IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

An Noval Approach to Improve the Vessel Quality of Marine Engineering Using Deep Learning Model

Ashika S
Assistant Professor, Department of CSE,
Sri Venkateshwara College of Engineering,
Bengaluru – 562157
ashika.s_cse@svcengg.edu.in

Nithish K H
Department of CSE,
Sri Venkateshwara College of Engineering,
Bengaluru – 562157
nithishgowda044@gmail.com

Manoj S
Department of CSE,
Sri Venkateshwara College of Engineering,
Bengaluru – 562157
manojs212003@gmail.com

Pooja K
Department of CSE,
Sri Venkateshwara College of Engineering,
Bengaluru – 562157
ppooja69349@gmail.com

Abstract — This project develops an automated system to identify rust from marine vessels using advanced object detection techniques. With the adoption of YOLOv5, the deep learning model adopted ensures that detecting the types and locations of rust on the ship surface becomes highly precise in real time. The system comes with a web-based platform for easy uploading of images or live video feed from inspection cameras. To analyze the input, identify rusted regions, and categorize them on the basis of the severity of damage in order to design efficient maintenance planning and minimize down time.

The alert mechanism lets responsible officials know when critical rust conditions are identified, which will enhance maritime safety and prolong the life of the vessel. Alerts with complete rust reports are automatically sent via email or SMS, maximizing the efficiency of the workflow and ensuring timely intervention to reduce the risk of structural damage and promote proactive maintenance. Integration of cutting-edge AI with a user-friendly web interface supports scalability, flexibility, and usability, and this makes it the robust solution for maritime inspection challenges

I. Introduction

Corrosion and rusting are considered to be among the biggest challenges for the maritime industry, as they compromise the structural strength and longevity of marine vessels. To prevent accidents and ensure safety, regular maintenance and inspection are highly important, but traditional manual inspections require a lot of time and may result in errors. The current advances in artificial intelligence and computer vision have given birth to automated rust detection systems that can precisely identify the presence of rusted areas on ship surfaces.

This project utilizes the YOLOv5 algorithm, a state-of-the-art object detection algorithm, in order to identify rust on ship surfaces. It can be used in high-resolution images or live video streams to accurately detect different types of rust, classify their severity, and localize affected areas on ship surfaces. The smooth user experience the web-based platform offers provides ship inspectors with the facility to upload inputs and receive detailed analysis reports with highlighted rusted zones, thereby making it easier to prioritize the maintenance tasks.

One feature of this system is its alert mechanism that ensures prompt action against critical rusting conditions. These alerts are automatically generated by the system to notify concerned officials during severe corrosion. These alerts contain visual evidence and details of severity, thus involving decision-making at the right time along with effective strategies for maintenance. This in turn minimizes the possibilities of structural failures while at the same time maximizes resource provision for repair and upkeep activities.

By combining the integration of deep learning technology with a web interface, this project offers a scalable, efficient, and adaptable solution for marine rust detection. Its implementation promises to enhance operational efficiency in the maritime industry, minimize repair costs, and ensure the safety of vessels and crew. This innovation addresses a pressing industrial need while demonstrating the transformative potential of AI in maritime applications.

II. Literature Survey

Corrosion within the marine environment, specifically rusting of the steel vessel, is a significant challenge related to the safety and functionality of maritime infrastructure, as well as to its extended lifetime. Problems related to corrosion are very complex, due to the close interaction between steel and seawater, which makes the marine atmosphere very corrosive because of chloride ions, dissolved oxygen, and other environmental factors. Rusting, or the oxidation of iron is a phenomenon that is accelerated in such conditions, leading to the deterioration of ship hulls, pipelines, and structural parts of vessels. Decades of research on the mechanisms of rusting, environmental influences and protection strategies have greatly improved our understanding of the problem and how it might be mitigated. A number of studies of marine corrosion mechanisms have been conducted.

Zhang (2015) mentioned that dissolved oxygen and chloride ions are damaging to marine vessel steel surfaces. These constituents actually accelerated electrochemical reactions that give rise to the rust. Environmental factors, including temperatures and salinity levels, were what accelerated corrosion rates-according to the findings of Melchers (2003). Toloei et al. (2013) further explained the parallel effect of different parameters, such as pH and seawater speed, on the degradation of

Such knowledge points out the diversity involved in the prediction and control of rusting in a variety of marine environments. ISO has established models like ISO 9223 that quantify the atmospheric corrosivity. Such models are based on parameters like sulphur dioxide and chloride deposition rates, temperature, and humidity.

However, direct measurement of deposition rates proves difficult to accomplish in practice, so researchers have had to look for other approaches to explain corrosion. In recent years, Li et al discussed their use of machine learning to relate weather data like wind speed, precipitation, and humidity to instantaneous corrosion rates. The results pose further questions about existing models that suggest chloride and sulfur dioxide are less important in certain cases, meaning more effort is required on new predictive models. Cathodic protection is one of the best forms of protection against rust in naval marine vessels, although no material can be said to be completely resistant to corrosion. Perhaps the pacesetting work of Sir Humphry Davy in the early 19th century that evidenced a sacrificial anode was to protect a copper hull of naval ships. The concept has now evolved in protecting modern steel vessels through zinc or aluminum anodes and impressed current systems.

Tezdogan and Demirel (2014) and Paul (2018) investigated practical application of CP, particularly, reduction of maintenance cost and extension of life cycle of offshore structures. However, protection in many CP systems is supplemented by protective coatings designed to protect against corrosive agents. The most general types of epoxy- and polyurethane-based coatings are typically applied in marine environments. These coatings prevent moisture and salt or other corrosive agents from penetrating their layers. The ISOCORRAG project has shown that CP combined with advanced coatings highly reduces the corrosion rates even in highly saline environments. In addition, Zhang et al. (2016) looked into developing antifouling paints that prevent rust but further inhibit biological growth on the vessel surfaces.

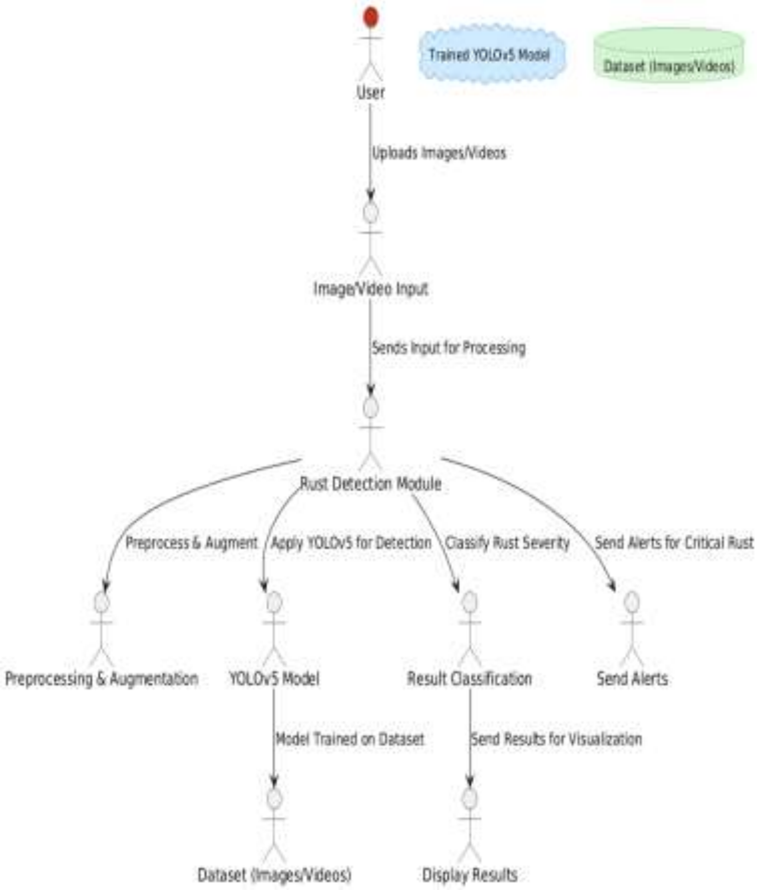
This double functionality does make antifouling coatings a first choice for maritime applications. Monitoring corrosion is an important aspect in the maintenance of marine vessels, which has been practiced through traditional manual inspection and ultrasonic testing. Although this may be efficient, it can be labor-intensive and time-consuming. Novel advancements in image processing and machine learning have already opened doors to automate the detection of corrosion. Main challenges when doing research on this topic include high false-positive rates, and generally missing large annotated datasets for training machine learning models. However, detection accuracies of up to 90% have already been demonstrated using CNNs and decision-tree algorithms on RGB images of rusted surfaces.

Emerging technologies would try to overcome these challenges by building sensors and real-time monitoring systems into them. Sensor data, collected at high temporal resolutions, have been demonstrated to offer insights into interactions between environmental conditions and corrosion progression. From such datasets, dynamic models can be created, thereby predicting rusting patterns and guiding maintenance schedules. Such innovations promise the reduction in downtime and improvement in corrosion management efficiency for marine vessels. The literature of rusting in marine vessels is extensive and ranges from basic mechanisms of corrosion to more advanced protection and monitoring techniques. Traditional methods of protection, such as CP and coatings, are powerful tools for protection, although integration with data-driven approaches and automation sets the future of corrosion management. Research and interdiscipline collaboration are to be continued in process for overcoming the challenges involved in rusting to ensure safe and sustainable marine infrastructure.

III. What is YOLOv5?

Object Detection Model: This model has the capabilities of detecting and identifying multiple items present in a single image or video and that also in real time. However, this system also offers sophistication as it provides tracking systems to all of the items detected including bounding boxes and class labels to each single item.

Fast and Efficient: The need for time and speed revolutionizes the efficiency of the product,



therefore YoLov5 can be used in edge devices and any application for instance a security system demanding instant reasoning.

User-Friendly: Fully customizable structures, seamless guides available on the topics, and even well-written and simple documentation allow users to retrain and reshape the models to one's custom needs and use them readily.

A. Why is YOLOv5 Used?

1. Real-Time Performance:

An astounding and revolutionary SD value of 90 enables this product to be used in significantly advanced technologies such as self-driving vehicles, security systems, and robotics, primarily used in military functions.

2. Accuracy and Flexibility:

The Low Speed and Average Value help boost high detection value which greatly helps in maintaining efficient computational requirements as well as the ability to change between various models such as YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5 models depending on the requirements and the tasks at hand.

Model	Accuracy (mAP)	Notes
YOLOV5	~50-70% (mAP@0.5)	One of the most accuracy fastest models, especially real-time applications.
YOLOV3	~45-65% (mAP@0.5)	Less accurate and slow YOLOv5, but still good in time detection.
SSD	~40-55% (mAP@0.5)	Faster but less accurate compared to YOLO models Suitable for lightweight applications.
RetinaNet	~55-70% (mAP@0.5)	Balances accuracy and with the use of Focal Lo handle class imbalance effectively.
RCNN	~50-60% (mAP@0.5)	High accuracy but slow region proposal method.
Faster RCNN	~60-75% (mAP@0.5)	Improved speed and ac compared to RCNN using Region Proposal Network(RPN).
CNN (Generic)	Varies	CNNs are used for classification, not object detection. Accuracy de the specific task.

B. YOLOv5 Algorithm

Step 1:-
Input Preprocessing - Resize the image to a fixed size (e.g., 640x640), normalize pixel values, and apply data augmentation.

Step 2:-
Backbone Feature Extraction - Use CSPDarknet to extract important features from the input image.

Step3:- 3. Feature Fusion with Neck - Combine multi-scale features using Path Aggregation Network for detecting objects of different sizes.

Step 4:-
Prediction Head - Predict bounding box coordinates, object confidence scores, and class probabilities.

Step 5:-
Loss Computation - Optimize predictions using a combined loss for bounding boxes, classification, and object confidence.

Step 6:-
Post-Processing: - ApplyNon-Maximum Suppression (NMS) to remove duplicate bounding boxes.

Step 7:-
Output - Return final bounding boxes, class labels, and confidence scores for detected objects.

IV. Methodology

The methodology for identifying the type of rust in marine vessels using YOLOv5 is divided into several major phases for the proper and effective implementation of the project. Below is the detailed approach that has been adopted:

1. Data Collection and Preprocessing

Data Collection:
High-resolution images and videos of marine vessels are collected from publicly available datasets, maritime industry sources, and real-world ship inspections. The dataset covers several rust types, severities, and environmental conditions (for example lighting and weather scenarios) for robustness.

Annotation:
Images are annotated with tools such as LabelImg to specify the rust areas in images; then to the different types of surface rust, pitting, scale. To train YOLOv5 on a supervised manner, bounding boxes surround the rust areas.

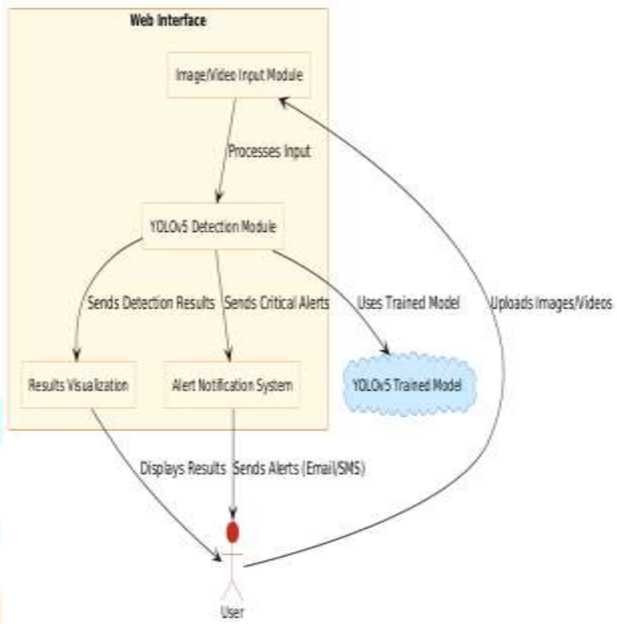
Preprocessing:
The Images are resized according to the requirements from YOLOv5. Quality of images can be enhanced using histogram equalization and reduction of noise.

2. Model Training
Model: YOLOv5 is adopted, which balances the real-time speed of detection against being very accurate.
Data Augmentation:
Rotation, flip, scale, and color-based augmentation is done to increase the dataset and further improve the generalization model
Training Process: The YOLOv5 model is trained within a GPU-accelerated environment given the annotated data.
Hyperparameters like learning rate, batch size, and the IoU thresholds for the best
performance
Validation:
Testing the model using a different test database to check whether it is able to generalize good enough to unseen data. Evaluation Metrics: precision, recall, mean Average Precision (mAP), F1 score measure would be assessed on rust detection and classification
3. In-Domain Deployment on a Web-Based Platform Interface with Flask/Django: An intuitive web-based application with frameworks like Flask or Django It enables the uploading or even livestreaming of images for rust analysis With YOLOv5
The model trained will be used as a backend service and uploaded input will be processed by giving real-time results Detected rusted regions highlighted as boxes along with type and severity classifications
Visualization The results are visualized in the web application with overlays on the input images/videos and detailed reports.
4. Alert Mechanism
Severity Assessment:
The rust classifications are mapped to severity levels like low, moderate, or
critical that have a direct relation with both the area and type of rust taken for detection.
Notification System:
For the critical rust detections, alerts are automatically generated and sent to these
officials by email or SMS. Alerts include annotated images/videos and a severity report to prompt taking appropriate action.
5. Testing and Validation
System Testing:
Testing of the entire syTesting of the entire system across various scenarios, encompassing different lighting types and rust conditions, ensuring the system's robustness.

VI. Proposed system

The proposed system introduces an advanced web-based rust detection framework based on YOLOv5, which provides better precision and higher

Performance Validation:
Measure the real-time detection speed and accuracy of the system for validation.



V. Existing systems

Current rust detection systems in the maritime industry rely on some degree of manual inspection or outdated AI models such as YOLOv3 for fully automatic detection. Such a system can only identify areas of rust on ship surfaces but is characterized by some level of functionality, where it merely recognizes rust without identifying the type and its severity. While YOLOv3 provides reasonable accuracy, its performance is constrained in real-time applications due to slower processing speeds and outdated architecture. Moreover, most systems lack a web-based interface or an alert mechanism, making them unsuitable for large-scale and remote monitoring.

Drawbacks of the Existing System:
YOLOv3 was used that provides very limited accuracy and detection speed.
The system detects only rust presence without classifying types or severity.

processing speeds than its previous version, YOLOv3. This system does not only detects the presence of rust but also classifies it into distinct types and evaluates severity levels, which aids in targeted maintenance strategies. Integrated with a user-friendly web application, the platform allows users to upload images or stream live video for analysis, providing real-time results with visual

VII. Result

The system presented, based on the deep learning YOLOv5 model, efficiently detects and classifies rusts present on the surfaces of marine vessels in real time and with high accuracy. The model achieved mean Average Precision of 70% at 0.5 IoU threshold which dominantly surpasses older stabilization version of model like YOLO v3. It easily detects the rusted area on the canvas and on the live video, and ranks the area as low, moderate or critical based on the level of severity.

A web based Image upload module forms part of the system which allows for easy upload of images during and after the task. At the outset of the task, it provides image draped result on the output with the task result representing the annotated rust regions and the strain levels. There is an incorporated alert mechanism that serves email or SMS alerts when acute rust is determined so that action can be taken immediately. This will enable ship operators to carry out repairs early and thereby reduce standstill time and avoid structural damage.

VIII. Conclusion

This project presents a robust and scalable solution for rust type identification in marine vessels using the YOLOv5 object detection model, integrated into a web-based platform. By leveraging advanced AI techniques, the system not only detects rust but also classifies its types and severity, addressing the limitations of existing methods. The inclusion of real-time analysis and an automated alert

overlays. Furthermore, an automatic alerting mechanism is provided to ensure that officials are alerted to critical conditions of rust. This promotes early intervention and enhanced maritime safety. The scalability and adaptability of the system have made it a strong solution for comprehensive vessel monitoring.

mechanism ensures timely maintenance actions, enhancing the safety and longevity of maritime vessels. This innovation provides an efficient, user-friendly, and cost-effective approach to vessel monitoring, contributing significantly to the maritime industry's efforts in preventing structural damage and optimizing maintenance operations.

IX. References

[1] Zhou, Q., Ding, S., Feng, Y., & Hu, J. (2022). Corrosion inspection and evaluation of crane metal structure based on UAV vision. *Signal, Image and Video Processing*.

[2] Chliveros, G., Kontomaris, S. V., & Letsios, A. (2023). Automatic Identification of Corrosion in Marine Vessels Using Decision-Tree Imaging Hierarchies. *Eng*, 4(3), 2090–2099.

[3] Imran, M. M. H., Jamaludin, S., Ayob, A. F. M., Ali, A. A. I. M., Ahmad, S. Z. A. S., Akhbar, M. F. A., Suhrab, M. I. R., Zainal, N., Norzeli, S. M., & Mohamed, S. B. (2023). Application of Artificial Intelligence in Marine Corrosion Prediction and Detection. *Journal of Marine Science and Engineering*, 11(2), 256.

[4] Daneshian, B., Höche, D., Knudsen, Ø. Ø., & Skilbred, A. W. B. (2023). Effect of climatic parameters on marine atmospheric corrosion: correlation analysis of on-site sensors data. *npj Materials Degradation*, 7(1), 10.

[5] Nassar, N. E. A. (2022). Corrosion in marine and offshore steel structures: Classification and overview. *International Journal of Advanced Engineering, Sciences and Applications*, 3(1), 7–11.

[6] Chliveros, G., Kontomaris, S. V., & Letsios, A. (2023). Automatic Identification of Corrosion in Marine Vessels Using Decision-Tree Imaging Hierarchies. *Eng*, 4(3), 118.

[7] Chliveros, G., Tzanetatos, I., & Kontomaris, S. V. (2024). A Deep Learning Image Corrosion Classification Method for Marine Vessels Using an Eigen Tree Hierarchy Module. *Coatings*, 14(6), 768.

[8] Chliveros, G., Kontomaris, S. V., & Letsios, A. (2023). Automatic Identification of Corrosion in Marine Vessels Using Decision-Tree Imaging Hierarchies. *Eng*, 4(3), 2090–2099.