كلية علوم الحاسب والمعلومات

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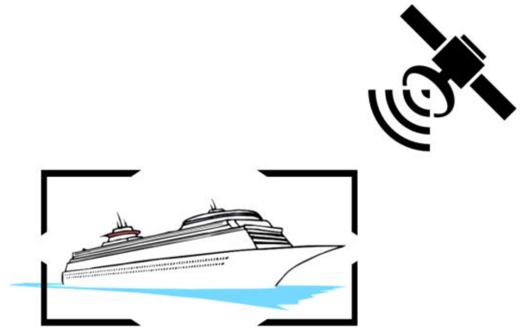

"Detecting Ships in Satellite Imagery"

CSC 496 – Final Report

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I.English Abstract

Object detection using computer vision and Neural Networks (NNs) is a form of Artificial Intelligence (AI). Ships detection in satellite optical imagery is one of many applications developed in the felid of object detection. Its importance arises in marine traffic security, surveillance and protection against illegal fishers and smugglers. This project aims to evaluate and test multiple ship detection algorithms in terms of accuracy and performance (time). To do this, NNs models will be built and trained for instance ship segmentation in satellite imagery. In addition, images datasets will be used to train models. Thereafter, models evaluation will be performed, using different algorithms and datasets to measure the detection accuracy and performance in terms of detection time.

Two major aspects of the models accuracy will be examined. First, classification accuracy, to measure the models capabilities of identifying ships from the images. Given a ground truth, datasets samples will be tested. Second, localization accuracy, to measure how accurate are the model in detecting ships location in the images. As an evaluation metric, each output will be examined using the Jaccard index (Intersection over Union) to measure similarity to the ground truth, a threshold value will be used to determine whether a model localization is similar to the ground truth or not. Moreover, results from classification and localization accuracy are used to construct two versions of confusion matrix. For each version, we will calculate accuracy, precision, recall and F1-score metrics for each test.

II.Arabic Abstract

تحديد الأشياء عبر تقنيات رؤية الحاسب الآلي والشبكات العصبية الصناعية يعد من أشكال الذكاء الصناعي. إضافة إلى ذلك يعد تحديد مكان السفن في صور الأقمار الصناعية من ضمن عدة تطبيقات تطور في مجال تحديد الأشياء. تكمن أهمية استعمال تقنيات تحديد السفن في أمن وسلامة حركة الممرات البحرية، الانقاذ والمراقبة، ومكافحة الصيد الغير شرعي وأعمال التهريب البحري. يهدف هذا المشروع إلى تقييم و اختبار عدة خوارزميات في تحديد الأشياء من ناحية الدقة والأداء (زمن العمل). ولتحقيق هدف المشروع سيتم بناء وتدريب عدة نماذج شبكات عصبية للتعرف على السفن، كما سيتم استعمال صور على شكل عدة مجموعات بينات (datasets) لتدريب النماذج، فيما سيكون استعمال مجموعات بيانات أخرى لتقييم واختبار النماذج.

جانبيين رئيسين من النماذج سيتم تقييمها. أولًا، اختبار قدرات التعرف على السفن من خلال الصور، حيث سيتم مقارنة نتائج النماذج بالنتائج الأصلية. ثانيا، اختبار تحديد موقع السفن خلال الصور، لتقييم مدى قدرة النماذج على تحديد المواقع من خلال الصور وذلك باستعمال اختبار (Jaccard index-Intersection over Union)، ولقبول النتائج الصحيحة سيتم تحديد قيمة تشابه معينة. النتائج من الاختبارات السابقة سيتم استعمالها لإنشاء نسختين من confusion matrix، ومن ثم حساب قياسات accuracy و precision و recall و F1-score لكل اختبار.

Table of Contents

List of Tables

Table of Figures

Chapter 1: Introduction

Ship detection in satellite imagery is essential for maritime traffic management, limiting illegal traffic, and enhancing surveillance and marine rescue. Ship detection includes classifying and locating ship instances in images. Existing ship detecting techniques, however, differ in their ability to detect ships in different weather conditions, different image qualities, and in performance in terms of time.

Manually monitoring maritime traffic has the advantage of using human cognition, which increases the ability to detect ships in different circumstances. However, manual monitoring is limited to a small area and a short period of monitoring. Automated ship detection, in contrast, has the advantage of large-scale monitoring operation and the ability to classify and locate a large number of instances in a short time.

There are several widely used ship detection techniques. Automatic Identification System (AIS), moreover, is a ship tracking system that uses satellite signals and an electronic kit installed on the ship that emits an identified codded signal in response to the satellite signals. Obviously, only ships with a pre-installed the electronic kit can be located, while ships without the kit cannot be located. Various Artificial Intelligence (AI) algorithms are used in ship detection in satellite imagery. Furthermore, two main categories of images are available. Firstly, Synthetic-Aperture Radar (SAR) imagery which are created from a radar wave. Secondly, satellite optical imagery which are optical images taken from spacecrafts. For both categories, AI models are used to classify and locate ships in the images. The ability to operate in different weather conditions is an advantage for SAR-based models. However, one drawback of SAR-based models is their ability to detect inshore ships due to noise produced by non-ship instances on the coastline. On the other hand, optical imagery-based models have a better detection accuracy in inshore and outshore images. Images pre-processing could be applied to enhance images resolution and reduce the noise and remove the fogginess, depending on the model design. Object detection models use Neural Networks (NNs) which are computer algorithms used to recognize patterns in different data types (text, images, voice, etc.).

The existence of different ship detection algorithms arises the need for a comprehensive evaluation. Different algorithms vary in their accuracy of classifying and locating ships, depending on the type of AI models and type of images and the conditions under which images were taken. The goal of this project is to implement several ship detection models and perform comprehensive evaluation on the accuracy and performance using different metrics.

1.1 Problem Statement

In this research, the focus will be on detecting ships in satellite imagery. We need ship detection to detect all kinds of crimes that are associated with ships like contraband trafficking, maritime piracy, illegal cargo transportation, smuggling exotic plants or animals and many other problems. Most papers written about this topic design or implement one algorithm with one data set, making their results somewhat confined. That problem is what we are planning to solve. We will implement several algorithms with datasets of images with different conditions, making our results broader and making it easier to decide which algorithm performs better under what circumstances.

1.2 Goals and Objectives

Our goal is to give a holistic evaluation of existing techniques as an independent research. Several algorithms will be implemented and evaluated on multiple datasets. These algorithms have been tested before on certain datasets, but the datasets that will be used in this research will have a variety of different weather conditions, image resolution and ship sizes meaning that the evaluation will be more generalizable. After the evaluation, results will be analyzed and compared to decide which algorithm performs best under what circumstances. Results will also be compared to previous results under different datasets. Our contribution to this subject will be an evaluation of models that covers datasets with different weather conditions and a discussion of the evaluations to compare and contrast the different models.

1.3 Solution

In order to solve the problem, we plan to contribute by collecting multiple algorithms and evaluating them in the same research. Datasets that will be used in evaluating the models will make the results more generalizable because of how diverse the datasets are in terms of different weather conditions, image resolution and ship sizes.

1.4 Research Scope

In this research, we will focus on evaluating many algorithms in several states of the image and different conditions, some algorithms find higher accuracy that depends in terms of different weather conditions, image resolution and ship sizes.

After testing several algorithms using different datasets, the algorithm is classified according to the highest accuracy under each condition. Among the most prominent reasons for conducting this research is the great effort to choose the right algorithm and many cases that the image passes through. As it makes it easier for the user to choose the optimal algorithm in terms of accuracy and performance depending on the usage scenario, this research makes the detect effort and saves the user time.

At the end of the research, after implementing many algorithms and studying them in detail, each algorithm will be classified and included in any dataset that will work more accurately and faster.

Chapter 2: Background

Computer vision is a multifaced scientific field that concerns how a computer can attain such a high level of awareness from digital images and videos. Computer vision can be utilized in many ways one of them is NNs which is widely used in object detection. From the viewpoint of engineering, computer vision aims to simulate or automate the functions that the human visual system can do. From a software viewpoint, it can be considered as one of the growing fields of artificial intelligence and deep learning that equips computers with an understanding that can make them interpret the visual world using images or videos.

Object detection algorithms use NNs models to classify and locate objects. NN models will be used in the evaluation to detect objects. NNs can be described as computing systems that try to emulate organic neural networks. These systems are trained to perform functions by dealing with examples without being programmed with certain rules. Furthermore, these systems may have multiple layers where each layer performs a part of the function to detect the object. For example, in detecting handwritten numbers from images or videos, NNs learn to identify patterns from frames that contain numbers. As shown in Figure 1, each layer will help in deciding what the number is. For instance, if the frame has a circular shape a layer will try to identify whether it is a circle in an 8 or a or 6 or a 9, the layer after will look for a straight line increase the possibility of choosing maybe a 1 or a 7.

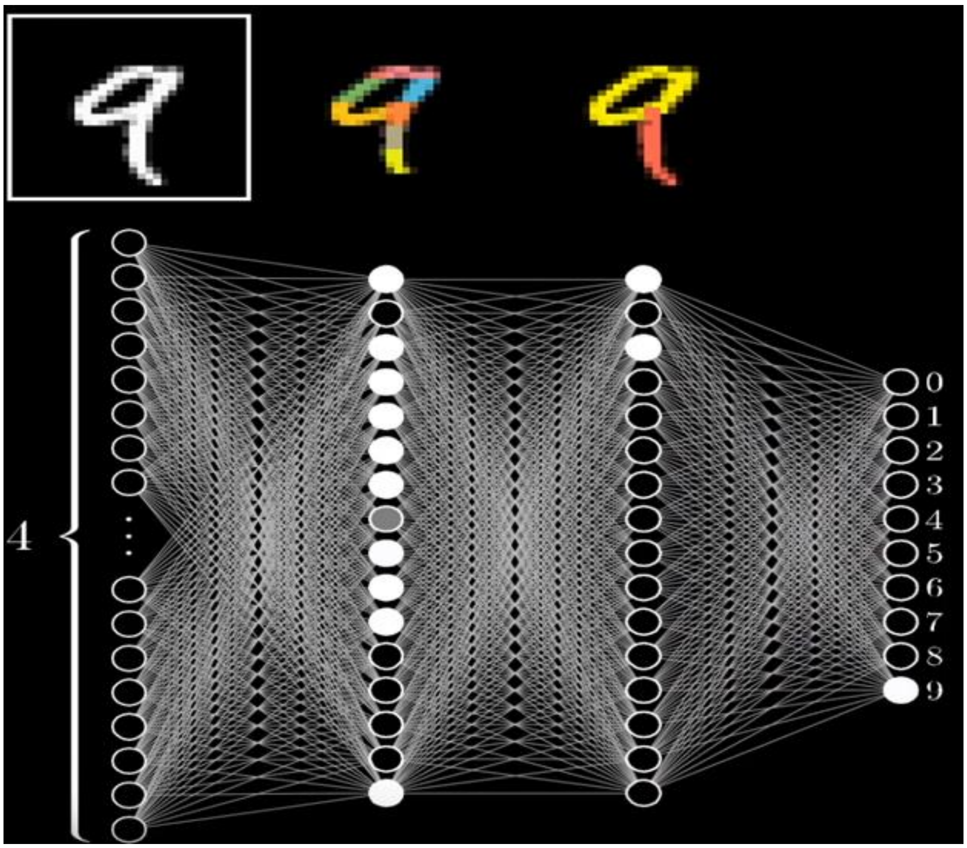

Figure 1: A representation of neural network layers.

In order to evaluate object detection models, datasets are used. Datasets are collections of organized and analyzed data used in AI models, images in our case. For models, to be trained and evaluated, datasets are needed. Different datasets are available; however, they differ in various properties. The main property images quality, which varies from high quality images with 0.5 - 10 meters resolution to medium and low qualities with 10-25 and 25-50 meters. Other properties, such as the number of images, weather conditions and images source differ in datasets.

The measurement of a model's performance includes two aspects. First, classification abilities to recognize and distinguish ship candidates in different backgrounds and conditions. Given a ground truth, results will be calculated and presented using accuracy, precision, recall and F-1 score metrics which will give a statistical representation of the model’s performance. Second, Localization ability to give the correct coordinating of a ship after correct identifying. Jaccard index (Intersection over Union) is used to measure the similarity to the ground truth. A threshold value is used to accept results, then accuracy, precision, recall, and F1-score are used to give the statistical representation of the model’s localization ability.

The metrics used to evaluate is the Jaccard index, as in Figure 2, it is a special measure of a set of data, where it measures the similarity between the data set the ratio ranges between 0% to 100%, the closer the ratio is to 100%, the more accurate the result is. The ratio is calculated by First, collecting the number of data shared between groups. Second, it collects the number of all shared and non-shared data in all cases. Third, the number of joint data is divided by the total number of data. Fourth, after getting the result, the result is multiplied by 3, then after getting the result it is multiplied by 100 in order to get the similarity between the data set. And used confusion matrix Table 1 to calculate the performance and the confusion matrix is in the field of machine learning and specifically in a statistical classification problem, error matrix is another name for the confusion matrix. It is a table layout that allows seeing the performance of algorithms and the system is confusion between classes. using confusion matrix can compute most of performance measures related to computer vision problems, a confusion matrix is a summary of prediction results on a classification problem and the key is the number of incorrect and correct predictions with count values and split into each class when it makes predictions the confusion matrix will show the ways in which your classification model is confused, for each row of the matrix represents what the machine learning predicted, and the column is represents an actual class, the number of categories is determining how many rows and column in the matrix.

Figure 2: The Jaccard index

	There is a ship	There is no ship
detected a ship	TP	FP
The ship was not detected	FN	TN

Table 1: Confusion matrix

True Positive (TP): the predicted positive and it is true.
True Negative (TN): the predicted negative and it is true.
False Negative (FN): the predicted negative and it is false.
False Positive (FP): the predicted positive and it is false.

The first metric we are going to evaluate in this project is accuracy, which is a description of systematic errors, a measure of statistical bias. In other words, accuracy is how close a measurements are to the actual value. In addition, accuracy is calculating all numbers in the true prediction and divided by the total number of a dataset, the best of accuracy is 1.0 and the worst accuracy is 0.0.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \qquad (1)$$

The second metric we are planning to use is Precision, which is a description of random errors, a measure of statistical variability. Precision is how close a measurements are to each other, and it also called positive predictive value, to calculate the precision is calculated the number of the positive true predicted and divided by total number of the positive predicted.

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (2)$$

One more metric we are planning to use is Recall, which is can be defined as the ratio of the total number of correctly classified positive. To calculate the recall is calculated the number of the positive true predicted and divided by total number positive actual.

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (3)$$

One of the metrics we are also planning to use is F1-score, which is helps to test the accuracy, it is use two measures recall and precision of the test to compute the score. F1 score is Harmonic Mean of the recall and precision and the best value is 1.0 and the worst value is 0.0.

$$\text{F1-score} = \frac{2 * \text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} \tag{4}$$

Another metric we are planning to use is a Receiver Operating Characteristic (ROC) curve which is a graph provides a simple way to summarize all information from Confusion matrix with different threshold, to identify the best threshold. The y-axis shows the TP rate (sensitivity) and the x-axis shows the FP rate (1-specificity).

The last metric we are planning to use is Area Under the Curve (AUC) which can measures the entire two-dimensional area underneath the entire ROC curve from (0.0) to (1.1). AUC is scale-invariant. It measures how well predictions are ranked, rather than their absolute values and the quality of the model's predictions irrespective of what classification threshold is chosen.

Chapter 3: Literature Review

In this Chapter, we will discuss the different related work. First, we will give an overview of the different datasets used to train and evaluate ship detection models, giving a brief in each dataset. Then, we will discuss the different algorithm, models, and tools used in object detection in general and ship detection in particular. Several papers are presented in this chapter.

3.1 Datasets

HRSC2016 [3] is a dataset containing images of ships offshore and inshore. The images were collected from google earth. The image resolution varies between 2 up to 0.4 meters. Images size range from 300*300 pixels to 1500*900 pixels and mostly are larger than 1000*600 pixels. Figure 3 shows an example of HRSC2016 images. Figure 4 shows an example of images labeled with the ground truth.

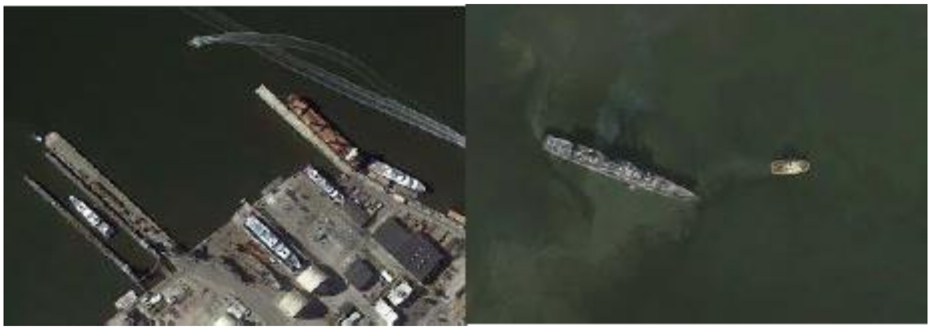

Figure 3: An example of HRSC2016 images [3]

Figure 4: An example of HRSC2016 ground truth images [3]

A 4000 images, 80*80 RGB for image, dataset by Planet Team (2017) [2] is used in order to train and evaluate the models. Images were extracted from Planet satellite imagery which was collected over San Francisco Bay and San Pedro Bay areas of California. Additionally, images are labeled with class, scene id, longitude and latitude. The pixel value data for each 80x80 RGB image is stored as a list of 19200 integers within the data list. Whereas, the first 6400 record contain the red channel values, the next 6400 the green, and the final 6400 the blue. Figure 5 presents samples of the dataset.

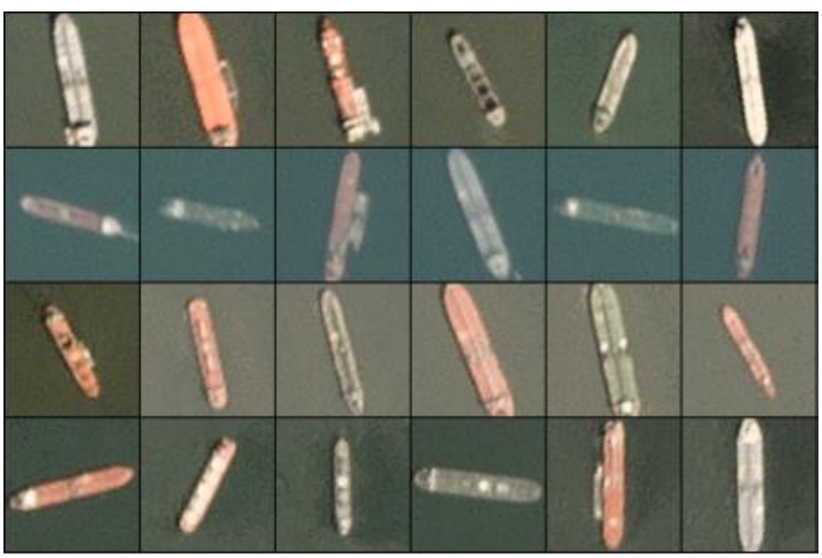

Figure 5: ships images in the dataset by Planet Team[2]

MASATI (Maritime SATellite Imagery) [21] is a dataset that contains more than 6000 satellite optical images taken from Microsoft Bing Maps. Images are labeled manually with seven categories which include: land, coast, sea, ship, multi, coast-ship, and detail. Figure 6 presents samples of each category. Another example of the dataset is shown in Figure 7 from the Coast & ship class. The images RGB and the average size of images has a resolution of 512*512 pixels. Moreover, the dataset was collected between March and September 2016 from different locations in Asia, Africa, and Europe.

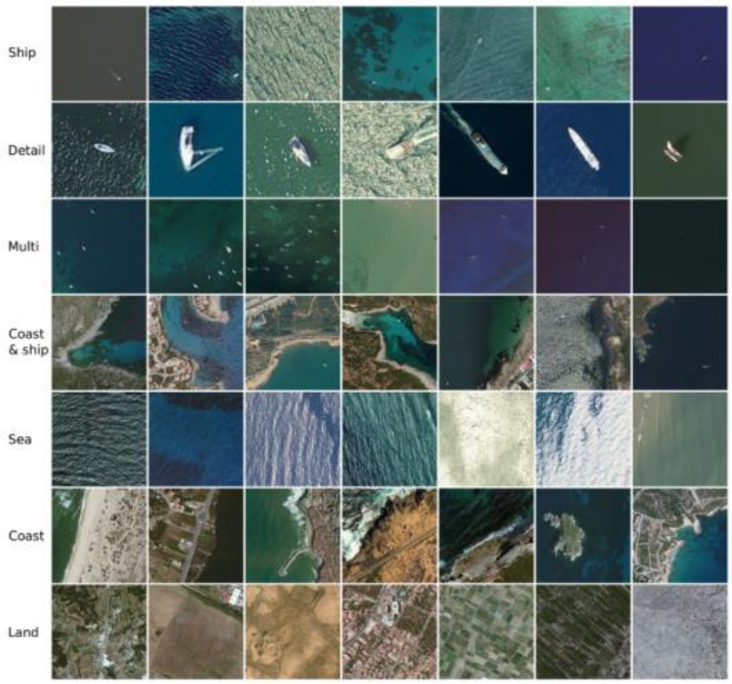

Figure 6: samples of each category in MASATI [21]

Figure 7: A sample of Cost & ship images in MASATI [21]

3.2 Related work

Many studies have taken place in the field of evaluating ship detection models. In consequence, different models, datasets, and metrics have been used in the evaluation. However, the development of new models and datasets arises the need for new evaluation researches. In order to put our work in the context with the other papers, we investigate different papers to extract the following parts:

- Main focus.
- The evaluated models and datasets.
- The evaluation criteria and metrics.
- Main challenges and difficulties.
- Future evaluation opportunities.

3.2.1 General object detection techniques

Research by Liyan et al. [5], titled "Image Main Objects Detection Algorithm Based on Deep Learning". Their focus was that how to identify the objects and understand the relationship between them. They have many objects in images how to identify the main objects what will be detected and the other object will not be detected. To detect and see different objects in the image they used improved Recurrent Convolutional Neural Network (RCNN) [11]. Network for object detection beyond deep learning, then to mark the image main objects their system does put forward the main objects scoring system and their system does use a scoring system to test Flickr8k [12]. The dataset used is 1000-class ImageNet [13] detection dataset. Their evaluation has two criteria. The first is expert knowledge of the rareness of objects, the second is what their need, there can set the rare level of class that appears high probability to allows the filtered region to meet their expectations.

3.2.2 Ship detection techniques

A research by Wang et al. [1], titled "Ship Detection in the Foggy Remote Sensing Image via Scene Classification R-CNN". Their focus was that optical images are very susceptible to weather conditions thus reducing the accuracy of ship detection. Their solution to this problem was to present image defogging methods toward object detection NN models and an SC-R-CNN structure that uses a classification NN to perform preclassification of images. The images can be classified into clear images and foggy images. Datasets used were 12650 optical images, with 1024 × 1024 resolution including images with dense fog. After testing, the results showed that the methods are effective and increase the ship detection accuracy by an average of 0.56%.

A paper by Kartal and Duman [7], titled “Ship Detection from Optical Satellite Images with Deep Learning”. The focus of the paper was that as a result of the rapid increase in shipbuilding and ship sizes. That presented a major threat to safe passage, especially in narrow traffic channels. Forcing some ports to take certain measures to ensure the safety of cruises. For instance, designate special anchorages and evacuation channels, but these canals can be used illegally by ordinary ships. The proposed solution is to present an extra option to ship detection algorithms by training TensorFlow Object Detection API using deep learning and NNs. When designing their system, the authors aimed that it should be open source code, execute fast and be easy to use. Dataset used consisted of a subset from Planet Team dataset [2]. Each image had one ship. After testing the system worked properly but had some false detections when an image had less than six ships. As the area covered by the image increased or the number of ships decreased, the accuracy of the system decreased. A proposed fix by the authors to increase the performance is to increase the number of images in the library.

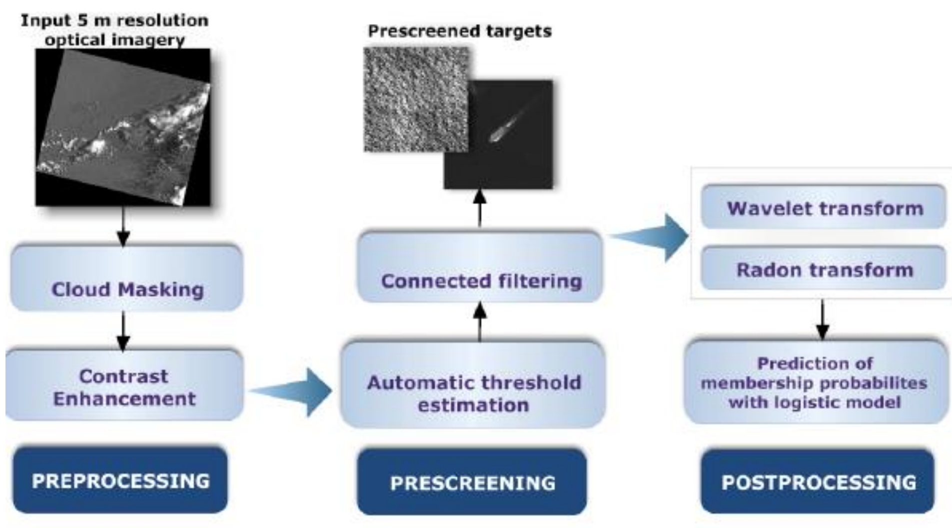

Figure 8: Detection Algorithm Stages [8]

Corbane et al. [8] work presented a new ship detection algorithm. The authors dedicated the first part of the paper to emphasize the procedure of detection and its different three stages, presented in Figure 8. The first stage was preprocessing which involves cloud masking using a routine developed by the authors based on the assumption that the cloud pixels correspond to the brightest pixels, and local contrast enhancement based on the normal distribution of the images. The second stage was prescreening which included automatic threshold estimation and connected filtering [18] which construct a 3d tree representation [19] of the gray level image and remove unneeded components using a mathematical formula. Postprocessing is the last stage, the purpose is to assign probabilities to ship candidates obtained from previous stages using wavelet transform [15][16] and random transfer [17]. authors validate their algorithm prototype and demonstrate its performance. The algorithm detected a total of 1098 possible targets, with 73 correct detection and 1027 false detection which is considered low performance compared to sophisticated NNs models.

A paper by Ying et al. [9], titled “Ship Detection and Classification on Optical Remote Sensing Images Using Deep Learning”. Although some methods are proposed to detect ships via Synthetic Aperture Radar (SAR), but it does not meet the requirements of real-world applications due to the limited number of SAR sensors and low accuracy, a deep neural network has been proposed based on automatic encryption, but it is unable to meet the requirements of real-world applications because it only works with simple and small data sets, so this paper proposes new methods for detection and classification using the convolutional neural network (CNN). The performance of their proposed ship detection and classification approach was evaluated on a set of images downloaded from “Google Earth” at the resolution 0.5m. 99% detection accuracy and 95% classification accuracy were achieved. Images shown in Figure 9 were downloaded from “Google Earth” and after ship candidates extraction, a dataset consisting 1200 images (containing ships, clouds, sea waves and islands) was obtained and used for performance evaluation Figure 9, 80% used for network training and 20% for testing. In order to be more convincing, another dataset shown in Figure 10, consisting images (10 categories of ships) with higher resolution was also downloaded and used for performance evaluation. Images shown in Figure 9 datasets by HRSC2016 [3] and after ship candidates extraction, used for performance evaluation Figure 9, 80% used for network training and 20% for testing, in order to be more convincing, shown in Figure 10, consisting images (10 categories of ships) with higher resolution was also downloaded and used for performance evaluation. As a comparison, Support Vector Machine (SVM) and Neural Network (NN) were used for classification on the dataset by HRSC2016 [3] and achieved 87% and 81% accuracy.

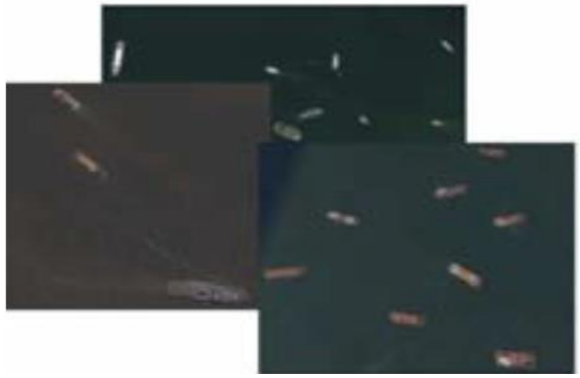

Figure 9: Google earth images

Figure 10: Ship categories

Paper by Yuchao Wang et al. [10], titled "Ship Detection Based on Deep Learning". Their focus was to detect the ship's target more accurately. This paper suggests an improved YoloV3 algorithm [14] to realize the end-to-end ship target detection system. Introducing Comprehensive Feature Enhancement (CFE) modules make the algorithm achieves high accuracy and fast ship identification, expand data for small targets, and make better for loss functions. Dataset consist of normal ship images taken from normal cameras not from satellite cameras nor drone cameras. The dataset used MS coco2017 [20], Pascal VOC and 1500 images made by the authors. The authors tested the YOLOv3 and different algorithms. The different algorithms that focus on precision and ignore real-time performance and have higher accuracy but cannot detect targets in real time. Their YOLOv3 algorithm is more accurate but has a lower real-time performance. The ship detection model of this paper is excellent in detection accuracy and speed in the case where the weather is fine and the target dispersion does not overlap.

As an example of models to be investigated. A model designed by Abhinav sugar [25], uses image classification, object detection, semantic segmentation, and instance segmentation. Where image classification is used to classify the key object type in the image. object detection to locate the position and identify object type using a box for all seen objects in the image. Semantic segmentation is used to identify object type for every pixel in each object in the image. Labels are class aware. Instance segmentation to identify all object occurrences of each pixel for every seen object in the image. Labels are instance aware.

3.2.3 Survey papers

In a survey paper done by More et al. [4], the main focus was to evaluate ten inshore ship detecting methods. There are two types of methods, the first method was the model-based method which eliminates the interference of complex background and colors. The second method was the contour-based method which extracts the seashore without the coastline. Multiple models were evaluated, one example is the phase saliency map and extended wavelet transform (PSMEWT). Complex background factors, such as shadow and different directions of shape and scales, affect the detecting of inshore ships. Researchers used recall and precision and other metrics to evaluate classifying and locating of the methods.

In a survey paper done by Voinov et al. [6], it aims to prevent or investigate illegal actions in the sea by means of modern high-resolution satellite sensors (VHR), Which in turn perform up to 0.3 meters per pixel. Where one of the problems that you face to determine the structure of the ship is the additions and climate conditions present in the image, which in turn causes difficulty in determining the structure of the ship, after using (VHR) and with an accuracy of 0.3 for each pixel, the image is sufficient to distinguish the ship structure and the characteristics of the ship from the location of the bridges and cranes and thus can differentiate between types of ship. Also, among the most prominent things presented in this paper are modern methods for automatic detection of vessels and identification of species by incorporating deep convolutional neural network structures (CNN), which have capabilities for real-time applications. They presented the first ship detection test results from VHR optical satellite images based on deep convolutional neural networks. The approach offered includes two different CNNs: first for rapid selection of areas likely to contain a satellite imagery vessel, and secondly, Faster R-CNN for the ultimate detection of objects. In the future, plans to split instances in order to extract parameters such as size (width and height) as well as their title.

Chapter 4: Methodology

The main step was taken to address the problem is defining the problem aspects. We will use the artificial Neural Networks (NNs) model. The main function of object detection models is to classify and locate objects in images. As a result, the problem aspects that will be investigated are the model's classification and localization. To classify the ship, we need to extract the ship's candidates. Then to evaluate model ships localization in the images, Jaccard index is calculated over the ground truth. After having test results from classification and localization tests we will have an overview of model performance.

In order to ensure reliable results after evaluating the models, some techniques will be applied. First, to maintain consistent results we need repeat tests and evaluations multiple times. We will use K-fold cross-validation, while it has some repeatability elements, it approaches testing differently. It has a parameter “k” which is the number of the group splits to the given dataset. Cross-validation [23][24][25], is mainly used in machine learning. The main purpose of cross-validation is to ensure that every unseen observation in the dataset has a chance to pop up after the evaluation.

The models we are planning to evaluate will be implemented in TensorFlow [22]. which is an open-source software library for performing high-performance digital calculations across a range of tasks. The nodes in the graph represent calculations, while the graph edges represent the multi-dimensional data arrays (tensors) communicated between them. The tensor is a dataset containing images from the satellite. It contains many images by classification “ship” or “not ship” classification. It is possible to improve and raise the efficiency of machine learning models on this data to be classified as any specific entry segment in any of these categories. With a well-trained model, this classification process can extend to a full ship. The image is moved across every pixel position in the image, extracted and categorized by model. The sites categorized as “ship” are then classified into one list. These detentions are highlighted with a bounding box with a copy of the original ship scene.

There are several steps that the image goes through when creating an object detection framework. First, TensorFlow is used to create a large group of surrounding boxes covering the image. Second, the visual features of each of the surrounding boxes are extracted from the hull and the shape of the ship is evaluated and determined what if the objects are located in tiles based on the visible features. Thirdly in the next step of processing after performing the visualization of the surrounding objects, the nested boxes combined into one bounding box.

Chapter 5: Experimental Design

5.1 Hypothesis and Research Questions

The classification and localization accuracy vary in different Algorithm. This difference could be due to the design of algorithms or the datasets image specification. However, we hypothesize that the algorithms vary in their performance in different datasets. For this research, our hypothesis is:

Different ship detection algorithms vary in their performance depending on the used dataset.

In order to test this hypothesis, we plan to answer the following research questions:

- RQ1: Which ship detection models are more accurate in detecting ships?
- RQ2: Which ship detection models are more accurate in localizing ships?
- RQ3: Which ship detection models are faster in detecting and localizing ships candidates?

5.2 Experimental Design

A set of algorithms will be investigated to answer these questions. Figure 11 shows a hierarchy of algorithms based on the technology they implement. In consequence, we will implement AI models in TensorFlow [22]. General object detection models to be tested are: Liyan et al. [5]. While the ship detection models are: Abhinav sugar [25], D. Moraite [27], and Wang et al. [1]. One model uses statistical methods and mathematical morphology purposed by Corbane et al. [8] work will be tested.

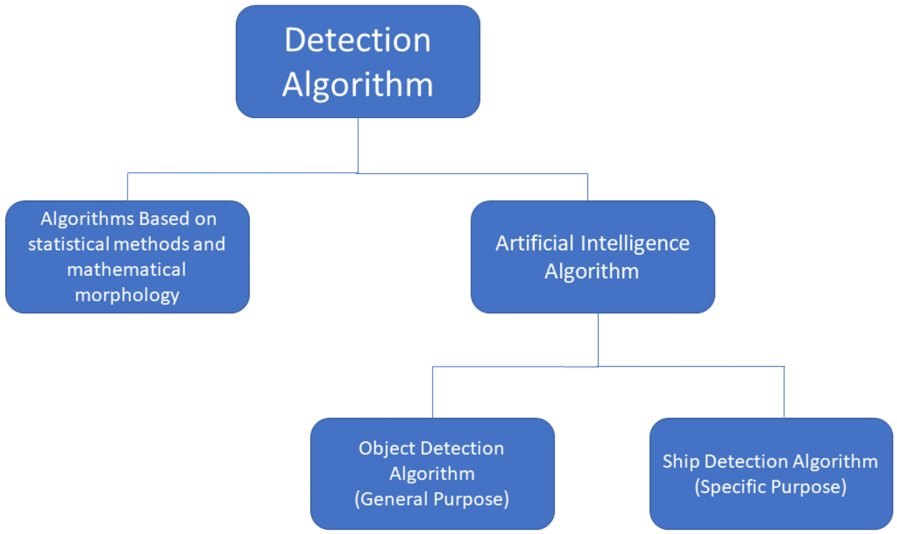

Figure 11: Hierarchy of algorithms based on the technology they implement

After implementing models, in TensorFlow [22], datasets will be used to train and test models. With a total of 12000 images in different sizes HRSC2016 [3], Planet Team (2017) [2], and MASATI [21] will be used in training and testing the models.

To answer RQ1, we will measure the classification accuracy for each model in each dataset using the accuracy, precision, recall, and F-1 Score. For RQ2, we will compute ROC and AUC over a sliding threshold of Jaccard index. Then calculate accuracy, precision and recall to the results. For RQ3, we will record the models' performance in terms of time in milliseconds. The average of training time and testing time will be calculated in 10 trails.

Since we are investigating the relation between datasets and models performance. The dependent variables in our experiments are the measures of the performance of the models. Independent variables in the experiments are the models and datasets. One nuisance variable is the conducting platform performance (hardware).

In order to minimize nuisance variable experiments will be repeated three times. Each measure will be found in different scheme. For example, classification will be accepted only if the model identifies ship candidate in all trials. In contrast, localization will be found in different way. The average of Jaccard Index on the correct classifications will be calculated. In consequence, to ensure reliable results, and as the K-fold cross validation method suggests, each dataset will be partitioned to a training set and a testing set.

Chapter 6: Conclusion

Ship detection in these times is needed to detect types of crimes related to ships such as oil discharge control, protection against illegal fisheries, traffic surveillance and sea pollution monitoring. Having various ship detecting algorithms results in a need for a thorough evaluation. After reviewing several papers related to object detection in general and ship detection, we noticed that most researchers design and implement new models. However, some models use simple statistical methods and mathematical morphology. We noticed that these models' performance is inadequate. Other models use NNs and deep learning techniques. Also, most papers test their models with one dataset. While some datasets may have a diversity of images, we think using more would make the results more generalizable due to datasets' differences in image sources, conditions and locations. In the next phase of this research, we plan to start implementing, evaluating and comparing the proposed models. After the end of this research, we hope to influence other researchers to use different types of datasets to make the results more generalizable.

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