing the dimensionality of the input images to capture the essential features for prediction.

*Model performance*: **Figure 2** show remarkable performance, with both training and validation accuracy stabilizing to around 100% with only 10 epochs. The loss plot shows a steep drop in the curve and then a stable plateau near zero, meaning it is developing into a well-regulated model with a lack of overfitting.

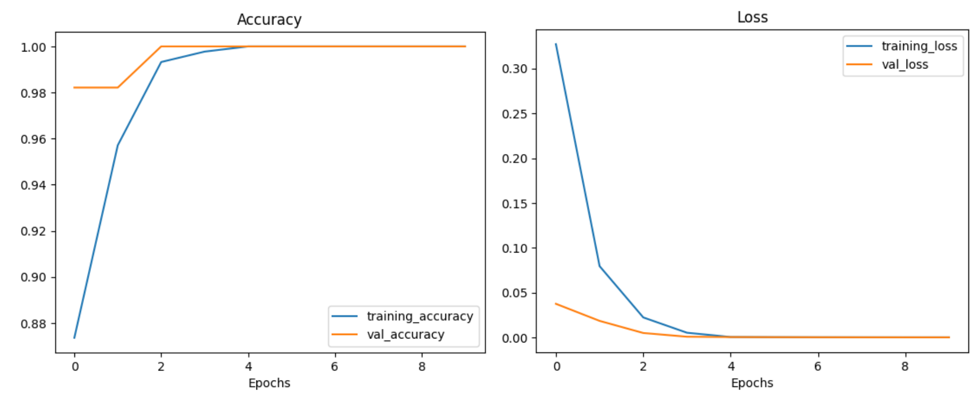



**Figure 2**. The accuracy and loss graphs for the training and validation for 10 epochs

## 4 Conclusion

The hybrid of the FEM-CNN represents the newest developed method in the structural integrity assessment of offshore pipelines. The combination makes use of FEM's potential in the detailed visualization of stress with the rapidity and accuracy found in the image-based analysis of CNNs. The research successfully demonstrated the capability of the developed hybrid FEM-CNN model for the prediction of the corrosion severity of offshore pipelines with high accuracy and reliability, yielding average confidence levels between 97 and 100 percent.

This research is far more important than the results obtained. For engineers, the method offers an expedited, efficient manner of evaluating pipeline integrity, requiring much less time and computational resources compared to traditional FEM-only approaches. Researchers and academicians benefit by increasing their predictive capabilities, further enhanced through the integration of advanced machine learning techniques, which open new potentials for exploration and innovation in the field of Structural Health Monitoring (SHM). The public and the nation benefit from having their critical offshore infrastructure maintained and operated more safely, reducing the risks of pipeline failures that could cause environmental disasters and financial losses.

Overall, the integration of FEM and CNNs will provide an innovative solution to the present challenge of monitoring and maintaining integrity in offshore pipelines in a way that is robust, effective, and scalable. This area of research leads to potentially new developments as well, with the closer collaboration between computational mechanics and artificial intelligence.

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