Abstract

Pipeline is one of the safest and most reliable means of hydrocarbon transportation. Corrosion on the external or internal surfaces of in-service pipes reduces the integrity of the pipeline system and potentially decreases the service life of the pipes. Computer vision-based real-time monitoring and quality control of pipelines are gradually being adopted in different industries due to the emergence of Industry 4.0. In this study, an attempt is made to investigate the effectiveness of classical image features in comparison with deep learning methods for identifying corrosion in pipeline images. The experimental dataset consists of 1,766 manually curated images, including 883 corroded and 883 non-corroded images, derived from 18 differently coloured pipes and captured under varied camera settings and imaging conditions. The following five sets of standard image features are considered in this study for their simplicity of interpretation and discrimination capability: Haralick texture features, Hu moments, moments from the histogram of a grayscale image, multiscale histograms, and Parameter-free Threshold Adjacency Statistics. Four simple and interpretable classical machine learning algorithms, namely Decision Tree, *k*-nearest neighbour (KNN), Logistic Regression, and Support Vector Machine (SVM), are used to design classifiers based on the extracted image features. Convolutional Neural Networks (CNNs) with existing vision-based architectures, namely VGG16, Inception, Inception-ResNet, and MobileNet, are used to identify external corrosion in pipeline images. The SVM model trained on classical features achieves an accuracy of 97%, whereas the MobileNet CNN model achieves an accuracy of 98.12%. However, SVM offers a significant advantage over CNNs in terms of model simplicity and interpretability. The original dataset is augmented using five image augmentation techniques: uniform blurring, Gaussian blurring, illumination variation, Gaussian noise, and salt-and-pepper noise. CNNs are also trained using the augmented dataset. Although the accuracy obtained with the augmented dataset is slightly lower than that obtained with the original dataset, the resulting model is more generalized because it effectively handles images captured under adverse conditions that simulate real-life industrial environments. An attempt is also made to use three Explainable AI (XAI) methods to understand which pixels or features in a given image are primarily

responsible for the model's decision regarding whether a pipe is corroded or non-corroded. In other words, understanding which pixels CNNs focus on to identify corrosion is essential for building trust in these systems. A custom CNN is designed, and salient pixels and salient regions involved in corrosion identification are obtained using Integrated Gradients (IG) and eXplanation with Ranked Area Integrals (XRAI), respectively. The importance of individual features extracted from the images is computed using Shapley values. A method is proposed to quantify corrosion on pipelines using the Hough transform and clustering methods. Since images captured on cylindrical pipelines require unwrapping to obtain the actual pipe surface for accurate inspection, a novel machine vision-based unwrapping method is proposed by imposing and exploiting the scene constraints of the inspection system. Experimental validation demonstrates that the proposed method successfully recovers 93.2% of the total cylindrical surface area after unwrapping the projected images.

Keywords: Corrosion; Machine Vision; Explainable AI; Integrated Gradients; SHAP; Image Features; Machine Learning; Convolutional Neural Network; Hough Transform; Clustering; Unwrapping.