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LIGHTWEIGHT MACHINE LEARNING FOR RAPID AND ACCURATE CORROSION DETECTION

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ABSTRACT

The deterioration of metallic structures due to corrosion presents substantial economic and safety concerns, contributing to nearly 4% of the global GDP. Despite the promise of machine learning in corrosion detection, progress is hindered by the scarcity of standardized datasets. In this research, the ARL-WPI corrosion dataset has been utilized to refine multi-label classification models through computationally efficient feature extraction and optimized machine learning techniques. However, Colour descriptors such as mean and standard deviation of Red, Green, and Blue (RGB) and Hue, Saturation, and Value (HSV) channels have been extracted for enhanced illumination invariance, along with texture-based attributes Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and Gray Level Co-occurrence Matrix (GLCM) to encapsulate structural patterns and wavelet-derived features (DWT) for multiresolution frequency analysis. Additionally, Principal Component Analysis (PCA) has been applied to preserve 99% of the variance while significantly reducing computational overhead. The optimization of machine learning models, particularly K-Nearest Neighbour(KNN) with 98.6% accuracy and 28.27s execution time and ensemble methods with 97.2% accuracy and 67.24s execution time has demonstrated superior performance over deep learning frameworks, which exhibit higher computational demands. The findings underscore the efficacy of lightweight classifiers with domain-specific feature representations in expediting corrosion assessment. This study fosters a robust synergy between AI-driven material diagnostics and industrial applications, offering a scalable, high-precision, and computationally viable approach for real-world corrosion monitoring.

Keywords: Corrosion Detection, Machine Learning, Feature Extraction, Optimization, Ensemble Methods, Principal Component Analysis (PCA).

1. INTRODUCTION

Corrosion is a natural process that deteriorates materials, particularly metals, leading to structural failures and safety risks. Traditional methods of corrosion detection are often labor-intensive and time-consuming, necessitating the exploration of automated solutions[1]. New possibilities for improving corrosion detection procedures are presented by recent developments in deep learning as well as machine learning. Using information from the literature and empirical findings, this study attempts to assess how well different models of machine learning and deep learning detect corrosion.

2. RELATED WORK

While there are existing studies utilizing traditional Machine learning techniques in material science[5, 7, 13, 15, 16, 19, 20, 21], the application of deep learning techniques has been relatively scarce. Some preliminary attempts to detect material defects have been made in recent years.

These include methods such as More rapid Region-based CNN [4, 14] and fully linked networks [3], used a dataset of 150 raw images of corroded pipes divided into three imprecise classes (nondefective, medium corrosion, and severe corrosion).[17]. Monitoring or detecting flaws in corroded pipelines, bridges, or artificial databases was the main objective of these earlier studies. In contrast, our work is centered on material discovery, making our proposed dataset distinctive as it has been specifically curated for scientific research over a decade.

3. METHODOLOGY

The current study builds and evaluates machine learning models for corrosion detection, feature extraction, model optimization, and performance evaluation using a quantitative study methodology. The process of feature extraction involved the use of texture-based properties such as HOG (Histogram of Oriented Gradients), LBP (Local Binary Pattern), and GLCM (Gray Level Cooccurrence Matrix)to capture structural patterns and color descriptors (mean and standard deviation of RGB and HSV channels) to improve lighting invariance.

To capture both spatial and frequency domain information, the variation, Principal Component Analysis (PCA) Discrete Wavelet Transform (DWT) was used for multi- significantly reduced computing overhead. resolution frequency analysis. By preserving 99% of the

Real-World Applications: Our research's corrosion panels can be used in a variety of industry sectors, governmental institutions, and nations. In every situation where paint is applied to surfaces to reduce corrosion, corrosion testing carried out in compliance with these guidelines is essential. This comprises industries such as automotive, aerospace, chemicals, construction, healthcare, and mining, in addition to government institutions such as the Department of Defence, Department of Energy, the Navy, Army, Air Force, Marines, and NASA, as well as similar organizations in allies[3,12]. Furthermore, similar studies are carried out for consumer goods like air conditioners. These corrosion evaluations are widely used and are crucial testing requirements for numerous sectors. Numerous studies presented at the DoD-Allied Nations Technical Corrosion Conference provide ample documentation of the use of these standardized tests[6,10,11].

Dataset Details: Our dataset consists of 600 images of

Figure 1: samples of our data set's corrosion rating classes 5-9

corroded panels, each measuring 4 inches by 6 inches, which were subjected to laboratory testing and captured at a resolution of 512x512 pixels[1]. To avoid significant imbalances in the corrosion ratings and to concentrate on the most pertinent ratings, we have included only those panels rated between 5 and 9. Ratings below 5 are typically regarded as failures, resulting in the exclusion of those samples from further testing. A rating of 10 is usually seen only at the very beginning of the testing process before any corrosion occurs. For each of the five rating categories (5-9), we have ensured a balanced dataset with 120 images allocated to each category.

4. DATA SET DESCRIPTION

Corrosion Panel Samples: A multi-layered arrangement of components, such as a topcoat, primer, pretreatment, surface profile, and substrate layer, is commonly used to evaluate test samples in coatings and corrosion research. Further details on this tiered structure are provided in the supplemental documentation document. To offer a statistically sound sample for assessing material performance, each sample's coating assembly is backed by numerous replicates [2]. When examining these coated panels, pay close attention to two crucial elements: the surface quality of the panel and the makeup of the assembly's five layers. The names of individual commercial materials are not included in this research or dataset due to proprietary reasons [1].

5. DATA PRE-PROCESSING

I. Feature Extraction: Colour descriptors (mean and standard deviation of RGB and HSV channels)

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were used to enhance illumination invariance, and texture-based attributes like Histogram of Oriented Gradients(HOG), Local Binary Pattern(LBP), and Gray Level Co-occurrence Matrix(GLCM) [20] were used to capture structural patterns.

II. Wavelet Analysis: Discrete Wavelet Transform (DWT) was applied for multi-resolution frequency analysis, capturing both spatial and frequency domain features [21].

III. Dimensionality Reduction: Principal Component Analysis (PCA) was used to preserve 99% of variance, greatly lowering computational overhead.

IV. Model Optimisation: Outperforming deep learning frameworks that demand more computational resources, the model achieved 98.6% accuracy with K-Nearest Neighbour (KNN) in 28.27 seconds and 97.2% accuracy with ensemble methods in 67.24 seconds.

ongoing difficulties in gathering big, high-quality, and consistently rated corrosion datasets in corrosion science are the driving force for these experiments[3].To achieve this, we first conduct an amateur corrosion assessment research, which shows that expert knowledge is essential for corrosion evaluation and that even people trained and supervised by expert raters cannot rate corrosion well.
This study reveals that even

those who have received training and are under the guidance of knowledgeable raters are unable to rate corrosion accurately. As a result, we investigate deep learning models (ResNet-18, CNN, LeNet, GAN, VGG16).[8,9,18] and adjust these models using different techniques. We examine the Machine Learning model to show that performance comparison can greatly enhance performance after tuning hyperparameters in learning techniques.

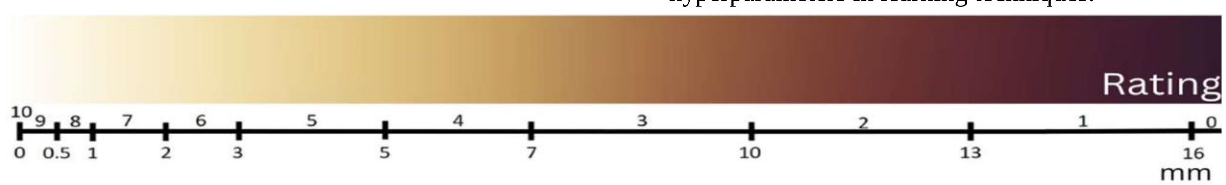

Figure 2: Rating system for corrosion. Higher ratings indicate less corrosion. Top: Each mm measurement range has a distinct corrosion rating; for instance, rating 10 corresponds to 0 millimeters and rating 0 to 16+ mm. Bottom: Average corrosion width measurements for a panel in millimeters.

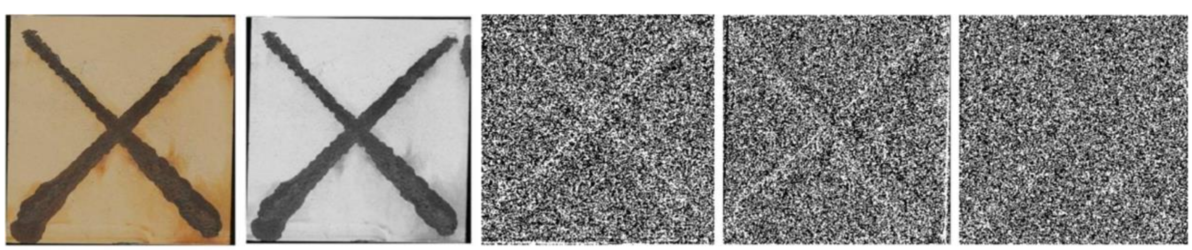

Figure 3: An example of a discrete wavelet-based image extraction. Transform the original image by applying the LL_Coefficient, LH_Coefficient, HL_Coefficient, and HH_Coefficient respectively.

6. EXPERIMENT

All studies and assessments in this experiment were carried out using the corrosion image data[1,2]. The

6.1 DEEP LEARNING NETWORKS

Neural networks having several layers are used in deep learning models, a subset of machine learning

techniques, to analyze different types of data. These models work well for applications like image identification because of their exceptional ability to handle big datasets and intricate patterns. The typical

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Lightweight machine learning models demonstrate excellent efficiency by delivering high predictive accuracy with substantially lower computational cost, as evidenced by the optimised KNN achieving 98.6% accuracy at a fraction of the execution time required by deep learning networks. Their reduced complexity and rapid inference capability make them well-suited for real-time and resource-constrained corrosion detection applications.

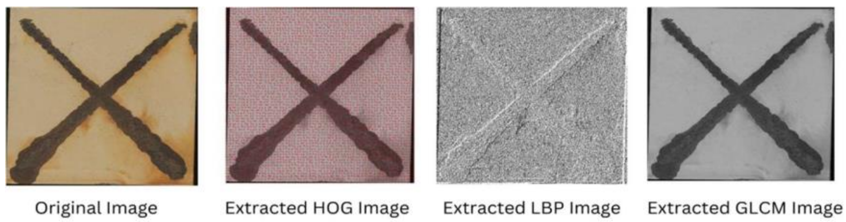

Figure-4: An image extrac on from the source image to Histogram of Orientated Gradients (HOG), Local Binary Pa ern (LBP), and the Grey Level Co-occurrence Matrix (GLCM).

elements of a deep learning model architecture are an input layer, several hidden layers, and an output layer. Activation functions like ReLU, Sigmoid, and Tanh give the model non-linearity so it can identify complex patterns.[8,9]. Metrics that guide the optimization process to reduce prediction errors and assess the model's effectiveness throughout training.

6.2 MACHINE LEARNING NETWORKS

Machine learning models are computational techniques that enable systems to make predictions or judgments based on data without requiring explicit programming. Several machine learning methods exist, including reinforcement, supervised, and unsupervised learning [5,7,13]. Support vector machines, decision trees, KNN, and linear regression are examples of supervised learning models that utilize labeled datasets to train their systems, allowing them to generate predictions based on new, unseen data. Finding the most pertinent variables that increase the model's predictive ability is known as feature selection, and it can greatly improve performance and lessen overfitting.

7 RESULT

Metrics like Accuracy, Precision, Recall, F1-Score, AUC, and Execution time were used to assess the performance of various deep learning (DL) and machine learning (ML) models. With an accuracy of 77.49%, AUC of 96.43%, and execution time of 617.72 seconds, ResNet-18 outperformed the other DL models in terms of predictive performance. KNN produced an astounding accuracy of 98.6%, an AUC of 98%, and an execution time of 28.27 seconds after hyperparameter optimization

The comparison findings show that while deep learning architectures, like ResNet-18, have excellent prediction performance, their high computational demands restrict their applicability for time-sensitive corrosion evaluation. On the other hand, the optimised KNN model shows the usefulness of lightweight machine learning techniques for effective and trustworthy corrosion detection by providing superior accuracy with noticeably shorter execution times.

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Table 1: Performance Indicators for the DL Model

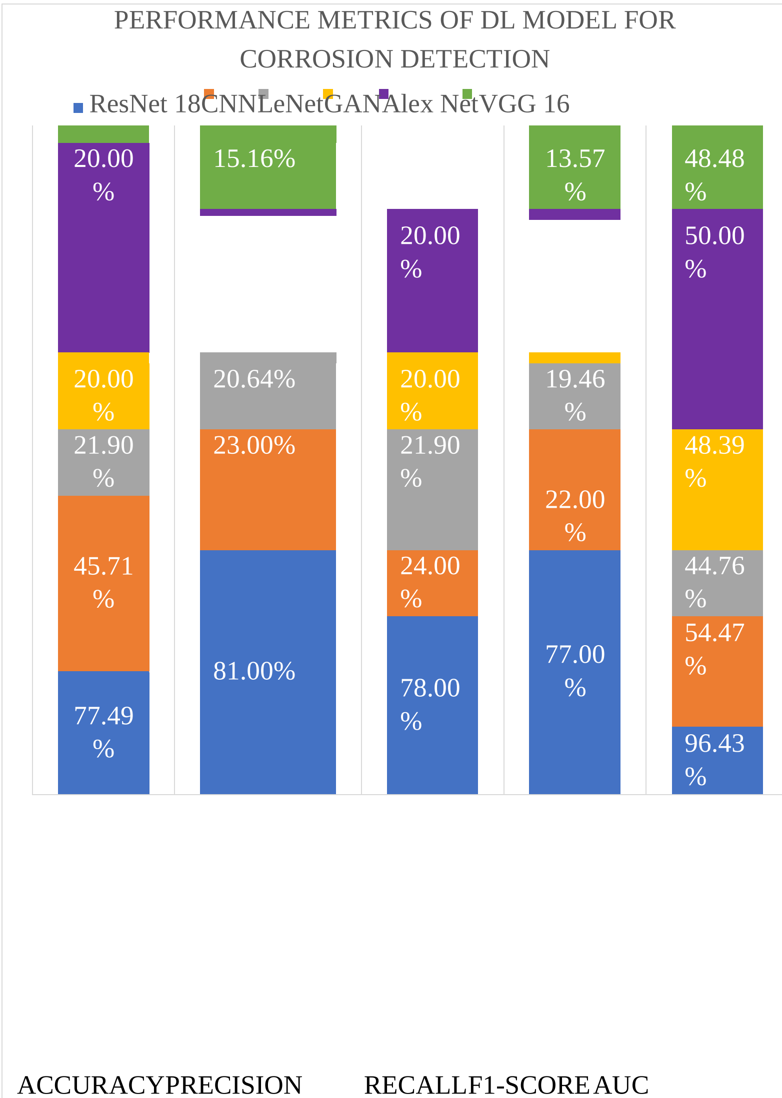

Table 2: Time Execu on of the DL Model

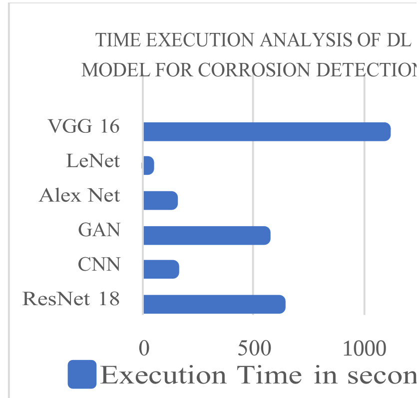

Table 3: Performance Metrics of ML Model

ML MODEL	Accuracy	Precision	Recall	F1-score	AUC	Op mized Hyperparameters	Execu on Time in seconds
KNN	98.6%	98%	95%	93%	98%	Number of Neighbors: 14 Distance Metric: Mahalanobis	28.27
SVM	67.9%	80%	81%	79%	83%	Kernel func on: CUBIC Box constraint level: 14.9538	671.07
Tree	82%	80%	81%	81%	42%	Max splits: 106	25.75

						Split criterion: Gini’s index	
Naïve Bayes	57.%	65%	66%	64%	68%	Distribu on name: Kernel Kernel type: Gaussian	57.46

8. CONCLUSION

In this study, we present a comprehensive evaluation of various deep learning and machine learning models for corrosion assessment, revealing a diverse range of performance outcomes. The ResNet-18 model stands out with an impressive accuracy of 77.49%, an AUC of 96.43%, and execution time of 617.72 seconds, indicating its strong capability in accurately classifying corrosion images. In contrast, other models such as CNN and GAN exhibited lower performance, underscoring the challenges faced when employing simpler architectures for this complex task. Furthermore, our exploration of traditional machine learning models demonstrated that optimizing hyperparameters can lead to significant improvements; notably, the KNN model achieved an outstanding accuracy of 98.6% with an execution time of 28.27 seconds. This highlights the critical role of model tuning in enhancing predictive performance. As we move forward, our goal is to refine these models further and investigate hybrid approaches that integrate the strengths of both deep learning and traditional machine learning techniques. This endeavor aims to improve the accuracy and efficiency of corrosion assessments, ultimately facilitating advancements in materials research and innovation.

9. ACKNOWLEDGEMENTS

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10. AUTHOR CONTRIBUTIONS

All authors contributed to the study conception and design. Material preparation and analysis were performed by Debadutta Sahoo, Soumya Mishra and Sanjeet Subudhi. The draft of the manuscript was written by Debadutta Sahoo. All authors read and approved the final manuscript.

11. STATEMENTS AND DECLARATIONS

11.1 Ethical Considerations- Ethical approval was not required for this study

11.2 Consent To Participate- Informed consent to participate was obtained from all participants prior to data collection.

11.3 Consent For Publication- Not applicable.

11.4 Declaration Of Conflicting Interest- The authors declare no competing interests.

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REFERENCES

[1] Yin, Biao and Josselyn, Nicholas and Considine, Thomas and Kelley, John and Rinderspacher, Berend and Jensen, Robert and Snyder, James and Zhang, Ziming and Rundensteiner, Elke. Corrosion Image Data Set for Automating Scientific Assessment of Materials, British Machine Vision Conference (BMVC), 2021.

[2] Brahim Aïssa and Maha Mohamed Khayyat. Selfhealing materials systems as a way for damage mitigation in composite structures caused by orbital space debris. In Handbook of Research on Nanoscience, Nanotechnology, and Advanced Materials, pages 1–25. IGI Global, 2014.

[3] Yongsheng Bai, Halil Sezen, and Alper Yilmaz. Endto-end deep learning methods for automated damage detection in extreme events at various scales. arXiv preprint arXiv:2011.03098, 2020.

[4] Young-Jin Cha, Wooram Choi, Gahyun Suh, Sadegh Mahmoudkhani, and Oral Büyüköztürk. Autonomous structural visual inspection using region-based deep learning for detecting multiple damage types.

ComputerAided Civil and Infrastructure Engineering, 33(9):731– 747, 2018.

[5] Yupeng Diao, Luchun Yan, and Kewei Gao. Improvement of the machine learning based corrosion rate prediction model through the optimization of input features. Materials & Design, 198:109326, 2021.

[6] Jeannine Elliot and Ronald Cook. Flexible chromatefree aerospace primer. 2019 Department of Defense Allied Nations Technical Corrosion Conference, 2019. URL https://sspc.org/.

[7] Xiaoyu Gong, Chaofang Dong, Jiajin Xu, Li Wang, and Xiaogang Li. Machine learning assistance for electrochemical curve simulation of corrosion and its application. Materials and Corrosion, 71(3):474–484, 2020.

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

[9] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4700–4708, 2017.

[10] Jiheon Jun, Adrian S Sabau, Zach Burns, and Mike Stephens. Corrosion performance of mil-prf-23377 primer coated of laser-interference structured aluminum alloy 2024. 2019 Department of Defense Allied Nations Technical Corrosion Conference, 2019. URL https://sspc.org/.

[11] Jesse C Kelly, Adrian Goff, Jeier Yang, Charles Sprinkle, and Sarah E Galyon Dorman. Effect of inhibitor leaching from several aircraft primers on the corrosion protection of aa7075-t651. 2019 Department of Defense Allied Nations Technical Corrosion Conference, 2019. URL https://sspc.org/.

[12] Manjula Panyam and Hariharan Venkatraman. Corrosion simulation tests: Analysis and improvement of corrosion resistance for automotive components. SAE International Journal of Materials and Manufacturing, 6(2):154–156, 2013. doi: 10.4271/2013-01-0335.

[13] Zibo Pei, Dawei Zhang, Yuanjie Zhi, Tao Yang, Lulu Jin, Dongmei Fu, Xuequn Cheng, Herman A Terryn, Johannes MC Mol, and Xiaogang Li. Towards understanding and prediction of atmospheric corrosion of an fe/cu corrosion sensor via machine learning. Corrosion Science, 170:108697, 2020.

[14] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards realtime object detection with region proposal networks. arXiv preprint arXiv:1506.01497, 2015.14 YIN ET AL.

[15] S Samudrala, K Rajan, and B Ganapathysubramanian. Data dimensionality reduction in materials science. In Informatics for Materials Science and Engineering, pages 97–119. Elsevier, 2013.

[16] Cher Tian Ser, Petar Žuvela, and Ming Wah Wong. Prediction of corrosion inhibition efficiency of pyridines and quinolines on an iron surface using machine learning powered quantitative structure-property relationships. Applied Surface Science, 512:145612, 2020.

[17] Daniel Vriesman, Alceu Britto Junior, Alessandro Zimmer, and Alessandro Lameiras Koerich. Texture CNN for thermoelectric metal pipe image classification. In 2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI), pages 569– 574. IEEE, 2019.

[18] Jingdong Wang, Ke Sun, Tianheng Cheng, Borui Jiang, Chaorui Deng, Yang Zhao, Dong Liu, Yadong Mu, Mingkui Tan, Xinggang Wang, et al. Deep high-resolution representation learning for visual recognition. IEEE transactions on pattern analysis and machine intelligence, 2020.

[19] Luchun Yan, Yupeng Diao, Zhaoyang Lang, and Kewei Gao. Corrosion rate prediction and influencing factors evaluation of low-alloy steels in marine atmosphere using machine learning approach. Science and Technology of Advanced Materials, 21(1): 359–370, 2020.

[20] Fathi, A., Monadjemi, A. H., & Mahmoudi, F. (2012). Defect Detection of Tiles with Combined Undecimated Wavelet Transform and GLCM Features.

International Journal of Soft Computing and Engineering
(IJSCE), 2(2), 30-34

[21] Vaidelienė, G. & Valantinas, J. (2016). Waveletbased Defect Detection System for Grey-level

Texture Images. Proceedings of the 14th International Conference on Industrial Engineering, Applications and Manufacturing

[22] Biao Yin, Thomas A Considine, Fatemeh Emdad, John V Kelley, Robert E Jensen, and Elke A Rundensteiner. Corrosion assessment: Data mining for quantifying associations between indoor accelerated and outdoor natural tests. In 2020 IEEE International Conference on Big Data (Big Data), pages 2929–2936. IEEE, 2020. YIN ET AL.: CORROSION IMAGE DATA SET 15

[23] Wen Yu Zhang. Artificial neural networks in materials science applications. In Applied Mechanics and Materials, volume 20, pages 1211–1216. Trans Tech Publ, 2010.