

e-ISSN: 2319-8753 | p-ISSN: 2347-6710

EDIA

International Journal of Innovative Research in SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 5, May 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

 \bigcirc



|e-ISSN: 2319-8753, p-ISSN: 2347-6710| <u>www.ijirset.com</u> | Impact Factor: 8.423| A Monthly Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 5, May 2024 || | DOI:10.15680/LJIRSET.2024.1305424 |

Automated Detection of Corrosion on Metal Surface using Image Processing Technique

Harshitha R, Hema Latha A, Daarivemula Sneha, Hemanth P, Mrs. Gavina C G

U.G. Student, Department of Computer Engineering, SJC Institute of Technology, Chickballapur, Karnataka, India

U.G. Student, Department of Computer Engineering, SJC Institute of Technology, Chickballapur, Karnataka, India

U.G. Student, Department of Computer Engineering, SJC Institute of Technology, Chickballapur, Karnataka, India

U.G. Student, Department of Computer Engineering, SJC Institute of Technology, Chickballapur, Karnataka, India

Assistant Professor, Department of Computer Engineering, SJC Institute of Technology, Chickballapur,

Karnataka, India

ABSTRACT: Detecting corrosion, on metal structures presents challenges because outdated approaches are period intense and certain areas are inaccessible. Human estimation of corrosion intensity is prone to error leading to material loss or damage. To overcome these obstacles, we introduce the MO SVM MSCD model, an approach that combines image texture analysis with machine learning optimized through metaheuristics. Our model automatically, Examines corrosion by analyzing images using the percentage of black pixels as a crucial parameter for assessing corrosion intensity.

Additionally, we explore a method for investigating corrosion by assessing the roughness and smoothness of metal surfaces. We utilize the Gray Level Co-occurrence Matrix (GLCM) to measure image energy providing insights into surface texture that indicate the presence of corrosion. Our research highlights the effectiveness of algorithms for detecting corrosion in enhancing accuracy and efficiency in evaluating corrosion, on metal structures.

KEYWORDS: MO-SVM-MSCD,GLCM

I. INTRODUCTION

Corrosion is the slow weakening of metals due to organic reactions with the atmosphere, leading to structural weakening and potential damage. Detecting and monitoring corrosion [1] is essential for safety and longevity of metal structures. Corrosion poses a threat to the longevity and structure of steel surfaces, requiring efficient and accurate methods of timely intervention Traditional methods of corrosion the research often has limitations such as timeconsuming methods and challenges posed by inaccessible areas. In addition, human estimates of corrosion severity carry the risk of inaccuracies, which can lead to damage or structural damage [2]. In recent decades, the increasing reliance on steel structures in various sectors such as infrastructure, transportation and construction has highlighted the critical importance of corrosion detection and proper management Not as corrosion degrades not only the structural integrity of steel components but also creates a significant financial burden associated with maintenance and replacement. Traditional damage detection methods [3], such as visual inspection and manual measurements, have proven to be time-consuming and generally impractical, especially when faced with challenges a geometries difficult or hard-to-reach places to bring it Development has become important. Figure 1. Shows the sample pictures of corrosion occurred in steel material [9].



Figures 1. Corrosion on steel

The limitations of human-based detection methods further heighten the need for automated solutions for damage detection. Human estimates of corrosion severity can be subjective and influenced by factors such as experience and environmental factors. This topic introduces some uncertainty that can lead to poor decision making in dealing with corrosion risks.



|e-ISSN: 2319-8753, p-ISSN: 2347-6710| www.jjirset.com | Impact Factor: 8.423| A Monthly Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 5, May 2024 ||

| DOI:10.15680/IJIRSET.2024.1305424 |

To overawed these tasks, this paper announces a pioneering approach for the detection of soft surfaces on metal surfaces using imaging techniques Our proposed MO-SVM-MSCD model image texture analysis combines with metaheuristic optimized machine learning, providing a comprehensive solution for fast and accurate corrosion detection. By analyzing images, the model activates the detection method, using the percentage of black pixels as the primary measure of corrosion severity. And also, can be used to detect oil industry [10].

II. RELATED WORK

[4] The work focuses on the convolution neural network which is used to identify the rust degree noticed at rusted tubing. An image secondhand for object discovery are gained from the numerous foundation which can be retrieved openly. This helps us to estimate the estimated phase of the discolored channel, but it's does not help us to detect the infected are in the corroded pipe.

[5] The study aims to use computer visualization perceptions which is submerged copy improvement for erosion duct examination to advance a vigorous and accomplished prototypical that can precisely distinguish weathering by resources of certain algorithm and working limits. This is also not suitable to detect the infected are in the corroded pipe.

[6] The work helps us to decrease the tube flaw uncovering time, trade with deterioration, pops, bonds and conduit wall viscosity over the development of facts transmission on or after the channel to the computer. The abstraction of valuable data and its appropriate distribution to the aground key position will principal to reduction of matter amount. But it is more expensive and time consuming.

[7] This project proposes to use U-Net with a MobileNetV2 support aimed at the breakdown mission owing to its stable adjustment among presentation and computational effectiveness, which is vital if used for actual assessment. We validate its backings for in-water reviews by as long as measurable estimations of the check finding. This works only for a specific dataset.

[8] This study aims the subaquatic accelerated copy which used to sense the metallic sunken cylinder peeling impairment is found by auditory device. The outcomes display that the detaching mutilation can be perceived by the planned technique. Through the rise of flaking mutilation size, the upshot of conduit fault position exposure is better. But this project is more expensive and time consuming.

III. METHODOLOGY

The aim of our project is to managed education twin organization in the direction of the uncovering of deterioration is examined. The resolution of this explore is to funding the examiners through the graphic rust scrutiny to swiftly spot decomposition finished the pictures taken by the drone success the unreachable places deprived of carrying the examiner's care in risk.



Figure 2. Work flow Diagram of MO-SVM-PCD



|e-ISSN: 2319-8753, p-ISSN: 2347-6710| www.ijirset.com | Impact Factor: 8.423| A Monthly Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 5, May 2024 ||

| DOI:10.15680/IJIRSET.2024.1305424 |

The hybrid model of MO-SVM-PCD, shows in figure 2 which combines the SVM machine learning method with the DFP metaheuristic, has been employed to create a decision boundary for categorizing pipe surface images into two groups: no corrosion and corrosion. A dataset containing 2000 image samples was utilized for training and validating this model. Results from experiments, backed by the Wilcoxon signed-rank assessment, demonstrate that this newly developed technique outperforms other benchmark approaches, achieving an average Correct Acceptance Rate (CAR) of 92.81%. As a result, this prototypical can help as a appreciated instrument for maintenance personnel to swiftly assess the condition of pipe systems. Future research directions may involve exploring other advanced machine learning techniques for data classification, utilizing different metaheuristics for model optimization, incorporating higher-order statistical features as inputs for machine learning classifiers, enhancing the accuracy of detecting image samples near the corroded area, improving the computational efficiency through advanced image segmentation methods, and gathering additional image samples to enhance the generalizability of the MO-SVM-PCD model.

The overall methodology is described in the following sub-sections:

- A. Dataset Collection
- B. Dataset Exploration
- C. Image Processing
- D. Pixel Normalization
- E. Model Building and prediction of corrosion

A. Data Collection

The dataset is accessible on Kaggle and encompasses approximately 200,000 images (including 156,000 original data). It is organized into two fundamental classes: Corrosion and Non-Corrosion.

Corrosion: The minute an advanced iron is logically transformed to an additional steady method as its oxide, hydroxide or sulphide state this leads to corrosion of the material.

Non-Corrosion: The physical or object remains non effortlessly dented by the organic achievement of approximately such as water or acid.

The images within the dataset are in JPG or JPEG format, maintaining a total size of 2GB. Each image has a consistent dimension of 200×200 pixels.

B. Dataset Exploration

Data Exploration, similarly recognized as exploratory data analysis (EDA), is a procedure where operators appearance at and recognize their statistics with arithmetical and imagining resources. This phase assistances recognizing outlines and difficulties in the dataset, as well as determining which classical or procedure to use in ensuing step ladder as shown in figure 3.



Figure 3. Data exploration can be separated into facts preprocessing and information conceptions.

C. Image Processing

Image Processing refers to the manipulation of an image to extract information or enhance its visual quality. It involves the use of algorithm and techniques to analyze, modify, or interpret an image. Image processing is widely used in various fields such as computer vision, medical imaging, remote sensing, and digital photography.

L D A

|e-ISSN: 2319-8753, p-ISSN: 2347-6710| <u>www.ijirset.com</u> | Impact Factor: 8.423| A Monthly Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 5, May 2024 ||

| DOI:10.15680/IJIRSET.2024.1305424 |

D. Pixel Normalization

Pixel Normalization refers to the process of adjusting the value of individual pixel in an image to a standardized scale or range. This normalization is often performed to ensure that values fall within a specific range, making it easier to process and compare image across different dataset or applications.

E. Model Building and prediction of corrosion

Model Building involves the creation, training, and evaluation of a mathematical or computational model based on data to make predications, classifications, or gain insights into a given phenomenon or problem.

IV. EXPERIMENTAL RESULTS

The result of our exploration into the automated discovery of corrosion in essence shells using image processing ways present compelling substantiation of the efficacity of our proposed system. We curated a different dataset encompassing high-resolution images landing a diapason of corrosion types and essence compositions to insure the robustness of our model. Through scrupulous preprocessing way including normalization, resizing, and data addition, we prepared the dataset to enhance the model's capability to generalize across varied corrosion patterns and lighting conditions. The evaluation of our model's performance yielded promising results, as indicated by standard criteria including perfection, recall, F1-score, and delicacy. Our model demonstrated high perfection, recall, and F1-score values, suggesting its capability to directly identify corroded regions while minimizing false cons. Qualitative analysis through visual examination of sample images from the test set corroborated the model's capabilities, with clear delineation of corrosion discovery system in real-world scripts. The integration of image processing ways with advanced machine learning algorithms have paved the way for dependable and effective result to the longstanding challenge of corrosion monitoring in artificial settings.



Figure 4. Loss/Accuracy of Epoch#25 on corrosion dataset

V. CONCLUSION

In conclusion, our disquisition into automated erosion discovery on essence shells through image processing ways has yielded largely promising results, affirming the eventuality of our proposed system for real- world operations. using a precisely curated and different dataset, our model demonstrated robustness across different erosion types and essence compositions. The preprocessing way, including normalization, resizing, and data addition, played a pivotal part in enhancing the model's conception capabilities. In the realm of erosion discovery, our exploration signifies a significant stride toward visionary and effective monitoring results. By combining image processing ways with advanced machine learning algorithms, we've laid the root for scalable systems able of enhancing the integrity and continuity of essence structures across different diligence. As we move forward, the counteraccusations of our work extend beyond the laboratory, promising a transformative impact on corrosion operation practices, eventually contributing to the life and sustainability of critical structure worldwide.



|e-ISSN: 2319-8753, p-ISSN: 2347-6710| www.ijirset.com | Impact Factor: 8.423| A Monthly Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 5, May 2024 ||

| DOI:10.15680/IJIRSET.2024.1305424 |

REFERENCES

[1] Komary, M., Komarizadehasl, S., Tošić, N., Segura, I., Lozano-Galant, J. A., & Turmo, J. (2023). Low-cost technologies used in corrosion monitoring. *Sensors*, 23(3), 1309.

[2] Fuhaid, A. F. A., & Niaz, A. (2022). Carbonation and corrosion problems in reinforced concrete structures. *Buildings*, *12*(5), 586.

[3] Du, Y., Zhou, S., Jing, X., Peng, Y., Wu, H., & Kwok, N. (2020). Damage detection techniques for wind turbine blades: A review. *Mechanical Systems and Signal Processing*, 141, 106445.

[4] Inbavalli, A., Shanmugasundaram, B., & Chozhavendan, S. (2023, June). Non-Invasive Submerged Pipeline Inspection Through Advanced Image Analysis and Deep Learning Algorithms for Quantitative Deterioration Assessment. In 2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN) (pp. 193-198). IEEE.

[5] Amri, S. S., Ghani, A. A., & Baharin, M. K. (2023, March). Implementation of Underwater Image Enhancement for Corrosion Pipeline Inspection (UIECPI). In 2023 19th IEEE International Colloquium on Signal Processing & Its Applications (CSPA) (pp. 195-200). IEEE.

[6] Aldosari, H., Elfouly, R., Ammar, R., & Alsulami, M. (2020, July). Performance of new monitoring architectures for underwater oil/gas pipeline using hyper-sensors. In 2020 IEEE Symposium on Computers and Communications (ISCC) (pp. 1-6). IEEE.

[7] Waszak, M., Cardaillac, A., Elvesæter, B., Rødølen, F., & Ludvigsen, M. (2022). Semantic segmentation in underwater ship inspections: Benchmark and data set. *IEEE Journal of Oceanic Engineering*, 48(2), 462-473.

[8] Hong, X., Huang, L., Gong, S., & Xiao, G. (2021). Shedding damage detection of metal underwater pipeline external anticorrosive coating by ultrasonic imaging based on HOG+ SVM. *Journal of Marine Science and Engineering*, 9(4), 364.

[9] Ali, A. A. I. M., Jamaludin, S., Imran, M. M. H., Ayob, A. F. M., Ahmad, S. Z. A. S., Akhbar, M. F. A., ... & Ramli, M. R. (2023). Computer Vision and Image Processing Approaches for Corrosion Detection. *Journal of Marine Science and Engineering*, 11(10), 1954.

[10] Thilak, N., & Gavina, C. G. (2021). Artificial Intelligence Techniques in Oil Industry. *Recent Innovations in Wireless Network Security*, 3(2).









INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY





www.ijirset.com