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Convolutional Neural Network (CNN) Applied to the Risk Analysis of Accidents in Vessels Navigating the Amazon Rivers

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***Abstract*— There are many rules to be followed to assess the safety of navigation, the certifiers and classifiers are responsible for ensuring compliance with all these rules that ensure the integrity of the vessels, however, this is not enough. The Naval District, in which the state of Pará is included, was the first in accidents that occurred in the year 2020 and the third in the year 2021. Due to these accident occurrences, concepts of artificial intelligence, machine learning and deep learning were applied in this area. Aiming to assist in this process, this work proposes to develop an application using Convolutional Neural Network (CNN) for image recognition (Vessels and plimsoll disk). In this sense, a Convolutional Neural Network (CNN) learning technique was used to identify the type of ship through a bank of supplied images, the same method was applied to identify if there is accident risk with the ship through the analysis of plimsoll disk images. To perform the training of the CNNs, six different network architectures were evaluated with: changing the number of filters in each convolutional layer; varying the amount of convolutional layers and; using transfer learning of the VGG-16 network with the fine tuning technique. The results achieved in this work are promising and demonstrate the feasibility of employing Convolutional Neural Network as a method for identifying the images of vessels as from the plimsoll disk).*

I. INTRODUCTION

In Brazil there are many navigable waterways, however, according to a study prepared by the National Transport Confederation (CNT, 2019), only 30% of the waterways are used. In numerical question, of the 63 thousand kilometers of rivers with navigation potential, only 19.5 thousand kilometers are actually used. From the study, it can also be stated that in the Amazon region, about 10 million passengers are transported per year and that in the last 8 years, until the year of the referred study, there was a growth of 34.8% in cargo transportation.

However, with the increase in demand for fluvial transport, the probability of accidents increases. The Navy, in turn, has prepared a document called the Administrative Inquiry on Accidents and Facts of Navigation (IAFN), which collects and organizes data on shipping accidents according to: nature, type of vessel, number of vessels per year, naval district.

The Naval Districts, according to Decree No. 2,153, have many attributions, one of them being to monitor maritime traffic. In order to cover the whole Brazilian territory 9 naval districts were created. The 4th Naval District is responsible for the states of Amapá (AP), Maranhão (MA), Piauí (PI) and Pará (PA), the latter being the study region. In 2020 about 34% of the occurrences belong to the 4th naval district responsible for part of the northern states, being in 1st place among the districts. Some of the causes that lead to accidents in rivers are due to the fact that boats, this being the means of transportation that had more occurrences, due to excess weight or wrong positioning of cargo and passengers

The total weight and the position of the weights directly influence the stability of a vessel and to be able to be evaluated, there are analysis criteria, for this case, the Freeboard, which is the distance from the waterline to the main deck and the transverse tilt will be addressed. About the positioning of the loads, not being done properly can lead to an inclination to one of the sides, which are the sides of the ship, called heeling.

When a vessel tackles it is possible to observe that one of the sides ends up with a low freeboard height, according to examples from Dokkun (2013b), and thus ends up not passing the requirements established by the Norms of Maritime Authority (NORMAM). In the case of excess passengers, the freeboard already decreases, but it gets even worse when the cargo and passengers are positioned incorrectly, which is very common, this increases the risk of people falling into the river and even the ship sinking. For this reason, it is very important to maintain a minimum height for the freeboard, as provided by the Norm of Maritime Authority for Inland Navigation - NORMAM 02 (MARINHA DO BRASIL, 2005).

To evaluate the risks of a vessel accident due to freeboard, one of the Deep Learning techniques will be used, which are called Convolutional Neural Networks (CNN). This programming technique is inserted within the Artificial Intelligence (A.I.) environment, to which has shown to be very effective for problems with images, such as: classification, pattern recognition (RONNEBERGER et al., 2015), character extraction (OCR's) (MICROSOFT, 2018) and object detection (GOOGLE, 2017), ship recognition using distributed self-organizing map (LOBO, 2009).

Based on the data provided by the Navy and the advances in Deep Learning techniques, the goal is to develop a CNN code capable of classifying images of regional vessels, from an analysis of the free edge and finally determining if the condition of the vessel presents a risk of loss of stability. Therefore, with the advance of computing and techniques of artificial intelligence, such as Neural Networks, and with the analysis of the history of occurrence of accidents in navigation obtained by the IAFN data, it would be important to raise the question: Is it possible that an AI with so many contributions to society, collaborate with the reduction of accident rates warning passengers about the risk of accidents before sailing?

II. THEORETICAL REFERENCE

Image recognition has been widely used in several branches of research, such as in medicine, for diagnosing a disease from the analysis of test results; in agriculture, applied in the identification of pests in crops; in autonomous cars, replacing human vision for decision making; among other applications (FERREIRA, 2017; PRETO, 2018; TRINDADE, 2018; VOGADO et al., 2019).

One of the methods that has been successfully applied in the processing and analysis of digital images, with high effectiveness to solve problems of pattern and object recognition in images, is the Convolutional Neural Network (CNN) (ALMEIDA, 2018). Aiming at identifying the components of a railway line, as well as the indication of disintegration and chips of its sleepers, from image analysis, Gilbert, Patel and Chellappa (2015) applied fully Convolutional Neural Networks for classification of 10 material classes. This architecture was proposed for the challenge of extracting accurate information from images generated by cameras installed in moving vehicles, which present distorted backgrounds in the railway environment. The approach of this work resulted in a material classification accuracy of 93.35% and proved the high capacity of Convolutional Neural Networks to capture more complex patterns, while reusing learned patterns with increasing levels of abstraction that are shared among all classes. Following the same line, Faghih-Roohi et al. (2016) applied a Convolutional Neural Network (CNN) solution for automatic detection of rail surface defects. In this work, raw images were used as input to the classification model and applied to three different CNN structures (small, medium and large) in size and number of parameters, in which they were compared for classification accuracy and computation time. The network was optimized using a minilot gradient descent method. In this paper, three types of the experienced results were reported, initially with six 16 classification classes (normal, weld, light defect, medium defect, large defect, and joint) where a high percentage of false results were found. Since then, the normal and weld classes have been integrated as Normal and all three defect classes as a single class. In this way, a new performance evaluation of the CNN models was presented with the three classes: Normal, Defect, and Joint. The performance of the three CNN models (small, medium and large) for the multi-class (3 classes) and binary (normal and defect) classifications based on the averages of the calculated performance metrics and the corresponding standard deviations were also presented. As a result, the defect classification performance achieved almost 92% accuracy across the three network structures, with the large one having the highest value and the longest time spent for training. It was found that the two-class training showed a difference of approximately 1% higher accuracy compared to three- class, which validated a good performance in multi-class training. (FAGHIH-ROOHI et al., 2016).

2.1 Artificial Neural Network

To understand how the Artificial Neural Network works, it is necessary to understand a little about the human brain. The human brain can identify images, sounds, and patterns through stimuli generated by the external environment. Behind this action and reaction of the person in relation to the environment, there is a sequence of processes that occur in neurons. According to Moreira (2017), biological neurons, represented by Figure 1, are basically composed of dendrites, cell body, and axon:

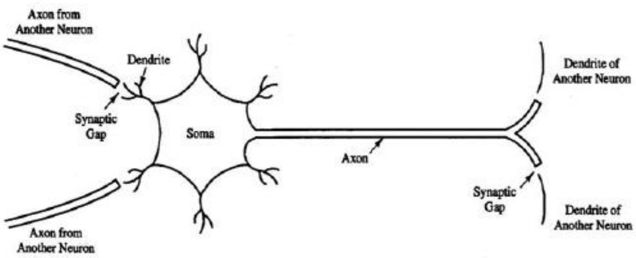

Fig 1: Biological Neuron

Source: Fausset (1994, p.6)

The dendrites (a) are responsible for receiving stimuli from other neurons or sensory cells, adjusting the impulses coming from other neurons. The cell body (b) contains the nucleus, where protein synthesis occurs. In the axon (c) is transmitted the nerve impulses from the cell body, while the endings of the axon (d) is where it contains the synapses, which establish communication with the dendrites or cell bodies of other neurons (Moreira, 2013). From this it was developed a system that mimics the neurons biological neurons, called artificial neurons, as representedin Figure 2

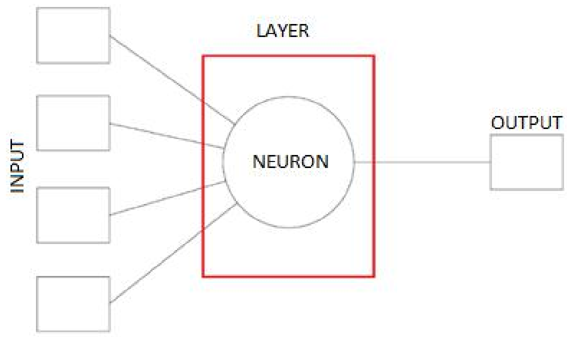

Fig.2: Artificial Neuron

Source: Authors (2021)

2.2 Conventional Neural Networks (CNN)

Among the various deep learning architectures, Convolutional Neural Networks (CNNs) have been achieving remarkable prominence in their main areas, having major advances in audio, video, and image processing (LECUN; BENGIO; HINTON, 2015). CNNs have been inspired by the hierarchical organization of the visual cortex and the classical notions of simple and complex cells. According to Hubel and Wiesel's (1968) experiments with cats and monkeys, it was observed that simple cells were activated when presented with simple patterns to the animal, such as lines; and complex cells were activated when more elaborate patterns, composed of combinations of simple patterns, were presented to the animal (HUBEL; WIESEL, 1968; LECUN; BENGIO; HINTON, 2015).

III. METHODOLOGY

For the identification of images by the CNN, it is necessary to go through a few steps, which consists of collecting images, training the neural network and evaluating the results and for this will follow a few steps until the end of the process. However, before detailing the procedure, it is important to present the tools and the architecture of the network

3.1 Tools

For the development and training of the network, a computer with the following configurations was used: Intel(R) Core (TM) i5-9300H CPU @ 2.40GHz, 8.00 Gigabyteof RAM and NVIDIA GTX 1650 card with 4 Gigas memory, with Windows 10 operating system.

The Python language plataforma used handling the libraries, environments and basic programming settings was Anaconda, due to its ease of handling. Within the platform an integrated development environment (IDE) was provided together with the facility to install the necessary libraries.

- Python: It is a high-level, dynamic, interpreted, modular, multiplatform and object-oriented programming language. It has a simple and easy-to-understand syntax and a wide variety of libraries (PYSCIENCE BRAZIL, 2022).

- Spyder: The IDE has a very intuitive interface for handling and programming. It has an advanced combination of editing, analysis, debugging, and profiling. Easy data exploration, deep inspection, and visualization features (SPYDER, 2022).

- TensorFlow: An open source platform that facilitates the development and implementation of Machine Learning (Machine Learning) (TENSORFLOW, 2022).

In addition to the TensorFlow/Keras library, the OpenCV, Numpy, Matplotlib, Scikit-learn and Imbalanced-learn libraries were used.

- OpenCV: also known as Open Source Computer Vision, is an applied image processing library for developing applications in the field of Computer Vision (OLIVEIRA, 2019);

- Numpy: multidimensional matrix processing package, which provides several tools to manipulate and manage them (OLIVEIRA, 2019);

- Matplotlib: biblioteca de software para criação de gráficos bidimensionais de visualização de dados (OLIVEIRA, 2019);

- Scikit-learn: Open source machine learning library that supports supervised and unsupervised learning. It also provides various tools for model fitting, data preprocessing, cross-validation, model selection and evaluation, among many other utilities;

- Imbalanced-learn: open-source machine learning library that supports supervised and unsupervised learning. It also provides various tools for model fitting, data preprocessing, cross-validation, model selection and evaluation, among many other utilities found in machine learning and pattern recognition applications

The methods are categorized into, subsampling, where samples from the majority class are discarded during the balancing procedure; oversampling, where new samples are generated in the minority class to achieve a certain balancing proportion; and a combination between subsampling and oversampling to balance the samples (LEMAITRE; NOGUEIRA; ARIDAS, 2017).

3.2 Network Architecture

In this work, two network structures were developed, one for vessel classification and the other for the plimsoll disk. The network structure is composed of 4 layers, being 3 convolution neuron layers and 1 fully connected neuron layer. The first layer is composed of 32 neurons (filter) with dimension 3x3, the second has 64, the third has 128. The first fully connected layer has 512 neurons that then passes to the second layer also fully connected that has 6 neurons, which are equivalent to the amount of responsefor vessel classification, Table 1.

Table 1: Network architecture for vessel classification

Convolution Layer 1	N. of Filters Dimension of Filters	32 3x3
Max-pooling Layer 1	Dimension of Filters	2x2
Convolution Layer 2	N. of Filters Dimension of Filters	64 3x3
Max-pooling Layer 2	Dimension of Filters	2x2
Convolution Layer 3	N. of Filters Dimension of Filters	128 3x3
Max-pooling Layer 3	Dimension of Filters	2x2
Fully Connected Layer 1	N. of nodes	512
Fully Connected Layer 2	N. of nodes	6

Table 2: Network Architecture for Plimsoll disk classification

Convolution Layer 1	N. of Filters Dimension of Filters	32 3x3
Max-pooling Layer 1	Dimension of Filters	2x2
Convolution Layer 2	N. of Filters Dimension of Filters	64 3x3
Max-pooling Layer 2	Dimension of Filters	2x2
Convolution Layer 3	N. of Filters Dimension of Filters	128 3x3
Max-pooling Layer 3	Dimension of Filters	2x2
Fully Connected Layer 1	N. of nodes	512
Fully Connected Layer 2	N. of nodes	3

Meanwhile, for the Plimsoll disk classification, the same network structure was used, but in the second fully connected layer, only 3 neurons were used, Table 2. It is worth noting that the first 3 layers of the network have the Max-pooling activation function with 2x2 dimensions.

3.3 Processing Flow

The following procedure will be used for the CNN, represented by flowchart 1:

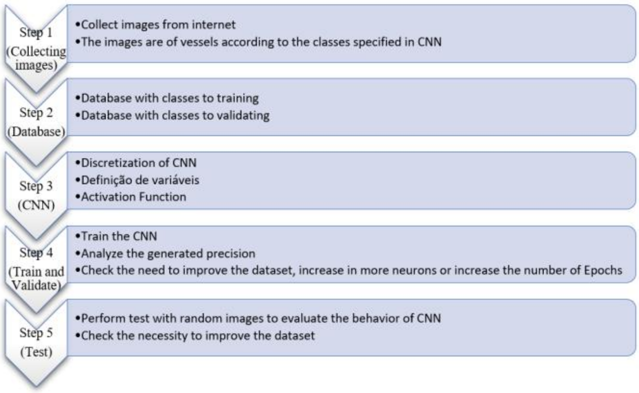

Fig 3: Flowchart 1 – Stage of the method applied to CNN

Source: Own Authors (2021)

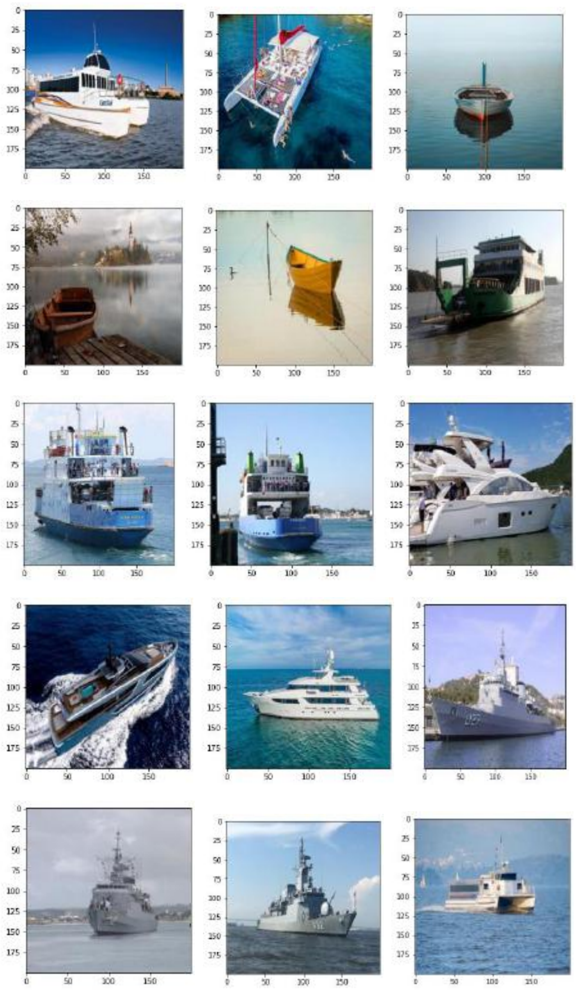

Fig.4: Example of Imagens used of the vessels – Database

Source: Own Authors (2021)

In step 1, we collected images from various sources, all specifically of the classes determined within the programming, which are Military Ship, Ferry Boat, Canoe, Catamaran, Sailboat and Yacht, as seen in section 3.1 and for the Plimsoll Disc, section 3.3. In step 2 we created a Database (Database) containing numerous images from the Internet, of the ships, Figure 4 and Figure 5, and of the plimsoll disc, Figure 6 and 7.

Fig.5: Example of Imagens used of the vessels – Database

Source: Own Authors (2021)

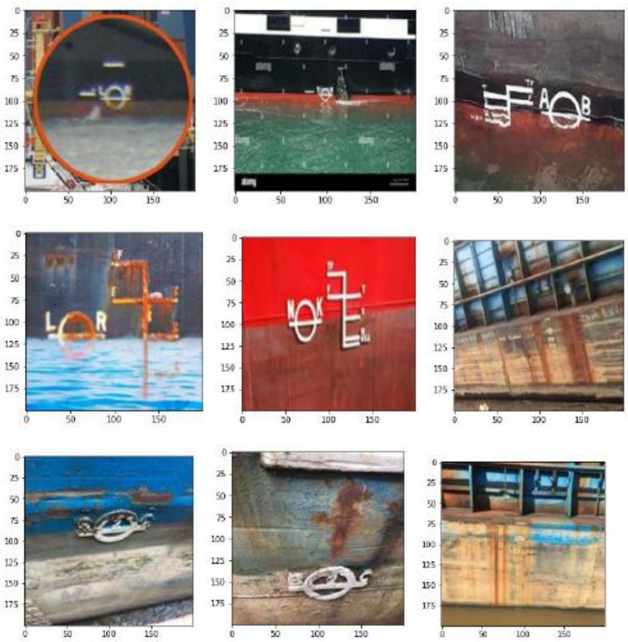

Fig.6: Example of Images used from plimsoll disk - Database

Source: Own Authors (2021)

All photographs are different for training and validation, asit is important that the program can refine its parameters based on various perspective points of the ship type, without risking biased training.

After the elaboration of the Dataset of images, following to step 3, the development of the code for image classification will be prepared in Python language, whose platform is considered Open Source (Open Resources), allowing users to use it for free, besides being able to enjoy numerous libraries, one of them being the TensorFlow (TF), created by Google Brain team. TF is an open source library for Machine Learning and the Application Programming Interface (API) that will be used for Deep Learning 'and Keras, which has a set of programming routines (GOOGLE, 2015). Both libraries will be imported by within the Python platform. In this step, we will discretize the Convolutional Neural Network (CNN) process, including. The number of neurons, layers, activation functions, epoch and the way the results are displayed on the screen

After configuring the CNN and proceeding to step 4, the tool will be executed, where it will train and validate its parameters for classification, trying to discard irrelevant features, for example the presence of water, and prioritize specific contents, such as hull shape. For details about its accuracy, the percentage will be displayed on screen during all training epochs.

Finally, step 5 consists of performing a test in which random images are presented, which are not in the database, and generating a prediction of the results. In this case, if there is any inconsistency in the results, this error may lead to the interpretation that it may be related to the photographs in the database or the number of epochs generated. This method will be applied both for the classification of the vessel type and for the analysis of the freeboard of the vessel.

IV. ANALYSIS OF THE RESULTS

Images of six types of ships were collected, as seen in section 3.1, and a database was created for the CNN to use for training. For the method mentioned in section 4, in step3, the settings regarding classification is specified in a categorical way, because there are more than two classesto be evaluated.

As the images obtained have very large dimensions, requiring a high demand of time and computational effort to process the pixels, they were resized to dimensions of 200 pixels long and 200 pixels wide, acceptable sizes for conventional computers. It was also determined that 5 layers of neurons would be used, the first containing 32 neurons, the second with 64 neurons, the third with 128 neurons, and the fourth with 512 neurons. The activation functions for these specified layers contain the ReLU function.

The fifth and last layer is the output layer, so the number of neurons is equal to the number of inputs. In this case, six classes were used, which are the types of vessels, and the activation function is Softmax. For the loss function the Categorical Cross Entropy was used, which collaborated with the evaluation of the epochs, to determine if the results were converging. After the configuration is done, in step 4 the CNN is trained. During the training the accuracy and loss values are generated for each (Epoch), as per Figure 7, for both training and validation.

```
Epoch 30/30
2/2 [==============================] - 2s 1s/step - loss: 0.4745 -
accuracy: 0.7895 - val_loss: 3.3653 - val_accuracy: 0.4231
```

Fig.7: Accuracy and loss values

Source: Own Authors (2021)

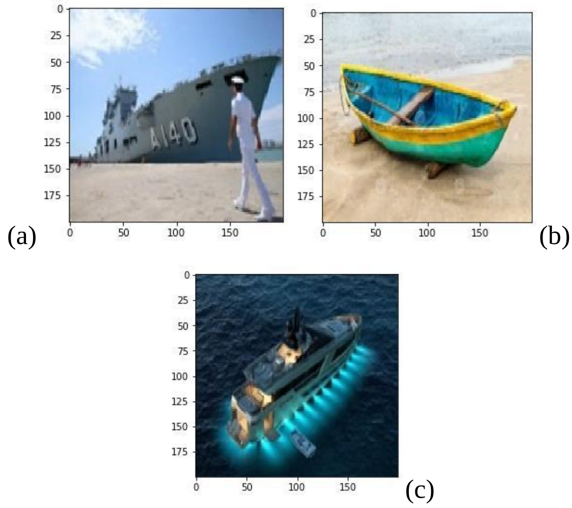

Fig 8: a) Military Ship, b) Canoe, c) Yacht

Source: Google (2021)

If after all epochs the accuracy value is not acceptable, the possibility of increasing the quantity of images to improve the distinction will be verified, or more layers of neurons will be added, or the number of epochs will be increased. If after training, everything is as expected, in step 5 the CNN will be provided with random images of vessels that are not in the database so that it can classify.

The Convolutional Neural Network (CNN) was programmed to classify images as to the type of ship. In the figures below results were obtained for photographs of vessels in which the correct order of responses would be: Military Ship (Figure 8-a), Canoe (Figure 8-b), Yacht (Figure 8-c), Sailboat (Figure 9-a), Canoe (Figure 9-b), andCatamaran (Figure 9-c). Tests were conducted with 30, 50 and 75 epochs and all with 2 steps per epoch, Figures 10, 11 and 12 respectively.

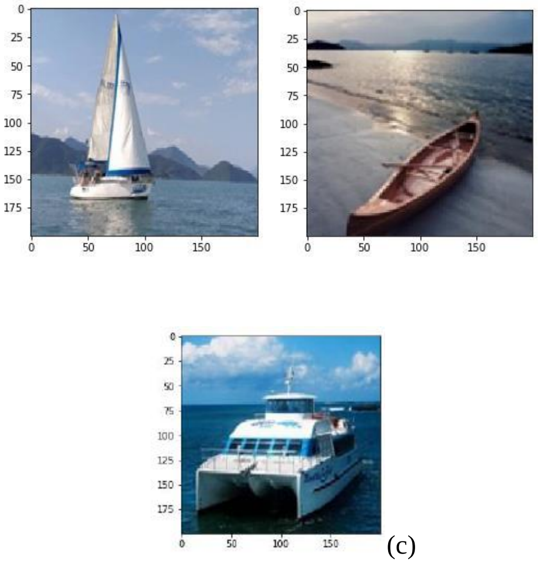

Fig.9: a) Saillboat, b) Canoe, c) Catamaran

Source: Google (2021)

Fig.10: Prediction result for 30 epoch training

Source: Own Authors (2021)

Fig.11: Prediction result for 50 epoch training

Source: Own Authors (2021)

Fig.12: Prediction result for 7 epoch training

Source: Own Authors (2021)

It can be observed that there was an error in the last classification for training periods of 30 and 50 epochs. However, for 75 epochs the network was correct in all its classifications.

For the Plimsoll Disk 3 types of loading were considered: light, loaded and overloaded, as specified in section 2.3. The number of neurons remained the same, but the number of epochs became 20 and the steps per epoch 5. Two cases were considered, the first in which 6 random images of the Plimsoll disk were provided for the neural network to analyze, see Figures 13 and 14.

(a) (b) ©

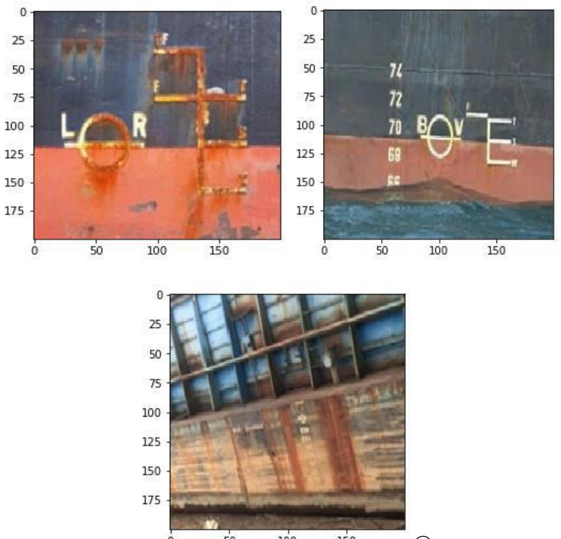

Fig.13: a) Lignt; b) Light; c) Light

Source: Google (2021)

Figures 12 and 13 show the order of images that was provided to the neural network, which the right answer 'e: Light, Light, Light, Light, Overloaded, and Overloaded. After the images were provided for the network to analyze, the following results were generated, Figure 14.

The neural network responded correctly in relation to the provided images, which can be observed that it achieved satisfactory results with respect to the predictions in different types of images and conditions. Next, taking advantage of the network, a case of a specific vessel was simulated, two images representing the In this case, it is possible to simulate a real situation, in the case of having images of the edges of the same ship, but one with the real image and the other with the same image, but modified so that it could simulate a real situation, in this case having images of the edges of the same ship. In this ship the one edge is overloaded, Figure 15a, and the other edge is in a light condition, Figure 15b, which represents a ship in web condition.

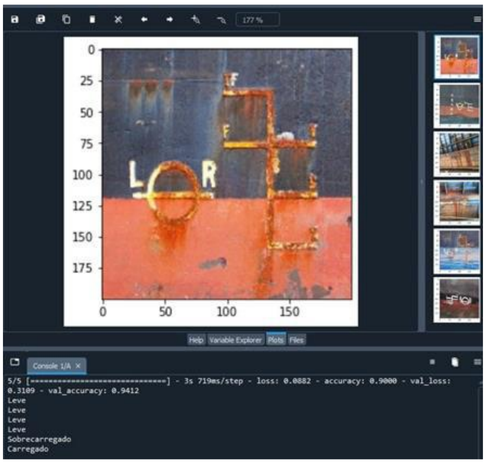

Fig.14: Prediction result for training 20 epochs with 5 steps per epoch

Source: Own Authors (2021)

(a) (b)

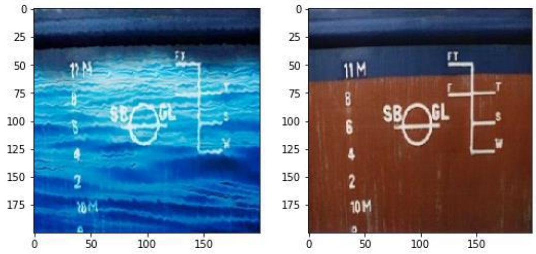

Fig.15: a) Overloaded; b) Light

Source: Google (2021)

After submitting the images to the neural network, it generated the following results, Figure 16. It can be observed that in a real condition, where it is provided images that belong to the edges of the same vessel, the neural network was correct in its predictions, which were: Overloaded and Light.

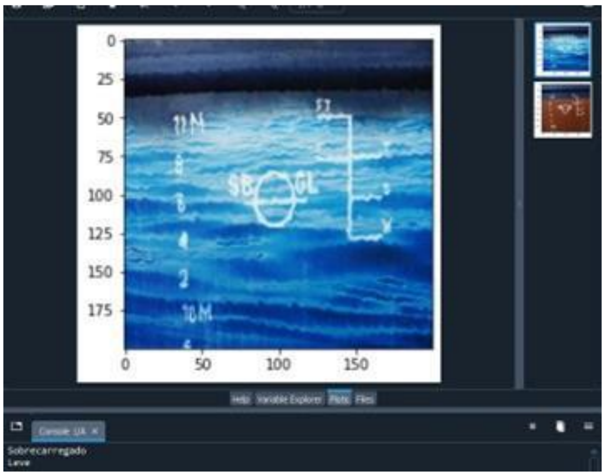

Fig.16: Simulation of the plimsoll disk from the same vessel

Source: Own Authors (2021)

V. CONCLUSION

With the development of this tool it was possible to assign a methodology using one of the areas Artificial Intelligence that is Deep Learning. Through this it was possible to create a convolutional neural network that could classify as to the type of vessel and the loading of the vessel through the plimsoll disk. Artificial intelligence has been increasingly used in all market sectors. In this case, it can be improved more and more to be used in ensuring the safety of navigation, which can impact in the future on a reduction of accidents. Not only through image analysis, but it can also be expanded and used in other ways. It can also be observed that the Convolutional Neural Network presented satisfactory results, despite the database not being vast, which normally on average reaches thousands of images, but it was able to train the network and learn to classify the types of vessels in different situations and the plimsoll disk in 3 types ofloading: Light, Loaded and Overloaded. It was collected images from the Internet and from the region for the elaboration of the database, despite the difficulty in arranging data from the plimsoll disk, due to the access to the vessels and the overloaded condition that is not common to be observed, it can be circumvented through the use of synthetic data.

For future works, it is possible to develop new networks or improve the CNN of this work to be analyzed in real time images, structure analysis, search for ship documents, increase the database to classify more types of ships, use neural networks in port security, observing ships that dock. The use of neural networks is quite vastapesar da dificuldade em arranjar dados do disco de plimsoll, devido ao acesso as embarcações e a condição de sobrecarga que não é comum de ser observado, pode-se contornar através do uso de dados sintéticos.

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