A Deep Learning Framework for Enhancing Maritime Coastal Security

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A Deep Learning Framework for Enhancing Maritime Coastal Security

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***Abstract*—The concerns of coastal security are very dynamic which depends on several factors like the neighbourhood of the country, the terrain and the marine traffic. As in the present system, only the vessels which emit Automatic Identification System (AIS) data streams can be detected and identified. Small vessels like some boats do not have AIS system setup, so they can get past without getting detected. Therefore, we propose a solution by framing a deep learning architecture namely faster region based convolutional neural network (Faster R-CNN) which accurately detects vessels in satellite images and outputs the latitude and longitude coordinates which when merged with AIS data helps identify whether the vessel is registered or not. Along with this, our paper also focuses on threat level detections from the unregistered vessels to analyze any terrorizing activity that may occur along the coastline.**

Keywords—AIS, Euclidian, Haversine, Faster Region Based Convolutional Neural Network, maritime surveillance.

I. Introduction

In the realm of a globalized economy, oceanic reconnaissance is of a fundamental interest. With the rapid increase in marine traffic, well-being and security are the major issues focused on by any developing nation's government. Over the last decade, the development of communication networks especially in the form of Automatic Identification Systems (AIS) has evolved into a new timeline in marine traffic surveillance [1]. Still, there lies a risk of boats going unnoticed because of huge traffic, by producing wrong manual information to the coastal guards as they do not have proper AIS setup installed [2].

Therefore, our paper addresses these issues and proposes a solution based on deep learning models and architectures, to develop a one-stop-shop automatic system web-dashboard solution that can process and discover, derive and outline useful static information for the unregistered vessels from the satellite imagery for maritime surveillance. Furthermore, continuous conveyance of sea circumstance maps is likewise essential for an assortment of exercises like smuggling detection, fishing exercises control, cargo-parcel recognition, oceanic contamination observing and so on [3].

This paper is organized as follows: in Section II, we produce a brief overview of the overall workflow of our proposed solution. Section III delves deeper into the classification-based deep-learning object detection task. The procedural transformation from a satellite image to a map is discussed in details in Section IV. The integration of the AIS data streams with the map is presented in Section V. Furthermore, the threat level detection techniques and their main features are shown in Section VI. The accuracy and the performance of detailed model is depicted in Section VII. Finally, conclusions and aspects for future work are presented in Section VIII.

II. Overall Workflow

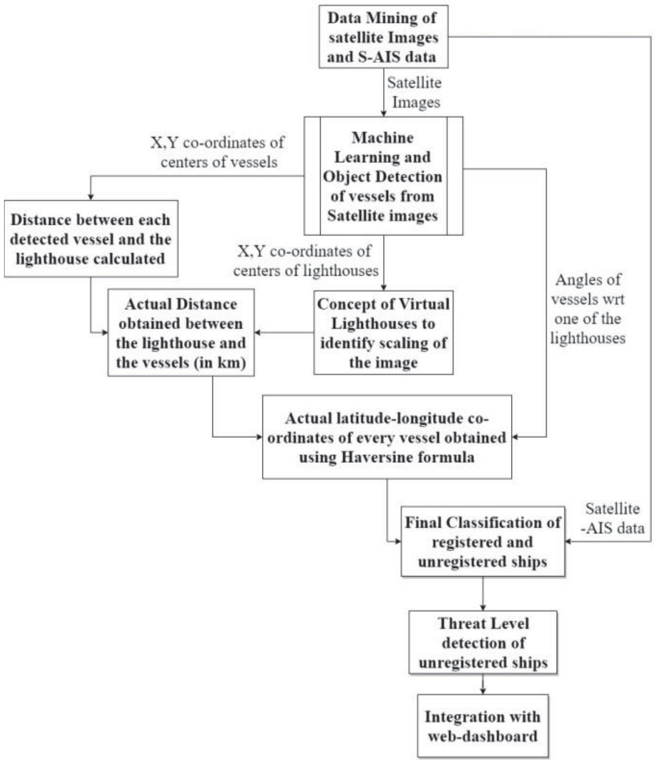


Fig. 1. Overall Workflow.

First, satellite images and their corresponding AIS data streams are fetched from online opensource data platforms namely Planet Globe as can be seen in Fig.1. Next, the satellite images are fed to the classification-based machine learning model, which helps in classifying an image as a ship or non-ship. This model is then imported for object detection inside satellite images, which finally outputs:

- X, Y coordinates of vessels,
- X, Y coordinates of lighthouses,
- the bearing angle of the vessels with respect to one of the lighthouses

The distance between the X, Y coordinates of the centres of the lighthouses helps in retrieving the scale of the image. On the other hand, the X, Y coordinates of the centres of the vessels helps in finding the distance of the vessels from one of the lighthouses in pixel measurements. Both the scaling as well as the distance measurement in pixel calculates the actual distance of the vessels from the lighthouse in kilometres.

The actual distance in kilometres and the bearing angle output from the computer vision model when fed into the Haversine formula provides the actual latitude-longitude coordinates of the vessels detected.

These latitude-longitude coordinates when matched with the incoming stream of satellite-AIS data helps to classify whether the vessels are registered or not, since only the registered vessels communicate using AIS signals.

Next, two techniques are modeled which accurately identifies threat levels from unregistered ships and according the coastal security guards can take actions against such vessels.

Finally, a web-dashboard is designed to create a one-stop-shop for the security officers who can monitor the activities of the vessels within 12 Nautical Miles range of the coastline.

III. Proposed Deep Learning Framework

Firstly, a 4000-image dataset containing 1000 ship and 3000 no-ship images is fetched from Kaggle datasets which helps in creating a classification model. Since, the dataset is imbalanced, Data Augmentation based Synthetic Minority based Oversampling Technique (SMOTE) is used which helps generate more 2000 images for the ship class, thus balancing the overall dataset with a total of 6000 images [4]. A Simonyan and Zisserman model (VGG-16) is then prepared which accurately classifies ship and no-ship images [5]. Pre-trained networks were not utilized since ImageNet or MSCOCO dataset do not contain satellite images. Therefore, the model is built from scratch, by changing the dimensions of the layers and then, the model and its weights are saved for future use.

Next, synchronous satellite scenes of San Francisco and California coastal bay with AIS signals are fetched from Planet Globe, on which object detection is incorporated to detect vessels within the scenes. There has been a lot of advancements in the object detection techniques specially driven by the region proposal networks and convolutional region-based neural networks (R-CNN). Although they are computationally expensive, their cost has been reduced to a greater extent with the evolution of Fast R-CNN and Faster R-CNN techniques [6]. In our paper, we use Faster R-CNN for the vessel detection from the satellite images. Here, is a brief explanation of the Faster R-CNN used [7].

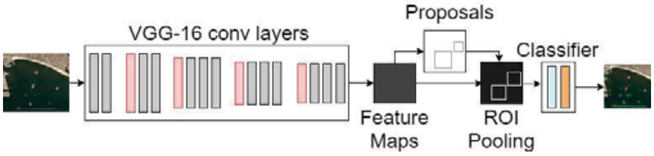


Fig. 2. Deep-Learning object detection framework

Fig 2 shows that the scenes are passed through the saved VGG-16 model layers. The last few layers are trimmed since they are not required, only the conv and max pooling layers with their respective activations are taken which helps in creating feature maps for the scene. Region Proposal Network (RPN) is stacked on these feature maps which outputs the proposals and their respective objectness score.

RPN uses sliding windows over these feature maps to generate anchor boxes of distinctive shapes and sizes. For each of the anchors, RPN predicts the probability that the anchors correspond to a vessel and also a bounding box regressor which adjusts the anchors so that they can accurately envelope the vessels in the scene [7].

Next, Region of Interest (ROI) Pooling layer is framed to convert all the proposals to a similar size, after which they are fed into a fully connected (FC) layer containing Softmax and linear regression layer to classify and predict the bounding boxes for the vessels [7].

Although this advancement has helped in faster processing compared to the earlier networks, yet the algorithm requires several iterations through a single image to extract the outline of the vessels, which act as a limitation for the model.

After the vessels are detected, there are three things which are processed as output of the deep learning framework:

A. *X, Y coordinates of centers of vessels*

For every vessel detected, the tuples of X, Y coordinates of the top left (X_1, Y_1) and the bottom right (X_2, Y_2) corners of the bounding boxes are stored in arrays in the form of (X_1, Y_1, X_2, Y_2). The center corresponding to these coordinates ((X_1+X_2)/2, (Y_1+Y_2)/2) are found and stored in arrays which are processed later.

B. *X, Y coordinates of centers of lighthouses*

Since a web map is to be prepared showing the detected vessels on the map corresponding to the satellite image, its important to calculate the scale of the image so that it can be finally integrated to the map. Hence, the concept of virtual lighthouse is developed as shown in Fig. 3. Two islands are manually indexed whose centres serve as fixed virtual lighthouses that helps in finding the scale of the image by simple use of Euclidean distance formula.

Fig. 3. Concept of virtual lighthouses

Again, the centers of these virtual lighthouses are calculated similarly which are used later in the procedure.

C. *Formulation of Bearing Angle of the vessels with respect to one lighthouse*

The coordinate system for the satellite image and the actual Cartesian coordinate is different. Anything to the North of the lighthouse has to be taken as 0° and corresponding to that all the angles are calculated after transferring the Cartesian coordinate system to the satellite coordinate system which is shown in Fig.4.

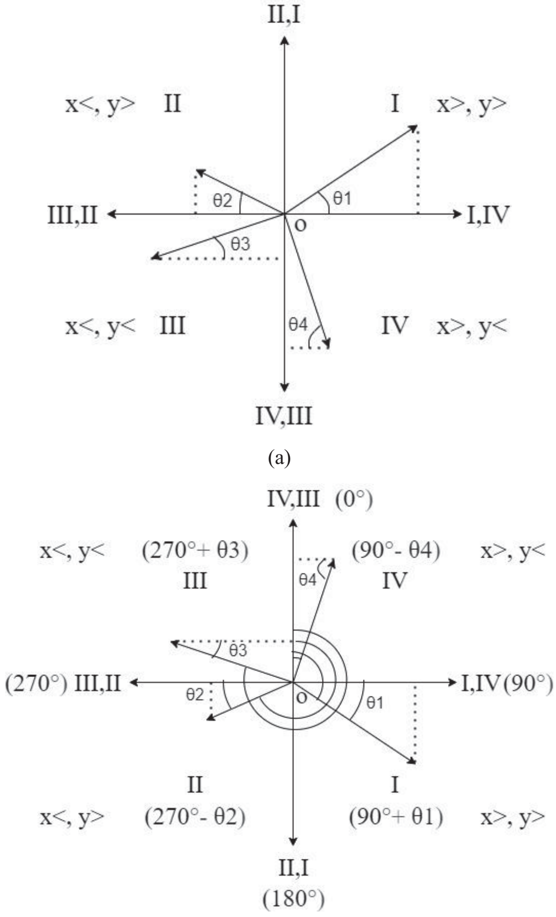


Fig. 4. (a) Cartesian Coordinate System, (b) Transformed cartesian Coordinate system to Satellite Coordinate System

The center of the coordinate systems are the X, Y coordinate of the fixed virtual lighthouse, from which all the angles are measured. The notation (x<, y>) denotes that vessel's x-coordinate is less than that of the lighthouse's x-coordinate and the vessel's y-coordinate is greater than the lighthouse's y-coordinate. Similarly, all the notations are used accordingly. As can be seen from Fig. 4. (b), the top right quadrant of the Satellite coordinate system resembles the 4^{th} quadrant of the Cartesian plane. Hence any vessel in that zone has an angle of (90°- θ4). Similarly, all the coordinates can be found depending on the location with respect to the light house. Finally, all these bearing angles are returned as output for further processing [8].

IV. OBTAINING THE VESSELS COORDINATES IN REAL-TIME

The Fig. 5. gives a detailed visualization of the processing of the outputs of the deep-learning model, which are fed as inputs here. Therefore, mathematically the inputs are as follows:

a) Image coordinates X_v, Y_v = {(x_{v1}, y_{v1}), (x_{v2}, y_{v2}), (x_{v3}, y_{v3}), …, (x_{vn}, y_{vn})} of all vessels, V = {V_1, V_2, V_3, ..., V_n}.

b) Image coordinates X_L, Y_L = {(x_{l1}, y_{l1}), (x_{l2}, y_{l2}), (x_{l3}, y_{l3}), …, (x_{ln}, y_{ln})} of the lighthouses L = {L_1, L_2}

c) Bearing Angles of the vessels with lighthouse L1, A = {θ1, θ2, θ3, …, θn}.

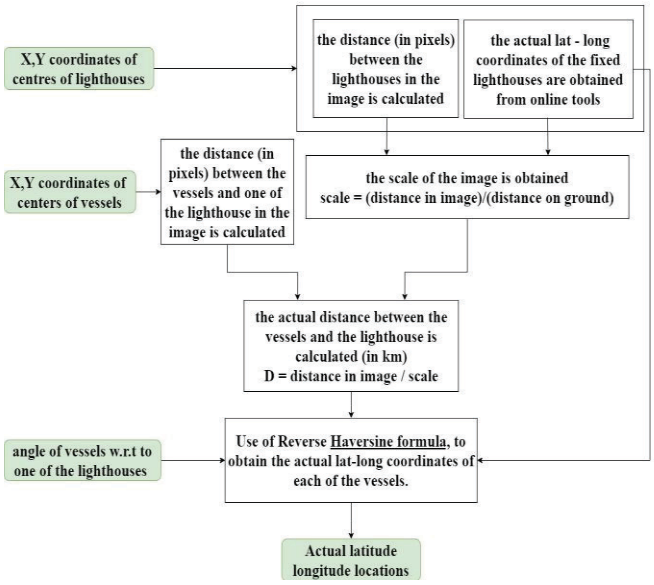


Fig. 5. Procedural Steps for obtaining the actual latitude-longitude location coordinates

A. *Obtaining the scale of the satellite image*

The Lighthouses are fixed locations, so their actual coordinates are obtained using online tools. Then we use the haversine formula to find the actual distance between them D_0 (in kms) [9]. The distance between them in the image d_0 (in pixels), was obtained using Euclidian distance formula [10]. Then the scale of image was calculated as-

$R_0 = d_0/D_0$ (pixels/km)

B. *Obtaining the actual distance between the lighthouse and vessels*

The Euclidian distance formula is used to find the image distance (in pixels) between the lighthouse L_1 and the vessels, d = {d_1, d_2, d_3, …., d_n} where d_i is the distance of the i^{th} vessel from L_1. Then, the scale of image R0 is used to find the actual distance between the vessels and L_1, D = {D_1, D_2, D_3, ….., D_n}, where D_i is the actual distance (in km) of the i^{th} vessel from L_1. [10]

$D_i = d_i / R_0$

C. Obtaining the actual coordinates of the vessels

Fig. 6. Actual latitude-longitude coordinates

The actual coordinates of each of the vessels are obtained using the Haversine formula in reverse manner [9]. The inputs to the formula were the bearing angles A, actual distance of vessels from L_1 (D) and the actual coordinates of L_1 (X_L, Y_L).

Hence, here are the two formulas which are used:
a) Haversine Formula: [9]
lat2 = asin(sin(lat1) * cos(d/R) + cos(lat1) * sin(d/R) * cos(θ))

lon2 = lon1 + atan2(sin(θ) * sin(d/R) * cos(lat1), cos(d/R) − sin(lat1) * sin(lat2))

The meaning of the notations are as follows:

- R - radius of the earth
- θ - bearing angle between the points
- d - distance between the points
- lat1, lon1 – fixed lighthouse coordinates
- lat2, lon2 – coordinates of the vessels

b) Euclidian Distance Formula: [10]

$$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

V. Integration of AIS Datastreams

The synchronised Satellite - Automatic Identification System (S-AIS) is utilized here which contains the voyage as well as static details of all the registered vessels. The actual lat-long coordinates of the vessels obtained above is matched with the S-AIS data [2]. If the coordinates of a vessel is present in the AIS data, it is put in the identified category otherwise they are categorized as unidentified. The criteria for matching are up to 3 decimal places, i.e., if both the latitude and longitude matches up to 3 decimal places, then the vessel is classified as identified. Hence, in this manner the final classification of registered and unregistered vessels is formulated.

VI. Threat Level Detection Techniques

The unidentified ships may pose serious threats to the nation if they are allowed to get in without proper checking and identification revealing. Two techniques are modeled which helps in predicting the threat levels accurately.

A. Static Details Prediction

AIS data reveals the ship's length and width measurements which can be used as features to classify the ship types and cargo types. A classical artificial neural network is modeled for the multilabel and multi class classification dataset [11].

TABLE I. CLASSES OF VESSELS

Vessel Code	*Vessel Class*
0	Not-Known
1	Reserved
2	Wing in Ground
3	Special Category1
4	High Speed Craft
5	Special Category2
6	Passenger
7	Cargo
8	Tanker
9	Other

TABLE II. CLASSES OF CARGO

Cargo Code	*Cargo Class*
0	All Ships
1	Hazardous A
2	Hazardous B
3	Hazardous C
4	Hazardous D
5	Reserved for future use
6	No addition
7	Not known
8	Reserved
9	Special Category

TABLE I and TABLE II shows the various classes of the vessels and cargos in the dataset.

The vessel types being the primary label, it is classified first using the length and width as features. Next for the classification of cargo, the vessel codes are transformed into one-hot encoded vectors which act as features along with the other static details.

Based on the model weights which are captured and the size of the area of the bounding box determined from the object detection algorithm, the cargo type and the vessel type of the unregistered ships can be identified. This helps register certain unique static details of the unregistered ships even without being present in the AIS data stream list.

B. Ripples Identification

The threat levels are divided into 3 categories, namely high, moderate and low. For determining the threat level, the distance of the vessels from the lighthouse L_1 is used. Closer the distance more is the threat level. The distance between the L_1 and the vessels is calculated using haversine formula as the coordinates of the vessels and the bearing angle is now already known [9].

This is viewed in the web-dashboard in terms of ripples. Three ripples indicate high threat level, two ripples indicate moderate threat level and single ripple indicate low threat level.

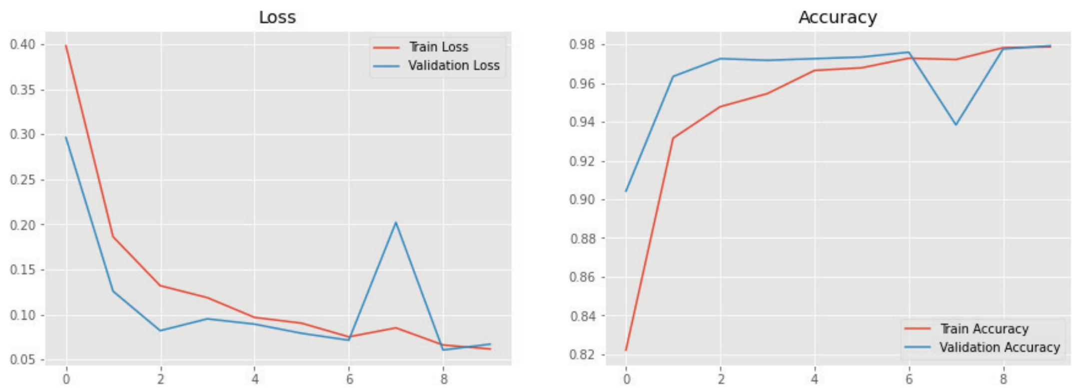


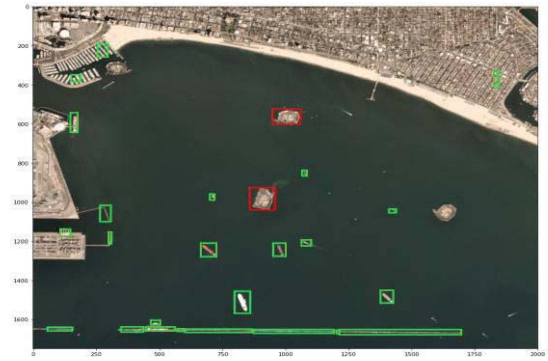
Fig. 7. Training and Cross-Validation Curves

VII. Observation And Results

The training and the cross-validation curves for the ship no-ship classification are shown in Fig.7.

As seen from the Accuracy Curve in Fig.7, the final accuracy achieved is around 0.98 approximately.

The final outcome images of the object detection algorithm are depicted from Fig.8.



(a)

(b)

(c)

(d)

(e)

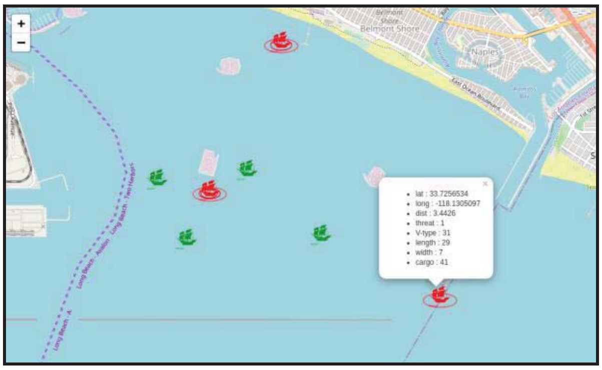
(f)

Fig. 8. Final Outcome of the Object Detection Algorithm

The red bounding boxes show the fixed virtual lighthouses, whereas the green boxes denote the vessels. Along with the bounding boxes, the X-Y coordinates are processed to formulate the final lat-long coordinates, which are then integrated with the web dashboard.

The web dashboard view is provided in the Fig.9. where the red vessels show that they are unidentified.

(a)



(b)

Fig. 9. (a) Web-dashboard view of trajectory of the vessels (b) Final Web-dashboard view of registered and unregistered vessels

Fig.9. also shows the ripple identification showing the threat levels. Even the static cargo as well as vessel details are shown when hovered around any unregistered vessel which helps the coastal security agencies to approximately predict the levels of threats or risk from such an unidentified ship.

VIII. Conclusion

Faster R-CNN object detection method along with the Haversine formulations help generate a web-dashboard view which can serve as enhancing the coastal security by giving approximate predictions of threats from any unregistered vessels.

The digital based maritime communications, VHF Data Exchange System (VDES) can be merged with the existing AIS messaging system. Addition of this, creates a two-layer security protection against such unregistered vessels' threats [12]. Thus, this will help ensuring better understanding of movement and vessel activity at sea, monitoring for activity where AIS signal has been turned off or lost by forecasting course prediction and tracking their changes in heading angle from real time synchronized data and observation of dark activity by validating with the corresponding AIS data and protection against spoofing.

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