Corrosion Detection on Ship Hull Using ROV Based on Convolutional Neural Network

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Abstract— **The Remotely Operated Underwater Vehicle (ROV) has several inspection functions. One of them is the inspection function for hull damage. The damage that often occurs in the hull is corrosion. The corrosion can cause a decrease in the strength of the hull plate, reduce the speed of the ship, and decrease the quality of the safety level of ships and passengers. This study aims to classify the level of corrosion intensity on ship hulls by implementing a Convolutional Neural Network (CNN). Identification is carried out on images taken by underwater cameras via a Remotely Operated Vehicle (ROV). The intensity of the area affected by corrosion is identified so that the level of corrosion intensity can be classified and it can be considered that the ship needs maintenance to prevent even greater losses due to corrosion. The dataset used is 240 image data divided into 3 classification categories: low, medium, and high corrosion intensity. The accuracy of the real-time testing of the CNN method on the dataset plate when conditions outside the water reached 91.1% and on the dataset plate when conditions underwater reached 86.6%.**

Keywords— **Corrosion, Hull, Remotely Operated Vehicle (ROV), detection, Convolutional Neural Network (CNN).**

I. INTRODUCTION

By looking at the construction of the ship's plate, the hull plate is the most susceptible to corrosion, this is because the surface of the hull plate, especially those below the waterline, is always submerged in seawater. Corrosion on the hull plate can cause a decrease in the strength of the hull plate, reduce the speed of the ship, and reduce the guarantee of the safety and security of the cargo of goods and passengers. To avoid greater losses due to seawater corrosion, the hull plates need to be periodically protected from corrosion attacks. Several methods are used to prevent corrosion on ships, including coating.

Deep learning enables machines to perform computations consisting of many layers of processes to learn the representation of data with various levels of abstraction. Based on this data representation, deep learning can make machines mimic human behavior such as speaking, recognizing objects visually, detecting certain objects, and so on. Apart from deep learning, the

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Convolutional Neural Network (CNN) is one artificial intelligence method that can detect and classify objects. To make it easier for humans to carry out surveillance. In this case, an ROV is used which detects corrosion on the ship's hull. In the process of detecting and classifying the corrosion using the CNN method. The ROV uses a camera to take images. It is hoped that this ROV can detect corrosion when it is below the surface of the water and can classify the level of corrosion through a comparison of the existing paint area with the area affected by corrosion or perhaps it can be said by classification of corrosion intensity. So, ROV can be an easy solution for checking ship hull conditions.

A. Corrosion of the Hull

A decrease in metal quality due to electrochemical reactions with the environment is called corrosion. In general, corrosion includes the loss of metal in exposed parts. There are several forms of corrosion, ranging from corrosion evenly distributed over the entire surface of the metal to corrosion spread over certain parts. Corrosion on metal occurs due to the flow of electric current from one part of the metal surface to another part of the metal surface. The current flow will cause a loss of metal in the parts where the current is discharged into the environment (anode reaction). Protection occurs at the point where the current returns to the metal surface (cathode reaction).[1]

The corrosion in the hull construction cannot be eliminated but can only be slowed down. The corrosion can reduce the strength of the plates on the ship's hull, the speed of the ship, and the guarantee of the safety and security of cargo and passengers. The following are the types of corrosion, parts of the ship that are susceptible to being affected, and some corrosion prevention that can be done. [2]

1. Types of corrosion that can damage ship parts:
    a. Uniform corrosion, namely the entire surface of the material is attacked by corrosion in a wide area.

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b. Pitting corrosion is corrosion that appears and is concentrated in certain areas. Perforations, namely on the surface of the material some holes are getting deeper and deeper.

c. Stress corrosion occurs in constructions that carry large loads. The magnitude of the pressure load on the concrete iron before undergoing the corrosion process will greatly affect the rate of corrosion that occurs on the iron. The greater the pressure (load) given to the specimen, the greater the corrosion rate.

d. Erosion corrosion occurs in materials that often receive collisions with liquid particles flowing at high speed.

e. Crevice corrosion occurs in areas of clamps, joints, and areas covered by excrement, bias animals, or marine plants.

f. Galvanic corrosion occurs in seawater because the material is in contact with other cathodic (nobler) materials with a large potential difference between the two materials.

2. Parts of ships that often experience corrosion:
   a. The area between the ship's full laden and empty laden.
   b. The stern area of the ship around the propeller and rudder of the ship.
   c. In the sewage channels.
   d. In the area of the watertight bulkhead plate.
   e. In the area of the deck plate under the bathroom and cooling room.
   f. In the sea chest
   g. In other areas, they are usually inundated by seawater.

3. There are two kinds of corrosion prevention on ships: active and passive painting. Before painting is done, the optimal painting results are cleaned. The plate or construction to be painted must be clean from dirt to maximize the paint's adhesion.

B. Convolutional Neural Network

CNN can recognize an object's predictive information even if the object is positioned anywhere on the input. CNN's contribution to the feature extraction layer is the convolution and pooling layers. Convolution works on the principle of sliding windows and weight sharing to reduce the complexity of calculations. The pooling layer is used to summarize the information generated by a convolution layer. Meanwhile, the vector resulting from several convolution and pooling operations in multilayer perception is the fully connected layer used to perform classification.

The convolution neural network itself is a combination of image convolution for the feature extraction process and a neural network for classification. Based on the LeNet5 architecture, there are 4 main layers in a CNN: convolution, relU, subsampling, and fully connected. The initial layer function is a feature extraction method, so the number of layers in a CNN does not have universal rules and applies differently depending on the dataset used. Because of this, the number of layers in the network and the number of neurons in each layer are considered

hyperparameters and are optimized using a search approach. [3]

Research on corrosion detection is mainly motivated by reasons of operational costs and risk mitigation with several publications in the last decade [4-9]. In addition, the development of innovation is supported by improvements in deep learning, computer vision, and the availability of increased computing power. Several publications regarding corrosion detection have been carried out, including research on the application of deep learning on material degradation which discusses corrosion detection [10], previous studies demonstrated the ability of modeling using deep learning to produce semantic segmentation maps, labeling each image pixel as corrosion [11-12]. Current corrosion detection also compares 3 model architectures: FCN, U-Net, and Mask R-CNN on private datasets [9]. By using edge detection to fine-tune the boundaries of the detected area, the best performance is obtained on the Mask R-CNN model, with an average F1 score of 0.71. To date, no openly labeled corrosion image dataset has been published, and the model is prone to misclassification. In this study, ROV is used which can detect corrosion on the ship's hull. In the process of detecting and classifying corrosion, the convolutional neural network (CNN) method is used. The application of CNN aims to classify the level of corrosion through a comparison of the existing paint area with the area affected by corrosion. Taking pictures is carried out underwater and as a comparison of system performance, tests are also carried out on objects when they are out of water. The challenge of this test lies in the water medium which is susceptible to noise interference [13-14].

C. Open CV

Open Source Computer Vision Library is a library software intended for real-time dynamic image processing, made by Intel, and now supported by Willow Garage and Itseez. OpenCV is released under the permissive BSD license which is free and provides complete freedom for commercial use without disclosing the source code. It also has an interface that supports the C++, C, Python, and Java programming languages, including Windows, Linux, Mac OS, iOS, and Android operating systems. [15]

D. GUI (Graphical User Interface)

A graphical computer interface (GUI) is a graphical image displayed on a computer screen that makes it possible to access software applications by using dropdown menus, dialog boxes, tabs, toolbars, icon shortcuts, and other tools. adding components that cannot be made in the base text. These components can be buttons, images, etc. The goal is to make it easier for users to use the program that was created. In this study, the GUI is used to facilitate the Convolutional Neural Network process, from data training to real-time testing. [16]

II. METHOD

A. Hardware Development

The camera on the ROV is directly connected to a computer/PC so that the image taken by the camera will

be detected and processed by the computer. The system will detect objects on the camera using a Python language program. Python comes with the OpenCV (Open Computer Vision) library. The image taken by the system will be stored as a temporary image so that the storage on the full HD camera will not fill up quickly. The captured image is then used as training data to produce weights which are the output of CNN.

The hardware for this detection system can be shown in Figure 1. ROV is a tool for taking pictures through an underwater camera and is designed to be able to move and communicate up to a depth of 30 meters. For more details, ROV specifications are shown in Table 1 and the underwater camera specifications used are shown in Table 2. The result of applying CNN is the classification of low, medium, and high corrosion levels.
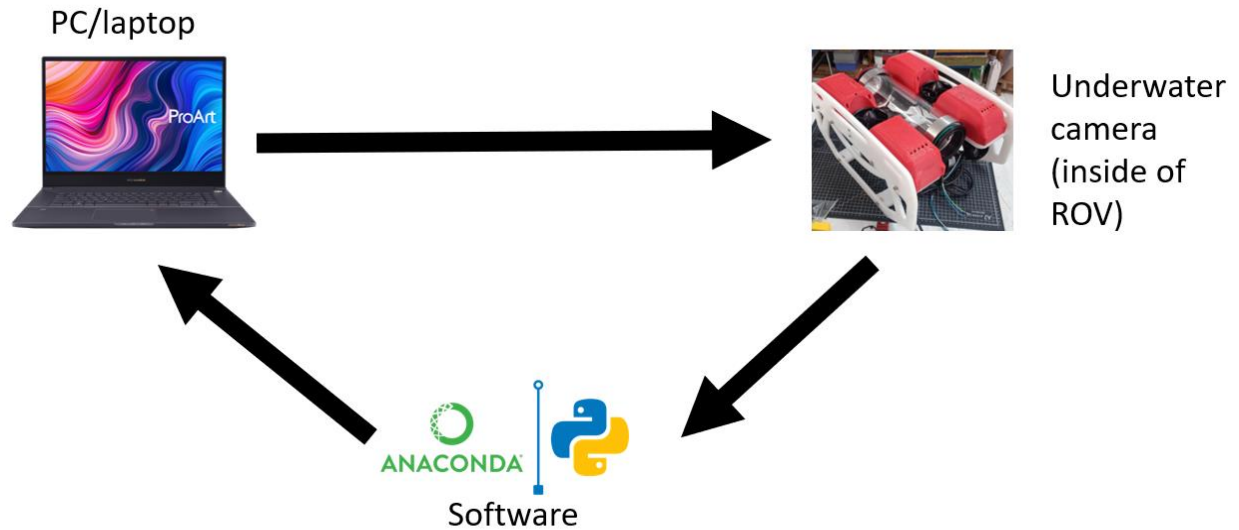

Figure 1. Hardware Development

TABLE 1.
ROV SPECIFICATION

Parameter	Value
Dimension	450 mm x 340 mm x 250 mm
Weight in the air (with ballast and battery)	11-12 kg
Weight in the air (without ballast and battery)	9-10 kg
Buoyancy foam	R-3318 urethane foam rated to 244 m
Construction	HDPE frame, aluminum flanges/end cap, & acrylic or aluminum tubes
Thruster configuration	6 thrusters: 4 vectored and 2 vertical

TABLE 2.
CAMERA SPECIFICATION

Parameter	Value
Type	Sony Exmor IMX322 / IMX323
Camera PCB Dimensions	32mm x 32mm
Mass (total)	17g
Mass (without cable)	13.5g
Working Temperature	-20 - 75°C
Total pixels*	2000(H) x 1121(V) ~2.24 MP
Recording pixels	1920(H) x 1080(V) ~2.07 MP
Minimum Illumination	0.01 lux
Sensitivity	5.0V/lux-sec@550nm
Compression format	H.264 / MJPEG / YUV2（YUYV）
Channels	single-channel, 44.1 kHz
Format	Linear-PCM (L16)
Supply Voltage	5 V
USB Version	2.0
Distortion	1%

B. Software Development

In creating an image processing application, it is necessary to install some software. Some of these applications are Anaconda 3 and the GUI display. Anaconda 3 is used for large-scale data processing,

predictive analytics, and scientific computing which can simplify package management and deployment. This software will run the whole program on image processing with CNN.

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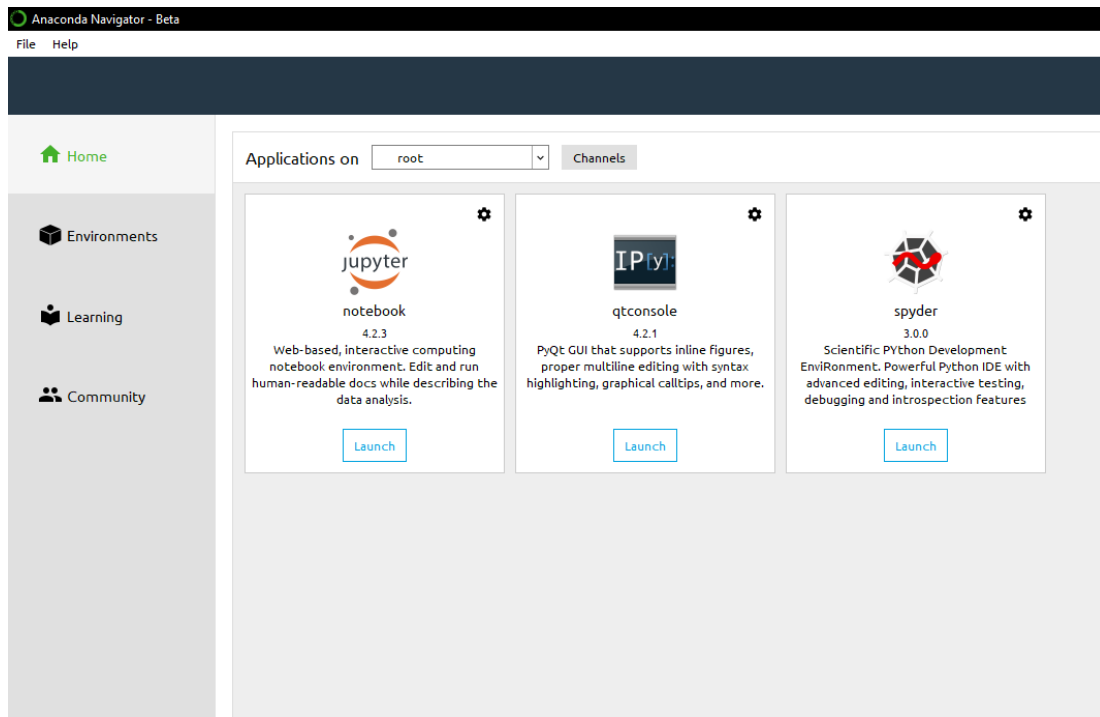*(pISSN: 2541-5972, eISSN: 2548-1479)*

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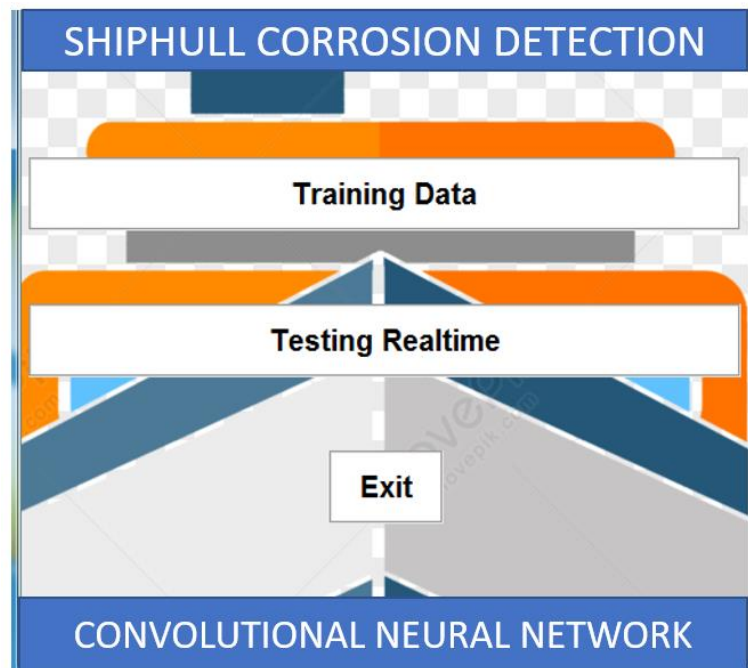
Figure.2. Anaconda Navigator Display

Figure 3. The GUI Display

Figure 3 is the main page display of the GUI. The GUI is used as a facility or shortcut for the corrosion detection process on ship hulls using the CNN method. There are some buttons for training data and real-time testing on that page.

C. System Design

There are several stages in building this corrosion detection system. The first is the ROV will determine the object detected and identified using the camera, then the image will be taken and divided into dataset classes according to each object. In the pre-processing stage, the input image will be processed and converted from RGB to grayscale. After that go to the processing stage. At this stage, the image will be processed using convolution to create a new input, then proceed to the max-pooling process.

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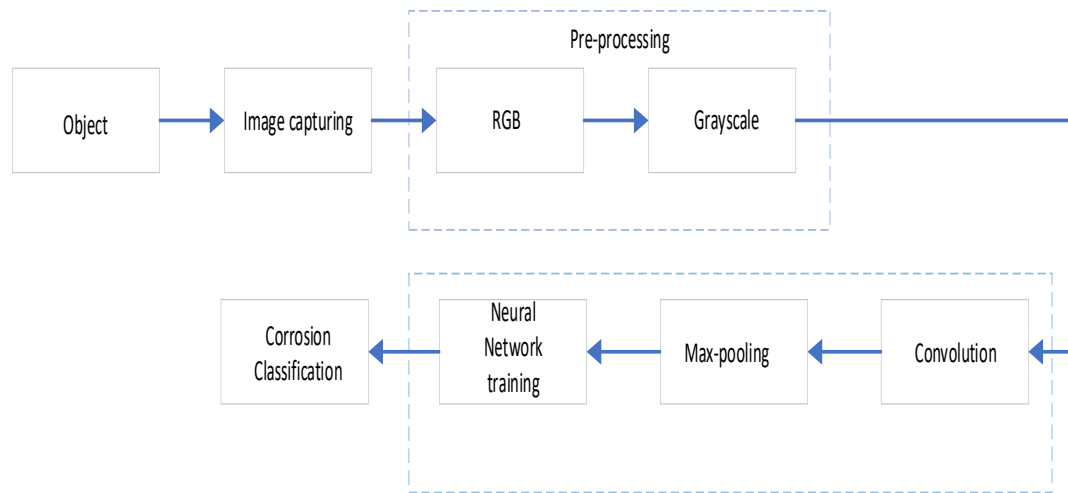*(pISSN: 2541-5972, eISSN: 2548-1479)*
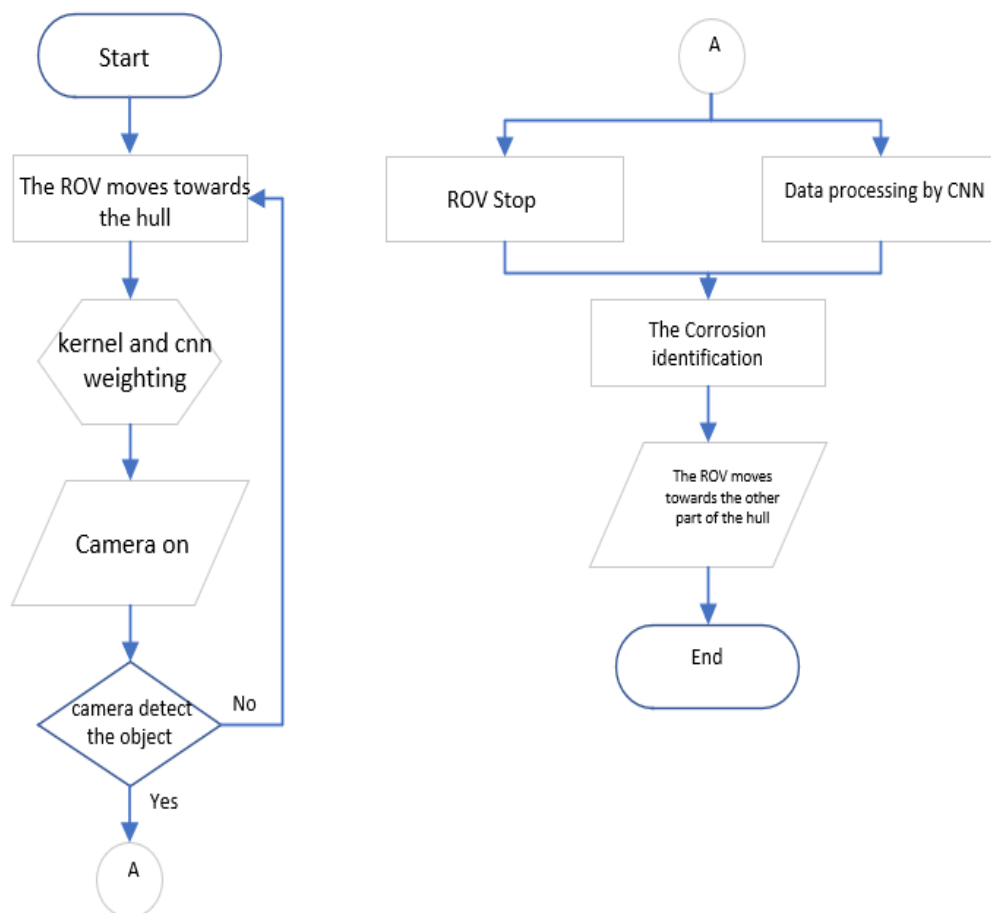
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Figure 4. The System Block Diagram

Figure 5. System Flowchart

This process aims to speed up the computational process in the program and to remove noise in the input image that was previously taken. The training process is the next stage using a neural network to generate weights for corrosion classification. The system block diagram can be shown in Figure 4. The flow of image processing is shown in Figure 5. First, the process starts when the ROV moves or operates in the water where the dataset and library for programming have been prepared. Then, the ROV camera will detect the presence of corrosion. After detecting the corrosion, the ROV stops and data is processed to identify the severity of the corrosion on the ship's hull. The ROV will move or switch to the other side to detect corrosion on the other side of the hull.
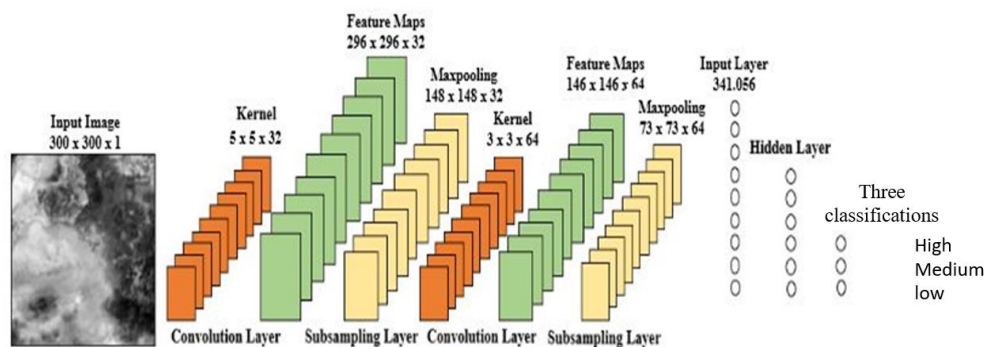
D. The CNN Architecture

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Figure 6. CNN Architecture

After going through the adjustment phase with the dataset, the image will be further processed using the CNN method. The CNN architecture is shown in Figure 6 with the pre-processing process consisting of two processes: dataset formation and dataset conversion into one layer. The next processes are image convolution, max-pooling, NN training, and softmax. The classification process is the last process that determines the output. The output of CNN is classified into 3 categories of corrosion: low, medium, and high corrosion.

E. Corrosion Detection Testing

Determining the optimal distance is needed to retrieve corrosion image data with the available camera resolution. If the optimal distance has been obtained, the image will have good quality for the detection process. The camera used in this test is a camera with a resolution of 1080 pixels. An optimal distance of 0.5 meters is obtained between the object and the camera by carrying out several image capture tests. At a distance of 0.5 m, the image captured is considered to have the best quality compared to other distances. In the image obtained, a relatively small noise or blur is found so that at that distance a dataset can be retrieved for further scaling to the size of the original object.

F. The Formation of Dataset

In the application of artificial neural networks, the initial stage carried out before the training process is the formation of datasets. In this study, all datasets and images used had a resolution of 300 x 300 pixels, while the dataset used consisted of 240 images. Retrieving the dataset is adjusted to the size of the original plate that is being scaled. The scale used is 1:4, meaning that 1 image dataset represents 4 parts of the plate divided into equal sizes. This is done so that the dataset images used are unbiased and there is no ambiguity in the process of taking the dataset on the plate observed in the test pond.

After scaling the plates for dataset retrieval, the data can be collected into several folders: low, medium, and high. In testing, two conditions were used: object data outside the water and underwater.

G. Convolution and Max-pooling Processes

The initial step taken on the architecture used is a convolution process with a kernel size of 5 x 5, and from this process, feature maps are produced. The next step is the max-pooling process with a kernel size of 2 x 2. Max-pooling is a basic operation in used convolution neural network (CNN) which is used to extract important features from an input image or signal. This operation reduces the dimensions of the data volume generated by the previous convolution layer, thereby reducing the number of parameters in the model and preventing overfitting. After the max-pooling process, the next step is the second convolution process with a 3 x 3 kernel. After getting the second feature map, max-pooling is then carried out again with the same size as the previous max-pooling, namely 2 x 2 kernels and 2 x 2 strides.

H. The Training Process

The training process is carried out after the convolution process. The process is carried out using the Spyder application and assisted by the keras.io library. Keras is a library for advanced neural networks with large computational scales. The Keras library provides the required components such as dense which is a variable declaration to determine the number of hidden neurons in the hidden layer, and the activation component is useful for determining the activation used. Flattening is changing the output of the convolution process in the form of a matrix into a vector. Convolution 2D facility as an image convolution process with various kernels in it and Maxpool2D for the subsampling process where the max-pooling matrix can be adjusted as needed.
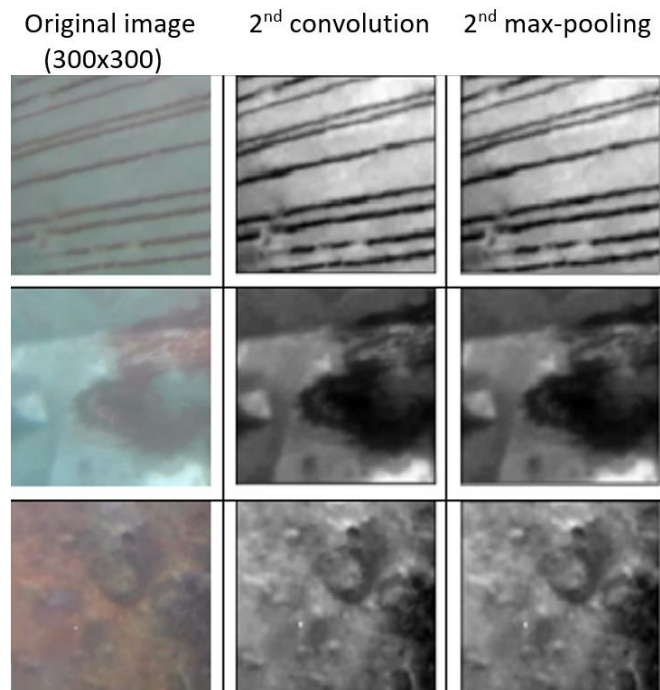
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Figure 7. Convolution and Max-pooling Process

III. RESULTS AND DISCUSSION

A. The Training Optimizer

The training process is carried out with the number of hidden layers on 256 hidden neurons and the ReLU activation function. Training is carried out when the condition dataset is underwater using the optimizer Adadelta, Adam, Adagrad, and Adamax. The next process is training by using the Adadelta optimizer. Figure 8 shows the training process using the Adadelta Optimizer. This process requires 40 epochs and 220 minutes of learning time. By selecting these parameters, the training accuracy is 0.9792 or 97.92% and the validation accuracy is 1.0. By using the Adadelta Optimizer the level of accuracy tends to increase, especially in the 5th to 15th epoch. From the 15th epoch onwards the graph between training accuracy and validation accuracy tends to fluctuate, but not much different. The graph in Figure 8 shows that the accuracy continues to increase and begins to stabilize starting from the 20th epoch. This shows that the Adadelta Optimizer is suitable for the CNN architecture in this study. Meanwhile, Figure 9 shows the Adadelta Training Loss graph which tends to decrease starting from 1.2 and then

dropping to around 0.03. In the 15th epoch, the value of the validation loss increased dramatically to 0.6 and then started to decrease again. The graph between training loss and validation loss tends to fluctuate not significantly a drift.

The result of training using Adadelta Optimizer is as follows: the training accuracy is 0.98, the training loss is 0.13, the validation accuracy is 1.0, and the validation loss is 0.0016. The Adadelta optimizer is proven to have the best training accuracy and validation in the test compared to the other two optimizers: Adagrad and Adamax optimizers.

Realtime testing is carried out to find out the accuracy of object detection using a model obtained from the previous training. Taking the underwater images is done by using the ROV camera. The system design stage is the overall work of the prototype to be made. In this system, a wireless joystick is used and connected to ESP 8266 so that it can move the ROV. the x and y-axis on the camera, Jetson Nano as an algorithm processor, and there is a camera module to capture objects and corrosion images on the ship's hull. The procedure for taking objects can be illustrated as shown in Figure 10
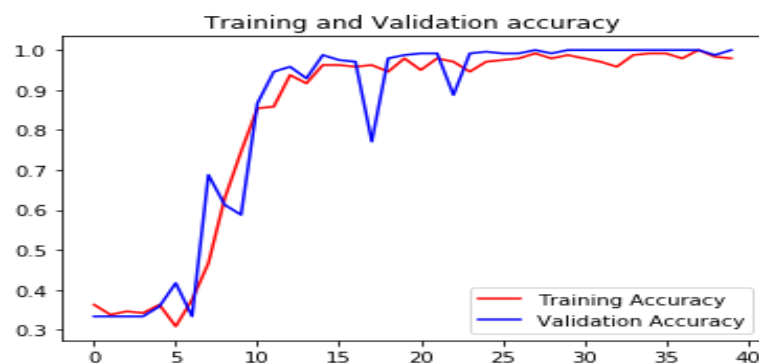

Figure 8. Adadelta Accuracy Training Graph

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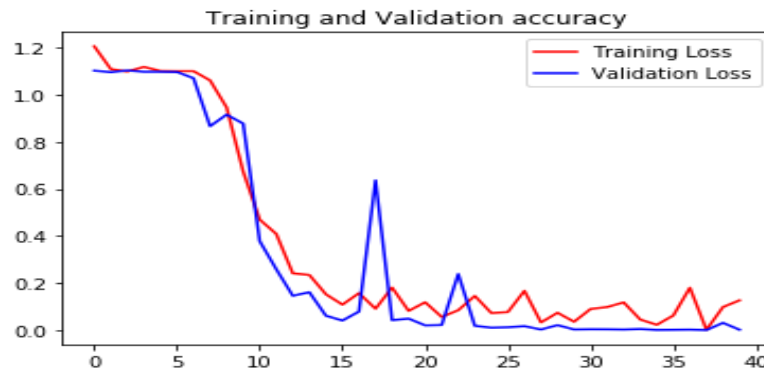*(pISSN: 2541-5972, eISSN: 2548-1479)*

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Figure 9. Adadelta Training Loss Graph

The test results show that by using the Adagrad Optimizer, a stable training accuracy from start to finish is obtained, namely 0.333 or 33.3%. The test used 40 epochs and 207 minutes of learning time. While testing using the Adamax optimizer obtained a training accuracy of 0.2792 or 27.92% and a validation accuracy of 0.3333.
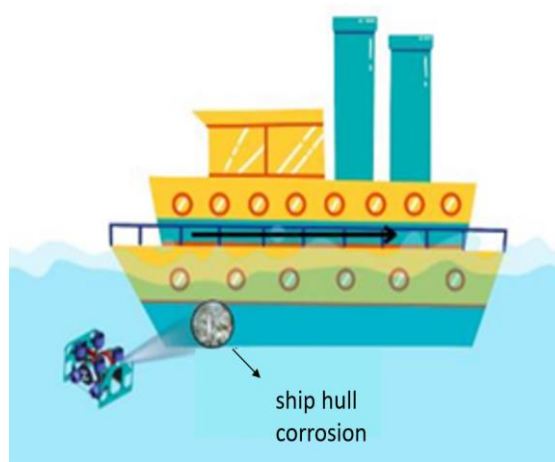

Figure 10. The Process of Taking Images on Ship Hulls

TABLE 3.
CORROSION DETECTION ON OUTSIDE WATER OBJECTS

No.	Real Condition	Detection Results	Software testing
1.	Low	Low	
2.	Low	Low	

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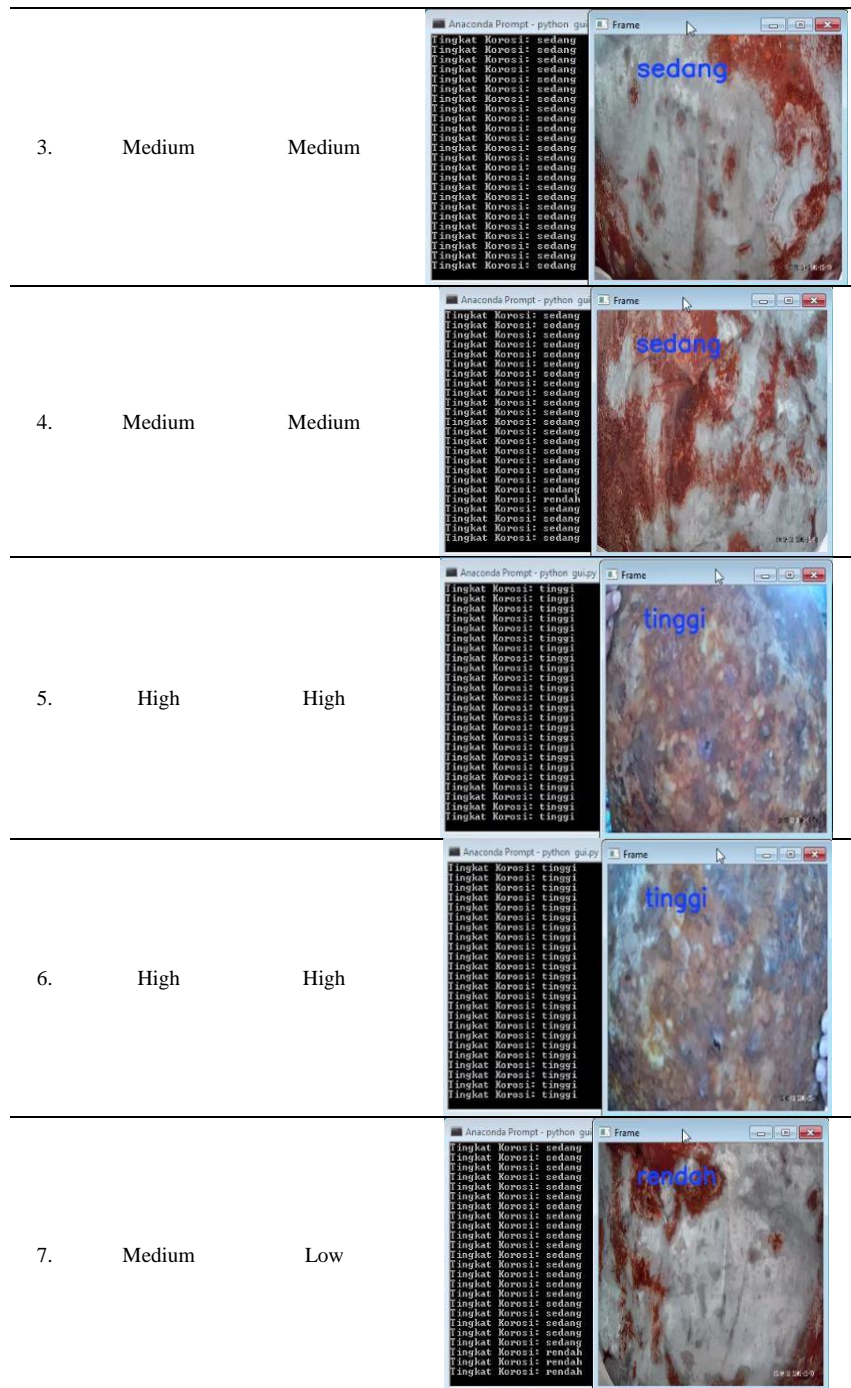|			
3.	Medium	Medium	
4.	Medium	Medium	
5.	High	High	
6.	High	High	
7.	Medium	Low	

Table 2 shows the test carried out in real-time outside the water. The test was carried out 45 times and the results obtained were 41 accurate data and 4 data errors so the accuracy obtained was 91.1%. Detection errors occur because of the system's difficulty in distinguishing medium and high corrosion classification classes.

Sometimes, most of the area is corroded at moderate level corrosion, so the image is identified as high-level corrosion. Table 3 shows the results of corrosion testing accuracy outside of water in real time.

TABLE 4.
THE CORROSION DETECTION ACCURACY OF OUTSIDE-OF-WATER OBJECTS

Corrosion Level	Number of tests	Accurately Defined Data	Inaccurate Defined Data
Low	15	15	0
Medium	15	14	1
High	15	12	3
Total	45	41	4

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TABLE 4.
CORROSION DETECTION ON UNDERWATER OBJECTS

No.	Real Condition	Detection Results	Software testing
1.	Low	Low	
2.	Low	Low	
3.	Medium	Medium	
4.	Medium	Medium	
5.	High	High	
6.	High	High	

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| 7. | High | Medium |

TABLE 5.
THE CORROSION DETECTION ACCURACY OF UNDERWATER OBJECTS

Corrosion Level	Number of tests	Accurately Defined Data	Inaccurate Defined Data
Low	15	14	1
Medium	15	13	2
High	15	12	3
Total	45	39	6

After detecting objects outside the water, the next process is the detection of corrosion on underwater objects or plates. The testing with these two conditions aims to compare the ability of the detection system on underwater objects and the objects when out of water. Underwater testing was carried out 45 times. The test results showed that there were 39 times the success of the system in detecting corrosion and defining the corrosion level correctly and there were 6 errors in defining the corrosion level. Thus, the test shows an accuracy of underwater detection is 86.6%. Detection errors are caused by misclassification by the system where underwater is greater than noise when outside water. This has an impact when taking pictures in water, objects become blurrier, thereby reducing the system's ability to detect corrosion on the plate. The results of corrosion detection tests on underwater objects are shown in Table 4 and details of corrosion detection testing on underwater objects can be represented in Table 5.

IV. CONCLUSION

After testing and analyzing the system, the following conclusions can be drawn :
(i) In this study, the Convolutional Neural Network (CNN) method was used to detect and classify the hull plate corrosion intensity with 3 classes namely low, medium, and high. The dataset used amounted to 240 images for each condition and the correct CNN structure was obtained, namely with the details of a 5x5 kernel with 32 filters for the first convolution and then continued with a 3x3 kernel with 64 filters for the second convolution. The convolution process in this architecture occurs 2 times and the max-pooling process occurs 2 times in the end resulting in 341,056 input vectors. The training process with a Neural Network with 1 hidden layer and a total of 256 hidden neurons.
(ii) The accuracy of the CNN method on the hull plate when the condition of the object outside the water

reaches 91.1% and on the plate, when the object is underwater, reaches 86.6%. Error detection occurs because it is difficult for the system to detect corrosion levels due to low lighting and poor water clarity when the object is underwater.
(iii) The main indicator of corrosion is the remaining plate thickness as a technical recommendation according to BKI rules. The CNN method is used as a consideration for a plate affected by corrosion and further detailed checking is needed to determine whether the plate should be replaced or not.

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