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Articicial Intelligence based techniques and applications in corrosion prediction as a mitigation tool in oil and Gas Facility.

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Abstract:

Corrosion and human interference in pipes, vessels, and equipment. Traditionally, the control of metal properties relied on physical methods, such as visual inspection aided by magnifying glasses. Various physical techniques, such as Ultrasonic, Acoustic Emission, Eddy Current, Magnetic Flux Leakage, and radiographic methods, are employed to measure the wall thickness of pipes, vessels, and tanks in oil and gas systems thereby aiding in the detection of corrosion. Artificial intelligence (AI) finds applications across various domains, addressing classification, diagnosis, selection, and prediction challenges in Oil and gas facilities. Artificial Intelligence was modeled to detect corrosion on pipes using Deep learning (DL) algorithms like Convolutional Neural Network (CNN) which focuses on the texture of the image. Artificial Intelligence (AI) can help sustain oil and gas assets by predicting e, which detects the texture of corroded regions of pipes, vessels and correctly classify them. The process is implemented using python and the TensorFlow deep learning framework. The techniques involve data collection from primary and secondary sources, data preprocessing, feature selection, model development, instantaneous prediction, and continuous improvement. The dataset were trained, validated and tested using improved convolutional Neural Network (CNN), where classes are labeled as Corrosion and No Corrosion. The CNN Model developed

performed very when compared with other DL models such as the conventional CNN, Resnet-50, VGG-19 and Inception-v3 models. Although, multiple executions of the model were conducted with various epochs, and it was concluded that between 4 and 5 epochs with three convolutional layers, the best results were obtained in terms of training and validation accuracy, achieving overall accuracy of 99.4%, which outperformed other works existing in the literature.

KEY WORDS; Artificial Intelligence, Convolutional Neural Network, Deep Learning, Prediction Resnet-50, VGG-19 and Inception-v3, epoch.

1.0 INTRODUCTION.

In recent years, there has been a significant rise in the use of artificial intelligence tools in the petroleum industry. This growth can be attributed to the increased availability of human experts and the publication of numerous successful case studies (Gharbi et al., 2005). Artificial neural networks, fuzzy logic, and evolutionary algorithms are the most used AI techniques in various petroleum engineering applications, including oil and gas reservoir simulation, production, drilling and completion optimization, drilling automation, and process control (Braswell, 2013). The industry has recognized the importance and applicability of intelligent models in solving various disciplinary problems, particularly in exploration, production, and hydrocarbon management.

Pipelines play a crucial role in the oil and gas industry, ensuring the safe delivery of products in both offshore and onshore environments. Typically constructed from carbon steel, pipelines are susceptible to corrosion, which is a primary threat to their serviceability (Birkland & Dann, 2018). Corrosion rates increase over time as pipelines age, highlighting the need for assessment and prediction of corrosion growth to prevent failures or leaks. Predicting corrosion growth rates also aids in risk assessment, enabling pipeline operators to make informed decisions (Zardasti et al., 2015). Intelligent pigging tools, such as Ultrasonic Tools (UT) and Magnetic Flux Leakage (MFL), are commonly used for pipeline inspection. Inspection data is used to forecast corrosion growth rates, facilitating future inspection planning, excavation planning, cost estimation, and pipeline maintenance or replacement decisions (El-Abbasy et al., 2014).

Artificial Intelligence (AI) plays a pivotal role in subsurface exploration. For instance, ExxonMobil employs AI-powered robots to detect natural oil seeps, reducing exploration risks and minimizing harm to marine ecosystems. Predictive maintenance powered by AI helps prevent unexpected equipment failures. By analyzing historical data, AI algorithms predict when maintenance is needed, minimizing downtime, and optimizing Production. AI, coupled with computer vision, accelerates the analysis of seismic and subsurface data. This aids in reservoir understanding, modeling, and predicting oil corrosion risks, ultimately reducing maintenance cost. Digital twins, virtual replicas of physical assets, allow real-time monitoring and predictive maintenance. AI-driven digital twins enhance asset performance and extend their lifespan.

Artificial Intelligence (AI) algorithms can identify defects in equipment, pipelines, and structures. Early detection prevents costly failures and ensures safety. Protecting critical infrastructure from cyber threats is crucial. Artificial Intelligence (AI) detects anomalies, monitors network traffic, and safeguards against cyberattacks. AI monitors safety compliance, identifies hazards, and prevents accidents in oil and gas facilities. Artificial Intelligence (AI) processes vast amounts of data, providing actionable insights for informed decision-making across the industry, AI helps track emissions, optimize logistics, and reduce environmental impact.

2.0 Current Corrosion Prediction Methods.

The common corrosion monitoring techniques are corrosion coupons, electrical resistance, linear polarization resistance, and galvanic monitoring. However, advanced monitoring methods includes biological monitoring, ultrasonic thickness monitoring, and hydrogen penetration monitoring (Available from: http//inspectioneering.com). Accurate monitoring of corrosion rates in any environment is critical when viewed in terms of the maintenance and repair costs associated with corrosion and material failure. Test coupons provide an inexpensive means of on-line monitoring that will allow you to effectively measure the corrosivity within your system. By observing the mils-per-year corrosion rate of an exposed coupon, valuable information can be provided regarding the material's life expectancy.

Ultrasonic Thickness Measurement, which is a direct non-destructive method for corrosion detection, monitoring and control. The Ultrasonic Thickness measurement determines the thickness of the starboard hull side plating and the fore peak section plating. In this study of Yang et al. (2023), a piezoelectric active sensing-based time reversal method was investigated for monitoring pipeline internal corrosion. The occurrence and development of corrosion in pipelines were generated by electrochemical corrosion, and nine different depths of corrosion were imposed on the sample pipeline. However, the WPE-CNN model in combination with the time reversal method has high application potential for monitoring pipeline internal corrosion.

3.0 REVIEW OF AI BASED TECHNIQUES.

Corrosion is a significant problem in various industries, including manufacturing, infrastructure, and transportation. It can lead to structural damage, reduced operational efficiency, and increased maintenance costs. Therefore, developing an AI-based techniques for prediction of corrosion can be highly beneficial in mitigating the adverse effects of corrosion. The design for an AI-based techniques for prediction of corrosion involves several key components and steps:

i. **Data Collection:** The first step is to collect relevant data on corrosion from various sources. This data can include environmental factors such as temperature, humidity, and pH levels, as well as information on the material being monitored for corrosion. IoT sensors can be deployed to gather this data continuously and transmit it to a central database or cloud platform.

ii. **Data Preprocessing:** Once the data is collected, it needs to be preprocessed to remove noise, outliers, and inconsistencies. This step involves cleaning the data and transforming it into a suitable format for further analysis. Data preprocessing techniques such as filtering, normalization, and feature extraction may be applied to enhance the quality of the data. Data annotation, Tunning, and Augmentation using Python. The data can be divided into training, testing and validation.

iii. **Feature Selection:** In this step, relevant features that have a significant impact on corrosion prediction are selected from the preprocessed data. Feature selection techniques such as correlation analysis and deep learning algorithms can be employed to identify the most informative features.

iv. **Model Development:** After feature selection, an AI model needs to be developed to predict corrosion based on the selected features. Various machine learning algorithms can be utilized for this purpose, including deep learning models such as convolutional neural networks (CNN) or recurrent neural networks (RNN). The model is trained using historical data on corrosion incidents and their corresponding features.

v. **Instantaneous Prediction:** Two sensors were employed for corrosion detection, one monitors the external surfaces of the pigging while other monitors the internal structure**.** Once the AI model is trained, it can be deployed to make real-time predictions on new data. The IoT sensors continuously collect data on environmental factors and material conditions, which are fed into the AI model for prediction. The model analyzes the input data and provides a corrosion prediction output in real-time.

vi. **Alerts and Notifications:** When the AI model predicts a potential corrosion event, alerts and notifications can be generated to inform relevant personnel or stakeholders. These alerts can be sent via email, SMS, or integrated into existing monitoring systems for immediate action.

vii. **Continuous Learning and Improvement:** The AI model will be continuously updated and improved based on new data and feedback. This process involves retraining the model periodically using the latest data to enhance its accuracy and reliability.

By implementing an AI-based techniques for corrosion prediction, several benefits can be achieved:

i. The system can detect corrosion at its early stages, allowing for timely intervention and preventive measures to minimize damage.

ii. By predicting corrosion in advance, maintenance activities can be planned more efficiently, reducing overall maintenance costs.

iii. Timely detection of corrosion helps prevent accidents or failures caused by structural integrity issues.

iv. With accurate predictions, resources such as manpower and materials can be allocated more effectively, optimizing operational efficiency.

v. The system generates valuable insights from the collected data, enabling informed decision-making for corrosion prevention and mitigation strategies.

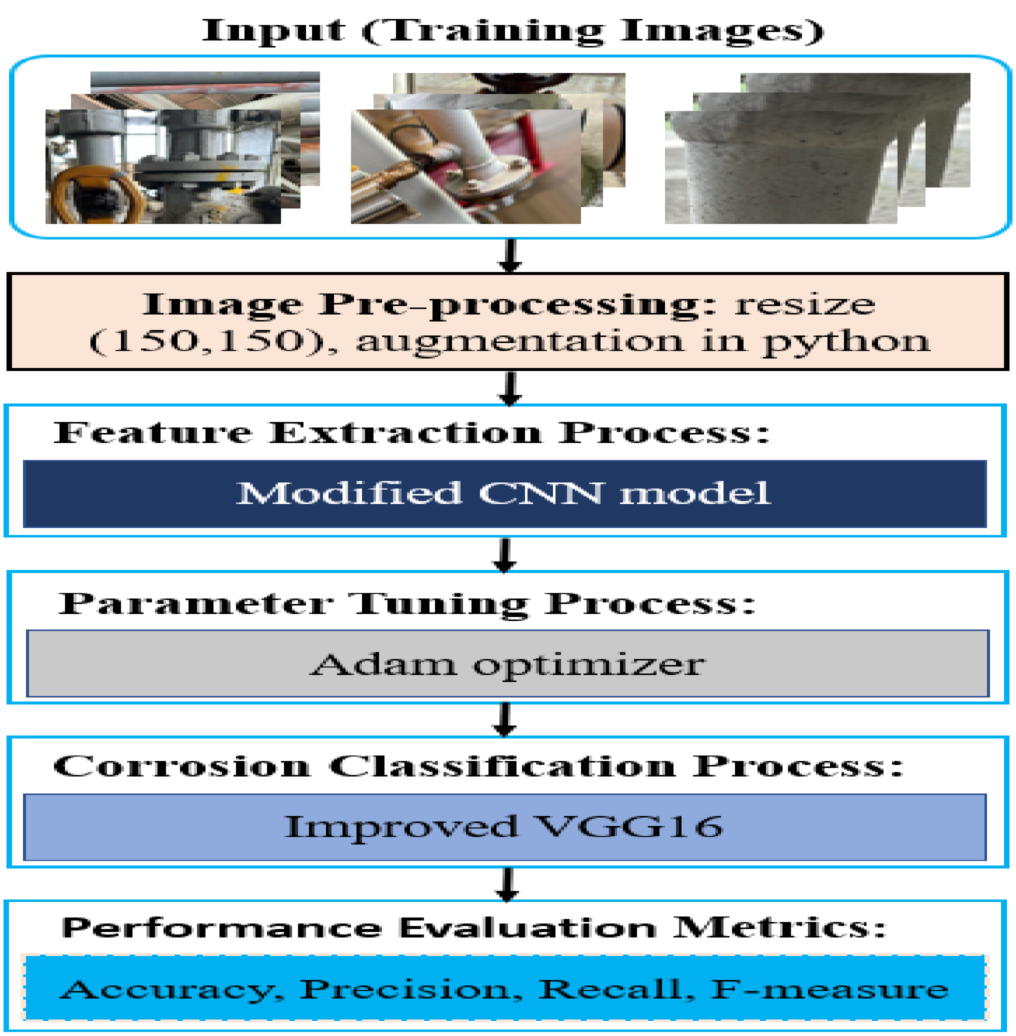

Fig.1: Methodology workflow for CNN Model Implementation

4.0 APPLYING ARTIFICIAL INTELLIGENCE (AI) IN CORROSION DETECTION

Different Deep learning models were trained with TensorFlow as the backend after splitting the dataset into training and testing sets of 80% and 20% respectively, where the improved CNN model was trained with 60% and testing sets of 40% with a batch size of 128 in Jupyter Notebook via Python 3.10.5 compiler. The distribution scaled (150-by-50) image samples according to classes is given below.

Scaling images to a uniform size (150-by-50 in this case) is a common preprocessing step in CNN-based image classification tasks. This ensures that all input images have the same dimensionality, allowing them to be processed efficiently by the network. For corrosion detection, where texture and color features are crucial, how the images are scaled and preprocessed can significantly impact the model's ability to accurately classify them.

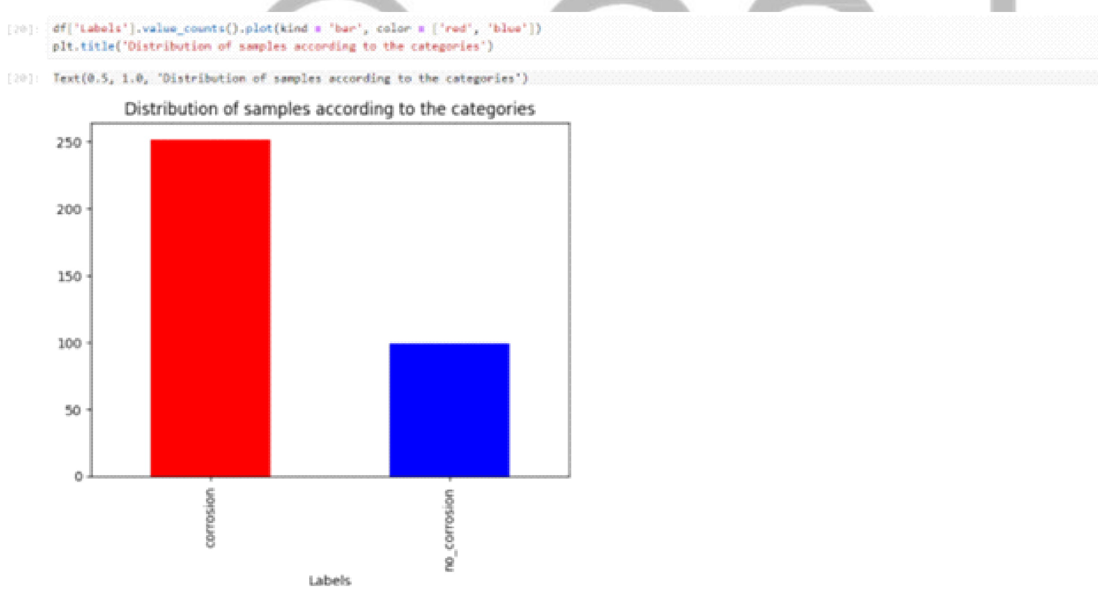

Fig.2: Image Classification using Python 3.10.5

4.1 Graphical User Interface (GUI) Design

To handle large numbers of images a graphical user interface (GUI) application was designed. Its layout can be found in Figure 3.1. It allows the user to iterate fast through images and allocate them in folders whether corroded or not corroded. It was developed using python programming language, which is a high-level general-purpose programming language. It has many GUI framework, but Tkinter is the only framework that is built into python standard library. It includes GUI layout and forms designer that allow the user to design the desired layout and retrieve the code.

Fig 3: Corrosion detection GUI

5.0 CNN model training and validation

The output of Convolutional Neural Network (CNN) model training and validation refers to the results obtained after training the CNN model with enhancements or improvements to achieve better performance in tasks such as image classification, object detection, or natural language processing. The training phase involves feeding the model with labeled data to learn patterns and features, while the validation phase assesses the model's performance on unseen data to evaluate its generalization ability.

During the training process, the CNN model learns to extract relevant features from input data through multiple layers of convolutional and pooling operations. The improved CNN model may incorporate techniques such as data augmentation, transfer learning, regularization methods, or architectural modifications to enhance its accuracy, speed, or robustness. After training, the model's performance is evaluated using a separate validation dataset to measure metrics like accuracy, precision, recall, or F1 score.

The performance of the corrosion image recognition system was evaluated with four Deep Learning models fig.5. It was observed that the improved CNN network achieved the highest accuracy of 99.4% with the minimum training time Fig. 4.
The training and testing accuracies gradually increased but stopped learning from 4 to 5 epochs to obtained 99.2% and 99.4% respectively. The early stopping was used to stop the training to avoid overfitting. Training stopped early after the completion of 4 epochs.

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Fig.4: Improved CNN Accuracy for Training and Validation.

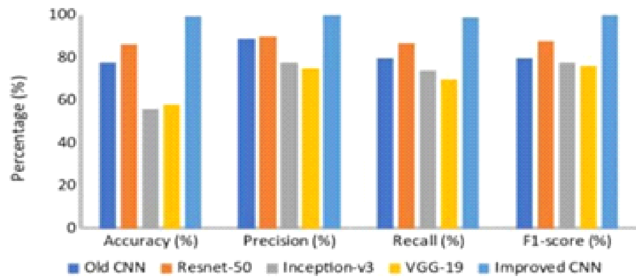

Fig.5: Comparison of four deep learning models

5.1 CORROSION DETECTION.

After the improved Convolutional Neural Network (CNN) model is trained to predict corrosion and no corrosion images, it utilizes its deep learning capabilities to analyze and classify the input images based on features related to corrosion. The output of the CNN model prediction for corrosion and no corrosion images typically consists of probabilities assigned to each class, indicating the likelihood of the presence of corrosion in the input image. For a given input image, the CNN model will produce a prediction in the form of a probability distribution across the two classes: corrosion and no corrosion. The model assigns a probability value to each class, with higher values indicating a higher confidence in the classification. In this context, if the CNN model predicts that an input image contains corrosion, it will assign a higher probability to the corrosion class compared to the no corrosion class, and vice versa.

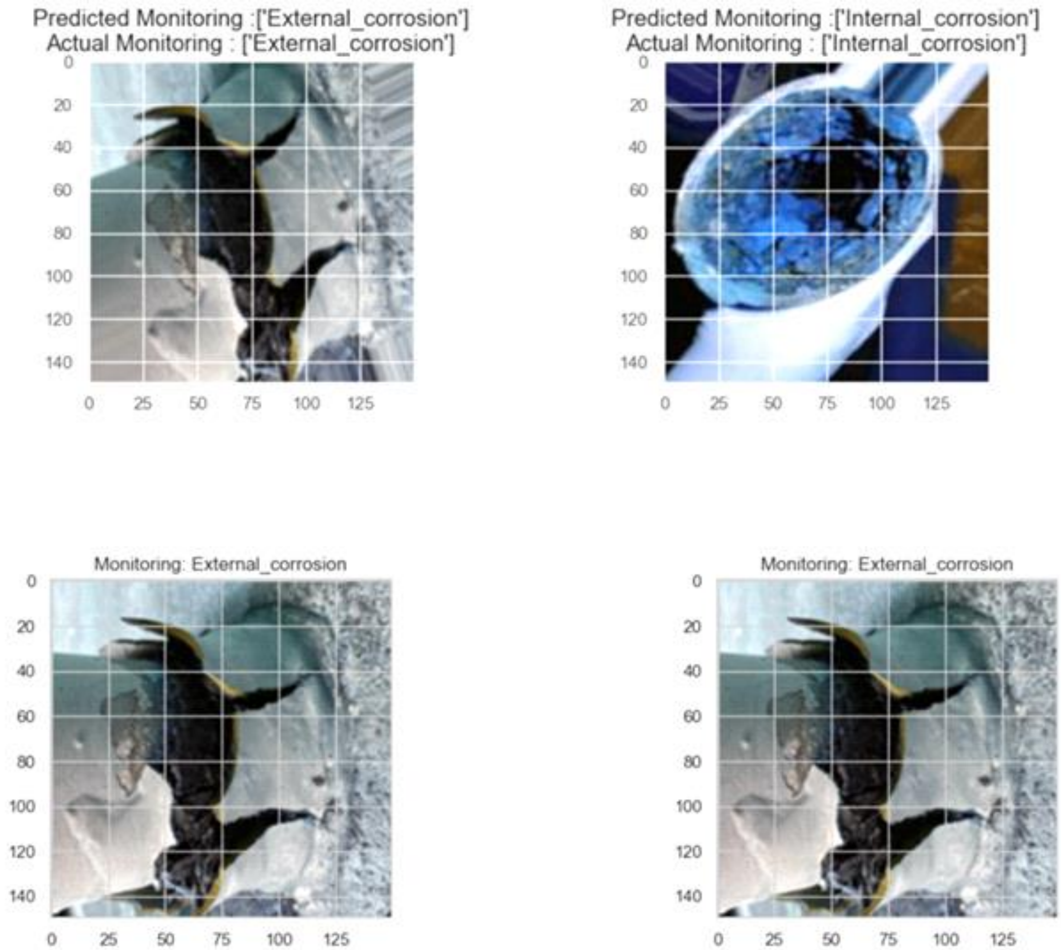

Fig 6: External and Internal Corrosion detection.

6.0 CONCLUSION

Corrosion detection is a critical area of research in materials science and engineering, as it can lead to structural degradation and failure in various industries such as oil and gas infrastructure. One innovative approach to corrosion detection is the use of Convolutional Neural Networks (CNN), a type of deep learning algorithm that has shown promise in image recognition tasks. By training the proposed CNN model on images showing corroded surfaces both external and internal sections of pipes, this gives an automated system that can accurately detect and classify corrosion patterns instantaneously.

However, the application of CNN in corrosion detection involves several key steps. First, was to acquire corrosion image data from both primary and secondary sources. These images are then preprocessed to enhance features relevant to corrosion. Next, the preprocessed images are used to train an improved CNN model through a process known as supervised learning. During training, CNN learns to recognize patterns associated with different types and degrees of corrosion.

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