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Digital Transformation for Offshore Assets: A Deep Learning Framework for Weld Classification in Remote Visual Inspections.*

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Abstract. Inspecting circumferential welds in caissons is a critical task in the offshore industry for ensuring the safety and reliability of structures. However, identifying and classifying different types of circumferential welds can be challenging in subsea environments due to low contrast, variable illumination, and suspended particles. To address this challenge, we present a framework for automating the classification of circumferential welds using deep learning-based methods. We used a dataset of 4,000 images for experimental purposes and utilised three state-of-the-art pretrained Convolutional Neural Network (CNN) architectures, including MobileNet V2, Xception, and EfficientNet. Our results showed superior performance of EfficientNet, with high levels of accuracy (86.75%), recall (91%), and F1-score (87.29%), as well as demonstrating efficient time. These findings suggest that leveraging deep learning-based methods can significantly reduce the time required for inspection tasks. This work opens a new research direction toward digitally transforming inspection tasks in the Oil and Gas industry.

Keywords: circumferential welds · offshore · remote visual inspections · EfficientNet

1 Introduction

Managing ageing offshore energy production infrastructure poses significant challenges for operating companies, particularly about caissons. Caissons are vertical tubes that hang beneath the platform topsides, often within the jacket's envelope. They are used for seawater intake, various discharge purposes, and as carriers for subsea infrastructure. [7]

The Topside, Splash-zone, and Subsea are the three primary segments of a caisson (See Figure 1). The Topside can be defined as the dry section zone located under the deck. The Splash-zone is the area of the structure intermittently in or out of seawater and is often submerged due to tides and winds. Finally, the

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underwater section is usually the longest section to inspect and where most anomalies are found.

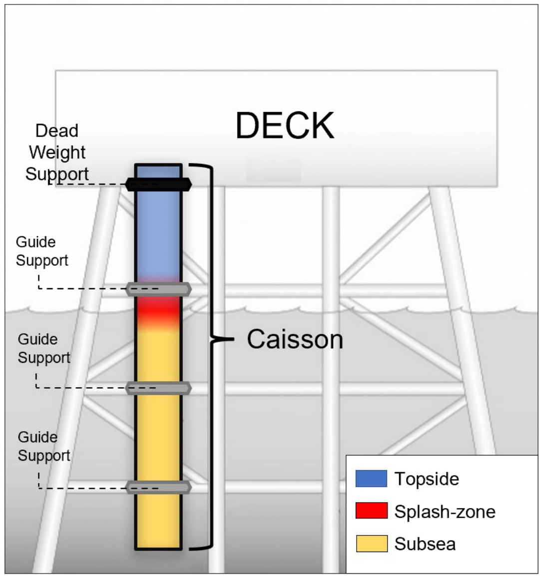

Fig. 1. Overview of the different caisson zones

Over the last few decades, caisson deterioration and failure have been significant problems in the United Kingdom Continental Shelf (UKCS) region, according to a recently published technical report [2]. Caissons are unlikely to lead to overall structural collapse. Still, they may have negative consequences if a failure occurs, which can escalate to a significant risk of dropped objects into subsea structures. Examples include damage to jacket infrastructure, pipelines, and risers. A failed caisson could hit the gas line resulting in gas release and explosion from the ignition. The loss of a firewater caisson capability could also disrupt operations, causing a shutdown of production platforms[2].

The vulnerability of caissons to internal corrosion is a major threat to their structural integrity, and their internal inspection is essential to detect this type of damage. General Visual Inspection (GVI) and Close Visual Inspection (CVI) are the most commonly used inspection techniques. GVI is carried out by a remotely operated vehicle (ROV) to detect major flaws and damages without prior asset cleaning. On the other hand, a CVI is more accurate and used to detect local defects or damages, which requires cleaning marine growth. The still images of anomalies detected during a CVI are usually manually inspected and reported. [1]

A full-caisson inspection commences with cleaning and surface preparation. Subsequently, robotic ultrasonic inspection equipment is remotely deployed to

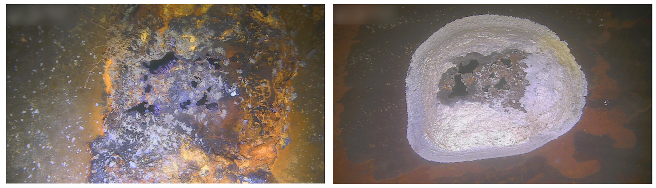

Fig. 2. Comparison between the same anomaly before cleaning (left) vs the post-cleaning (right)

collect thickness measurements throughout the entire length of the caisson, giving real-time inspection data that can be analysed to provide an initial evaluation of the caisson condition. Finally, inspection cameras are remotely deployed to offer visual confirmation of flaws and abnormalities discovered during the ultrasonic inspection and the condition of the caisson surface and welds.

Residual stresses are inherent in welded components, with the magnitude of the pressure reaching the yield strength of the material. The presence of tensile residual stress has a detrimental effect on the structural integrity of engineering constructions [13]. Therefore, during remote visual inspections of caissons, a crucial aspect is the evaluation of the welds. Caissons are typically joined through circumferential welds (CWs), which connect two round objects around their circumference. Since CWs are subjected to stress induced by surface tides and ocean currents, localised corrosion and fatigue are likely to occur [14] (Figure 3).

The remote visual inspection of circumferential welds in caissons is challenging due to various factors that can affect the image quality, including lighting conditions, material reflectivity, water motion, and water turbidity when inspecting underwater. These challenges can lead to errors and significant time consumption during the inspection. In other words, existing inspection manual practices are prone to errors and are time-consuming.

Fig. 3. Example of a 180° caisson panoramic view of a circumferential weld with defects.

This paper presents a deep learning-based framework to classify circumferential welds in caissons. An efficient classification system can help automate the inspection process and speed up the asset integrity assessment, which will be beneficial in the long run. The rest of the paper is organised as follows; Section 2 briefly presents related work, Section 3 explains the data collection process and procedures, Section 4 presents methods and the experimental validation, and Section 5 concludes the paper.

2 Related Work

Automating inspection tasks has been a crucial area of research, with several approaches developed to classify images and detect anomalies, mainly relying on computer vision and deep learning-based methods. In recent years, deep learning-based methods have shown promising results in image classification and anomaly detection tasks. Various techniques in the literature utilize deep-transfer learning and fine-tuning, where a pre-trained model is used as a starting point to train the model further for specific tasks.

Ren et al. [9] proposed a deep learning approach for automated surface inspection using a pre-trained deep learning model to extract patch features from images and generate a "defect heat map." Similarly, several other researchers have proposed deep-learning models for image classification. Luciane et al. [11] proposed a deep-learning approach to classify underwater images into four categories of corrosion severity. Bastian et al. [3] proposed a deep learning-based framework that utilizes Convolutional Neural Networks (CNN) for detecting and classifying corrosion in pipelines transporting water, oil, and gas. The study reported an overall classification accuracy of 98%, indicating the effectiveness of deep learning-based approaches for identifying pipeline defects.

Furthermore, Fu et al. [5] used a SqueezeNet pre-trained model to detect anomalies in steel surfaces, which outperformed state-of-the-art frameworks such as Enhanced Testing Machine (ETM) and Deep Convolutional Activation Features with Multiple Logistic Regression (DCAF-MLR). However, the proposed model was only evaluated on a single dataset(NEU), which may not represent all scenarios in real-world steel surface defect classification tasks.

In another study, [8], the authors presented an experimental framework for automating corrosion detection in subsea images using state-of-the-art computer vision and deep learning techniques. They compared three different architectures and image pre-processing methods and concluded that Mask R-CNN is the most suitable algorithm for detecting corrosion instances in subsea images. However, using a dataset not specifically tailored to subsea inspection may limit the generalizability of the results to other subsea inspection scenarios.

Despite recent advances in deep learning, some methods still rely on traditional machine learning approaches that require explicit feature extraction. For example, in a study by Hoang and Tran [6], Support Vector Machines (SVM) were employed to detect corrosion in pipelines, where the quality of the extracted features played a critical role in achieving accurate results. In such cases, the choice and design of the feature extraction method can be a crucial factor in the model's overall performance.

In summary, it can be said that most existing methods in the literature that handles inspection tasks of offshore or onshore energy assets rely heavily on deep-transfer learning methods, where models that have been trained on large public datasets (e.g. ImageNet) are then reused to perform specific inspection tasks.

3 Methods

Circumferential welds have varying sizes, thicknesses, and colours depending on various factors. However, all circumferential welds have a visible top and bottom horizontal line, resulting from the Heat-Affected Zone (HAZ) created during the welding process. The HAZ is a critical area of the weld that can have a different microstructure and properties than the parent material due to the heat generated during welding. Despite the horizontal line being a characteristic feature the human eye can quickly identify, CWs can be challenging to spot on the subsea section due to low contrast, suspended particles in the water, and highly variable illumination.

3.1 Data Collection

A database of hundreds of remote visual inspection jobs was filtered to ensure a representative sample of CWs covering different geographical regions and caissons' configurations. A Pareto chart was created to visualize the number of inspection jobs per global region. This approach aimed to develop a robust model with diverse CWs and background types. Afterwards, a team consisting of a mechanical engineer, senior inspection engineer, and offshore operation manager were consulted to establish clear guidelines for image classification under the labels "cw" and "non-cw" (See Figure 4)

Fig. 4. Circumferential weld (top) and non-circumferential weld (bottom)

A total of 4,000 images were obtained from the filtered database. These images contained inspection stills in different format sizes and were manually selected and labelled. The dataset was split into two labels named *cw* and *non-cw*. Table 3.1 shows the data distribution between the training, validation and test sets.

Note that all annotated data (stills and labels) have been checked for annotation correctness three times; one from the inspection technician that collected

Label	Training	Validation	Test	Total
cw	1400	400	200	2000
non-cw	1400	400	200	2000

Table 1. Dataset distribution

and reported the data, subsequently on-shore by the senior inspection engineer for the approval of the report, and finally during the manual extraction of the dataset itself by the offshore operations manager.

3.2 Data Pre-processing

Internal inspections can be affected by challenging environmental conditions and lighting factors that negatively impact the quality of the captured images. To address this issue, previous research, such as the study conducted by Pirie et al.[8], has explored various filtering methods, including contrast-limited adaptive histogram equalization (CLAHE), Grayscale, and Inpainting, to improve image quality under such conditions. For our dataset, we found that a combination of these three techniques was the most effective. In Figure 5, a comparison is presented between the different filters we tested and our final custom filter applied. The results show that the filter enhances the visibility of the top and bottom horizontal lines of the weld and attenuates light reflection, leading to a more uniform brightness across the image.

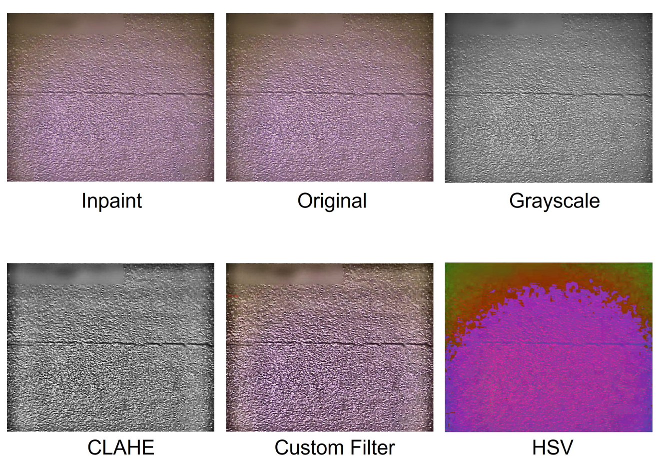

Fig. 5. Comparison of a circumferential weld using different filters.

3.3 Transfer Learning

Transfer learning is a popular machine learning technique used to transfer knowledge from pre-trained models to solve related problems. Instead of training a CNN from scratch, transfer learning allows the reuse of pre-trained model weights and adaptation for specific outputs by adding additional layers. This technique offers faster training and better prediction results. To assess the accuracy of state-of-the-art pre-trained CNN models in classifying CWs, experiments were conducted using MobileV2, Xception, and EfficientNet.

MobileNet V2 is a highly efficient and simple CNN architecture commonly used for mobile applications. Its unique feature is the depth-wise convolution, which reduces model size and complexity with the low computational power required for transfer. The architecture has 32 filters followed by 19 residual bottleneck layers. Compared to its predecessor, MobileNetV1, this architecture uses 30% fewer parameters and half the operators, enhancing prediction speed performance while requiring minimal GPU requirements [10].

Xception is a CNN that contains 71 deep-layers and is considered a variation of Inception architecture. The Xception model is based entirely on depthwise separable convolution layers. The main idea of this architecture is to fully decouple the cross-channel and spatial correlations in the feature map of the convolutional neural networks. Xception achieves a top-5 accuracy on the ImageNet database of 94.5%, outperforming state-of-the-art models such VGG16, ResNet-152 and Inception V3 [4].

EfficientNet is a CNN architecture designed to optimize the accuracy and efficiency trade-off by scaling the network's depth, width and resolution. It introduces a new compound scaling method that uniformly scales all three dimensions of depth, width, and resolution in a balanced way. EfficientNet-B0, the smallest variant, achieved a top-1 accuracy of 76.3% on the ImageNet dataset with only 5.3 million parameters, whereas EfficientNet-B7, the largest variant, achieved a top-1 accuracy of 86.5% with 66 million parameters, surpassing other models such as ResNet, DenseNet, and Inception-v3 on the same dataset. In this study, EfficientNet-B0 was chosen for the experiment. [12]

4 Experiments and Results

4.1 Experiment Setup.

Image augmentation techniques were applied to the training dataset to optimize the performance of the binary image classification models on detecting CWs. Random rotation and flip were used to account for the possibility of CWs appearing in different positions within the inspection image. As most CWs tend to appear horizontally in the middle of the image, the flip technique was used to create horizontal mirror images, and the rotation technique was used to make slight variations in the angle of the CWs. These techniques helped to generate additional training data, which allowed the model to learn to generalize better to new images and reduce over-fitting.

The batch size was set to 64 in this experiment. The models were compiled with the Adam optimizer, binary cross-entropy loss function, and accuracy metric. The learning rate for the optimizer was set to 10^{-4}. The models were trained for 25 epochs.

4.2 Results

The binary image classification model was trained and evaluated using three CNN architectures: MobileNet V2, Xception, and EfficientNet. To present the performance of each model, this section features confusion matrices displayed in Figure 6. Additionally, Table 2 provides a detailed comparison of each model's performance, measured by accuracy, recall, precision, and F1 score.

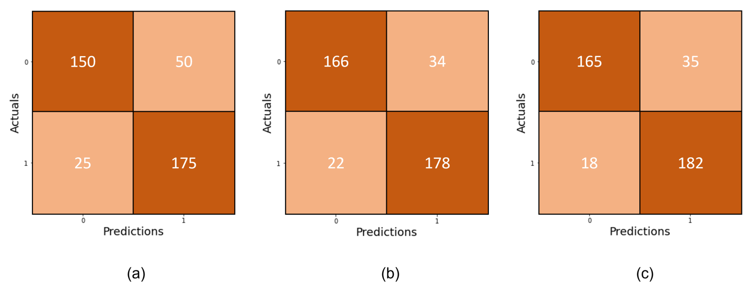

Fig. 6. Confusion Matrix (a) MobileNet V2, (b) Xception, and (c) EfficientNet

The presented results demonstrate that all three models achieve considerable accuracy, with EfficientNet performing the best, attaining the highest scores in accuracy, recall, and F1-score of 86.75%, 91.00%, and 87.26%, respectively. Regarding precision, Xception outperforms the other two architectures, while MobileNet V2 exhibits the lowest precision score among the three models.

Architecture	**MobileNet V2**	**Xception**	**EfficientNet**
Accuracy	0.8125	0.8600	**0.8675**
Recall	0.8750	0.8900	**0.9100**
Precision	0.7778	**0.8396**	0.8387
F1 Score	0.8235	0.8641	**0.8729**

Table 2. Comparison of CNN architectures for classification task

Careful consideration of all relevant factors, including model performance and inference time, is necessary to select the most appropriate model for a given application. While Xception achieves slightly higher precision than EfficientNet, a thorough evaluation of model performance and inference time combination revealed that EfficientNet is the preferred model for the classification task.

5 Conclusion and Future Work

In this paper, we presented a framework for the automated classification of circumferential welds (CWs) in a caisson. A dataset of images representing inspection tasks was collected, labelled and enhanced using image processing methods. The prepared dataset was then used to train three state-of-the-art CNN architectures: MobileNet V2, Xception, and EfficientNet. Based on extensive experiments, EfficientNet emerged as the preferred model for the classification task due to its strong accuracy, sensitivity, and F1-score metrics performance while exhibiting a favourable trade-off with inference time. The methods developed in this paper were deployed in production and used for visual inspection jobs, achieving an average accuracy of 86.75%, a sensitivity of 91.00%, and an F1-score of 87.29%. Currently, the framework is being integrated into the company's data pipeline process under the supervision of senior inspection engineers. In future work, the authors plan to explore a multi-label classification model to automate the identification of other types of anomalies, including pitting, cracks, thru-wall defects, and localized wall loss commonly seen in caissons, especially in the underwater section.

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