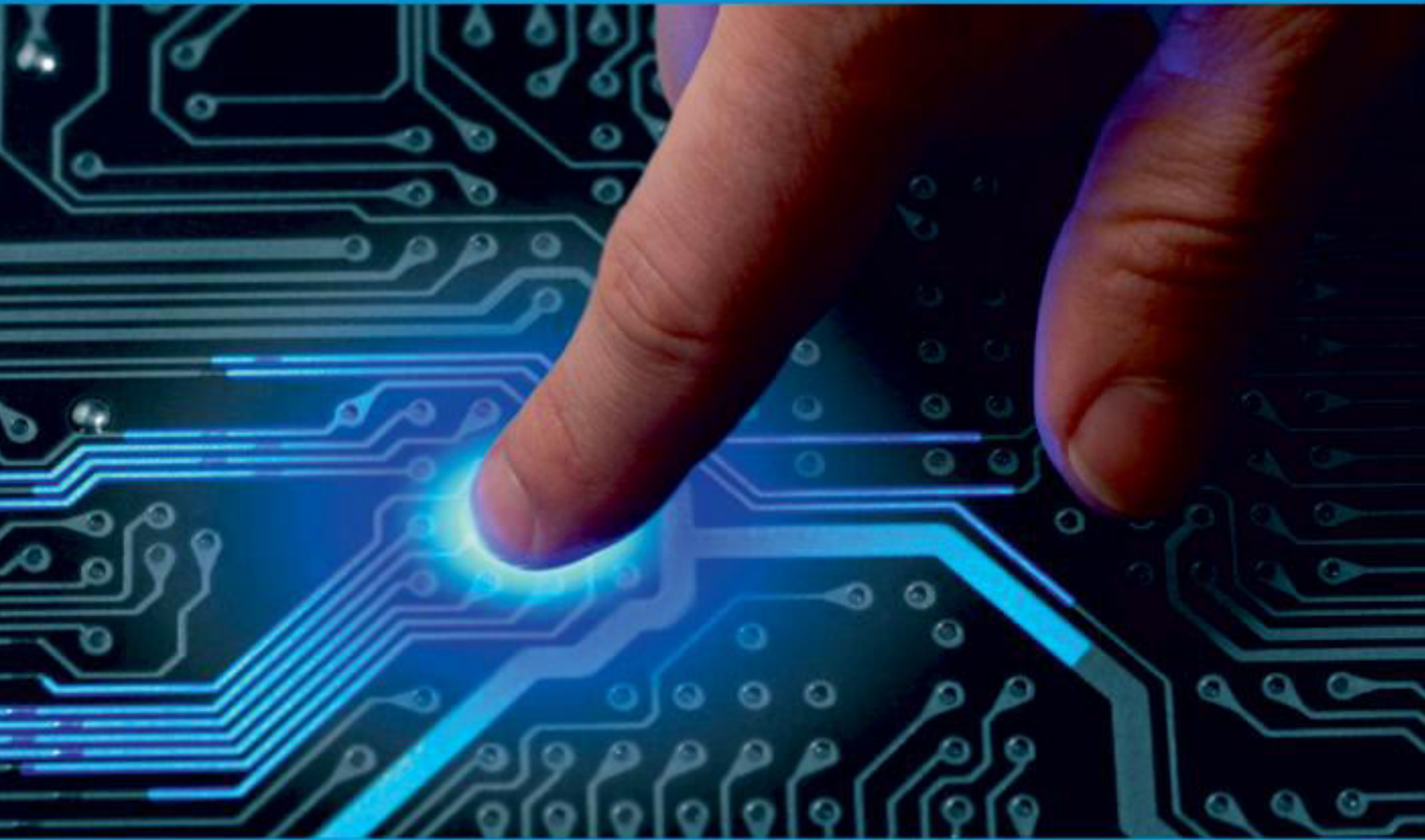
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 7, July 2021

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.542

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542 |

|| Volume 9, Issue 7, July 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0907006 |

Abnormal Maritime Navigation Detection from Satellite Imagery

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ABSTRACT: In today's technological world Artificial Intelligence (AI) and Machine Learning (ML) are now being used in almost every industry on enormous scales. Artificial intelligence is progressing at a very fast pace in the field of computer vision with new methods and algorithms being developed almost every week. The most recent development in object detection, segmentation and instance detections include R-CNN (Regions with CNN Features), fast R-CNN, faster R-CNN and Mask R-CNN which are modified and improved way of detecting any object from images using machine learning, artificial intelligence and deep learning. The Authors have taken advantage of one of the most efficient machine learning algorithms to develop models for instance detection and segmentation as well as clustering the instances into groups. Authors have used the Kaggle Airbus Detection Challenge dataset which contains a total of 108k images of ships along with their instance masks which are well divided into training and testing set. The Kaggle challenge was to find ships from satellite images which was further extended by the authors to group the ships into clusters based on their location and their orientation. Clusters which are considerably small with respect to other clusters would be considered as abnormally navigating ships. The authors have implemented the above by using Mask R-CNN model and mean shift clustering algorithm. Authors have compared their experimental results with the existing approaches and found that the proposed reasearch work although in its preliminary stage, is promising and successful in its objective of detecting abnormal ship movements from satellite images.

KEYWORDS: Satellite images, Instance detection and segmentation, Mask R-CNN, Mean shift clustering .

I. INTRODUCTİON

In mid-2020 Indian government announced its decision which allowed private organizations to use Indian airspace for commercial products which lead to the emergence of a lot of Indian aerospace start-ups. The Indian National Space Promotion and Authorisation centre (IN-SPACe) is the regulation body over these private organizations and their projects. Many of these intent to make use of satellites to provide computer vision based services such as traffic detection, maritime monitoring, etc.A few of these start-ups are Skyroot Aerospace Private Limited, Dhruva Space Private Limited, Bellatrix Aerospace Private Limited, etc. All these start-ups are purely driven by innovation and invention to revolutionise the Indian aerospace industry.These start-ups will provide an opportunity to young machine learning and artificial enthusiasts to pursue a career in the field of aerospace, thus these technologies are a must have for the recent graduates with big ambitions about their career goals.

One of the widely implemented applications of machine learning using satellite images can be observed in maritime industry for tracking ships and the marines to prevent illegal entry in the country. These software applications use exact geographical coordinates of ships to guide them as well as report the weather conditions ahead of time thereby saving millions of worth of imports and export articles as well as the lives of the crew from any potential danger

In this research work, the authors have designed a instance detection and segmentaion model to make use of the existing computer vision techniques and algorithms along with deep learning models to develop a tool for accurately detect ships from satellite images and divide them into clusters for identifying the groups of ships heading in the same direction (based on their coordinates and their orientation on the image) and identifying any ship or group of ships moving differently from its surrounding ships. This topic has been taken because the authors want to implement an engineering technology in the field of aerospace and maritime industry. The recent breakthroughs in the field of machine learning and has made it possible for us to train a sytem to identify and segment objects from an large images quickly. The most common tools developers use are Jupyter Notebook of Anaconda Navigator as Python IDE.

This proposed model will be able to perform the following tasks-

- Detect presence of one or more ships in a satellite image.
- Perform instance segmentation for each of these detected ships.
- It uses mean shift clustering algorithm to group these ships into any number of clusters.
- Visualize any ship or group of ships showing abnormal movement based on the clustering results.

II. LİTERATURE STUDY

Withing the last decade there have been many research works done in the field of machine learning models for instance detection and segmentation, a few of these are discussed below.

A Faster R-CNN based ship detection model using SAR images by Yiding Li, Shunsheng Zhang and Wen-Qin Wang, et al [1], a research work on using Faster R-CNN (Regions with CNN Features), a lightweight object detection model which uses a RPN(Region Proposal Network) for generating region proposals which are useful therby saving a lot of computation time. This model uses ROI (Region of Interest) Align, anew method to takle the loss of data caused by ROI Pooling. This model is limited by the old SAR image technology used by satellites hence its implementations are limited despite is remarkable accuracy and speed with respect to its preecessors. Moreover the Faster R-CNN algorithm has no provision for instance segmentation.

Attention Mask R-CNN for Ship Detection and Segmentation From Remote Sensing Images by Xuan Nie, Mengyang Duan, Haoxuan Ding, Bingliang Hu and Edward K. Wong, et al [2], is a research work on developing a end to end trained model to detect ships along with their mask by using Mask R-CNN along with the attention mechanism and bottom up structure to enable efficient transfer of data from the lower layers to the top layers of the model .The main drawback of this approach was the resulting decrease in efficiency of the overall system as compared tp the spatial attention method.

Detection of Abnormal Vessel Behaviours from AIS data using GeoTrackNet: from the Laboratory to the Ocean byDuong Nguyen, Matthieu Simonin, Guillaume Hajduch, Rodolphe Vadaine, Cedric Tedeschi and Ronan Fablet, et al [3], have prepared a research work on developing an automated anomaly detection model using the real time AIS data and using that data to train the model to identify patterns in vessle movement using the assumption that all the training data has no anomalies .

Review Paper on Clustering Techniques by Amandeep Kaur Mann and Navneet Kaur ,et al [4], have done a review paper on the various clustering algorithms along with their implementations which provide us with detailed comparitive analysis of the algorithms which provided valueable information required in this paper.

A review of mean-shift algorithms for clustering by Miguel A. Carreira-Perpin´an ,et al [5], have done a review paper on the mean shift clustering algorithm, the author has provided an in depth explanation of the algorithm, its drawbacks and advantages with respect to the other clustering algorithms.

A survey of deep learning-based object detection by L. Jiao, F. Zhang, F. Liu, S. Yang, L. Li, Z. Feng, and R. Qu, et al [6], have done a survey on the various kinds of deep learning models used for object detction along with their working and architecture.

High-speed ship detection in sar images based on a grid convolutional neural network, by T. Zhang and X. Zhang, et al [7], have done research work on a high speed object detection model using Grid Convolutional Networks.

Faster R-CNN: towards real-time object detection with region proposal networks, by S. Ren, K. He, R. B. Girshick, and J. Sun, et al [8], have done research work on implementaion of Region Proposal Networks to achieve higher accuracy in object detection.

R2-cnn: Fast tiny object detection in large-scale remote sensing images, by J. S. Z. X. H. F. Jiangmiao Pang, Cong Li, et al [9], have done research work on implementaion of self reinforced region based convolutional network to detect tiny objects from satellite images accurately.

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A detailed study of clustering algorithms, by K. Bindra and A. Mishra, et al [10], have done research work on stdying and analyzing the various clustering approaches to create evenly shaped clusters from a given data.

III. METHODS

On top of the line, the software tools used in the maritime industry for tracking of ships based on their GPS signal, these signals are sufficient on their own but tracks only the ships whose tracker is functioning and is costly in terms of hardware and maintenance.

There is another pre-existing system that uses satellite imagery and combines it with the ship data from port authorities as well as ships transmitter and other sources to identify the ships based on their location and the route which they are supposed to take.these systems keep an eye on all the sea routes used for transport and monitors the ship movement on these routes.

These systems are very complex and require a large private infrastucture to keep the data safe and readily available. These systems are also very costly to maintain and works by means of subscriptions which again is a costly approach.

A better cost effective way can be to make use of machine learning and satellite images to detect the location of these ships as there are many open source satellites that transmit these images free of cost moreover it can be used to detect any untagged ship or a ship showing abnormal travel behaviour.

This research makes use of Mask R-CNN model to detect ships which works by the task of instance segmentation using deep learning. This model is fast as compared to traditional R-CNN models in terms of training and inference of images. The mask R-CNN return the object classification along with the bounding box vertices and the mask which is further being used in clustering algorithms to form groups in order to detect abnormal navigation.

In this research work, the authors have tried to implement a object detection and instance segmentation model which will detect and segment the ships in satellite images. This result is further passed as input to a clustering algorithm to group the ships based on their location and direction. The authors start by collecting the training dataset containing images of ships along with their masks. The second step is to clean and preprocess data to make it suitable for our needs. The third step is to split the data into testing and training set. The fourth step is to train the deep learning model for object detection and instance segmentation. The fifth step is to gather the output from the previous step and then translate the bounding box to its centroid as well as find the inclination of the object with respect to horizontal on the image to generate features to perform clustering. The sixth step is to obtain the clusters from the previous step and color code them on the image according to their clusters. The seventh step is to identify the outliers as abnormally moving ships. The last step is to display the final result .

IV. IMPLEMENTATİON

4.1 Gathering data:

The dataset has been taken from the kaggle airbus detection challenge which has about 108k images of ships along with their bounding box coordinates and mask data. These mask are provided in RLE (Running Length Encoding) and as a part of the challenge was required to be decoded by the participant so the authors also needed to decode the mask data for our research work. Encoded Pixels contain in run-length encoding format, [StartPosition] [Length] pairs of masked pixels. For example, '1 2 10 4' implies pixels 1,2,10,11,12,13 are to be included in the mask. This is implemented by a function which takes input as the encoded mask and decodes it by using a loop starting with every even index position and continuing up to the next length-1 pixels where length is the immediate next element of the encoded mask.Finally the dataset was trimmed down to 58162 images by combining the results of images having multiple ships into a single record.

4.2 Train test and validation splitting:

For the purpose of training the authors only took those pictures which had mask data and ignored the rest of the images. Then the authors made use the sklearn train test split function to generate 34044 training masks, 8512 validation mask.

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Training:

1. Loading the Mask R-CNN model from matter plot repository on GitHub

2. Transforming the dataset into a trainable format: The authors created a new class called AirbusShipDataset inheriting the mask R-CNN's utils. Dataset function to create a dataset class and then overriding the init, load_dataset, image_refernce and load_mask functions in this class to provide the path and class of our dataset.

3. The model configuration: the model configurations are given below:

   GPU_COUNT = 1

   IMAGES_PER_GPU = 2

   NUM_CLASSES = 2 (ship or background)

   IMAGE_MIN_DIM = IMAGE_WIDTH #786

   IMAGE_MAX_DIM = IMAGE_WIDTH #786

   STEPS_PER_EPOCH = 300

   VALIDATION_STEPS = 50

   SAVE_BEST_ONLY = True

   DETECTION_MIN_CONFIDENCE = 0.95

   DETECTION_NMS_THRESHOLD = 0.05

4. The authors then preloaded the coco training weights to provide a better starting point for the model to boost the training process.

5. After initial weights are loaded the model training is started with ResNet101 as the backbone layer for CNN, all the layers of the model are trained on the ship dataset for 21 epochs.

4.3 Detection:

1. The inference class for detection is created where the model is loaded as Mask R-CNN inference mode.

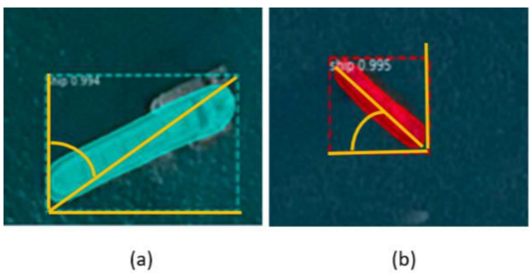

Figure 1: Ship orientation estimation

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The figure 1 represents calculation of the orientation of the ships with horizontal taking 0 degree on left side. For figure 1, (a) marked angle is calculated by equation 1, as width (w) is greater than height (h) given below.

Orientation=90 + tan-1(w/h) …………… [1]

In figure 1 (b) where height (h) is greater than width (w) the orientation is given by equation 2.

Orientation=tan-1(w/h) ………………… [2]

2. The detected ship is bounding box centroid and angle of inclination of diagonal of the bounding box with respect to horizontal are stored in a list and are passed into the clustering algorithm.

4.4 Clustering:

1. Sklearn.cluster package is used to cluster these centroids and orientation angles. This clustering model is fitted with our data and is further transformed to generate clustered classes for these points. For the purpose of this research work, the mean shift-clustering algorithm is used.

2. All these detected ships are then color coded cluster wise and visualized in the input image for the final output.

4.5 Environment:

In this research work, the authors have used Anaconda Navigator as the main development environment. All the coding is done in python 3 using the the jupyter lab which is a web browser based code editor of Anaconda Navigator.

Various machine learning libraries like os, numpy, scikit learn, tensorflow, keras etc are used in this research work.

NumPy is is a very widely used machine learning library. It provides array interface.Keras is the coolest machine learning library in Python. It easily expresses and implement neural networks. Keras provides tools for processing and compilation of models, generating comparison and dependency graphs etc.

Keras uses either Theano or Tensor Flow internally in backend. Keras is slower compared to ML libraries given the fact that it uses back-end definitions. Keras models are portable. Scikit-Learn is used with NumPy along with keras. It is a library for working with complex data. It has lots of training methods like KNN, apriori, logistics regression etc.A Python ML code uses a library known as Tensor Flow.It was developed by Google along with the Brain Team. It is used in many Google apps. Developers and researchers can implement new algorithm involving lots of ML operations computational graphs can be used to make algorithms, it represents data in N-dimensional matrix. Flask is a library used to create webapps in python programming language.

4.6 Algorithms:

Mask R-CNN:

To solve the task of object instance detection Mask R-CNN was introduced. From figure 2 it can be seen that the architecture of Mask R-CNN is very similar in working to that of Faster R-CNN but instead of fully connected layers it has a fully convolutional network for mask creation.

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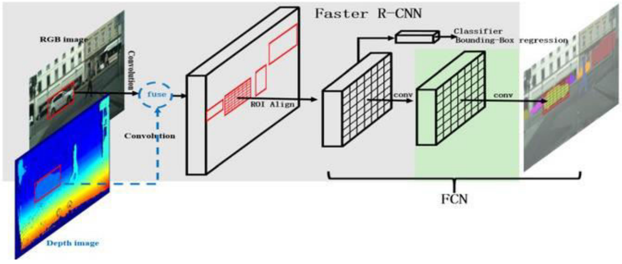

Figure 2:Mask R-CNN Architecture

The input image is passed through a convolutional neural network (CNN) for feature map detection. These feature maps are passed through a Region Proposal Network to detect Regions of Interest (ROI) to save computational power.

RPN (Region Proposal Network) was introduced after the CNN in fast R-CNN which is also used here, the task of this RPN was to identify the region of interests for each image without generating a lot of useless region proposals.

It performs the class detection and bounding box offset detection in parallel with the mask detection task. In the previous faster R-CNN it was observed that the concept of ROI pooling resulted in a loss of useful data so a new concept of ROI Align was introduced to tackle this problem. The task of ROI Pooling was quantised that is it converted the floating point numbers obtained by dividing the dimensions by the stride to integers, in ROI Align no such quantisation is performed and the values are kept as floating point numbers only.

Suppose there is an image of size 10X10 and a sliding window of size 3X3 with a stride of 3 then a grid of 3X3 cells of 3.33X3.33 dimensions is obtained. Now for each of these cell divide them into 2X2 sub cells. Then find the coordinates of these sub cells and then interpolate the value of these cells using bilinear interpolation. In this method there is no loss of spatial data.

Then on these sub cell values max pooling or average pooling is performed. Then this aligned region proposals are passed into a fully connected network (FCN) to perform pixel to pixel classification to generate the output object mask.

After ship detection the centroid for the detection bounding box coordinates are calculated for each ship bounding box coordinatesas well as find the inclination of the object with respect to horizontal on the image to generate features to perform clustering .

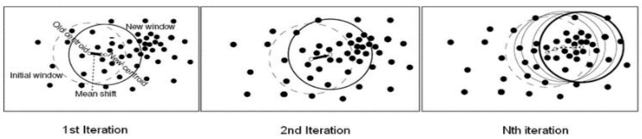

Figure 3 :Mean Shift Clustering

Mean Shift clustering:

The mean shift clustering works by defining the centroid of the data points in repeatedly with increasing density and then stopping when no density increase is possible any further in any direction.

As it can be seen from figure 3 mean shift clustering as follows:

1. Define n arbitrary points among a given set of points
2. Continuously move these points towards the direction of increasing density.
3. Find the new centroids by finding the mean of x and y coordinates of all the points.
4. Repeat step 2 until there is a possible increase in density of points from the centroid in any direction.
5. Remove duplicate centroids pointing to same cluster.

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Advantage:

1. No need to predefine the number of clusters.
2. All ports within the map coordinates (if present) are found from the predefined list of ports and their coordinates.
3. Coordinates of all the ports present are transformed into the image coordinates and are represented by a circular mark on the image.
4. These clusters are then color-coded and then visualized using PIL and matplotlib libraries.

V. RESULTS & DİSCUSSİON

Dataset: the dataset was trimmed down to 58162 images by combining the results of images having multiple ships into a single record. The figure 4 shows a bar graph showing number of images, which have same number of ships present in them. It can be seen that nearly 35000 images have two ships per image; approx. 4000 images have three ships per image and images in the range of 500-1000 containing 6 to 14 ships per image.

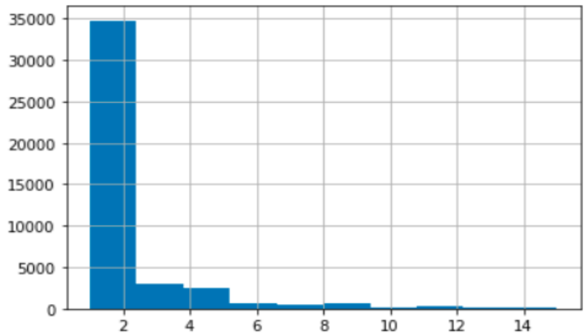

Figure 4: total number of images in the dataset containing same number of ships per image

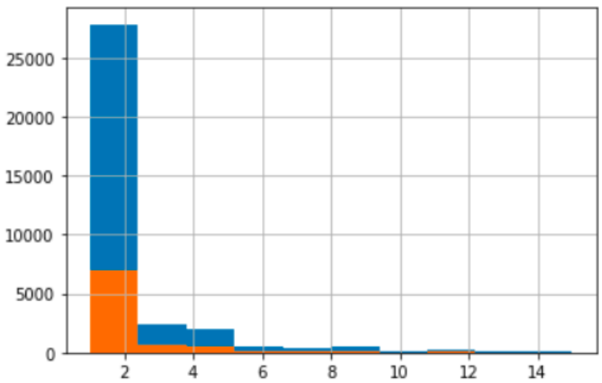

Figure 5: number of test (orange) and training (blue) images vs. number of ships per image

The dataset is further divided into testing and training set where 20% of the data is for testing and 80% data is for training as shown in figure 6. Number of training and testing images containing different number of ships per image can be seen through figure 5.

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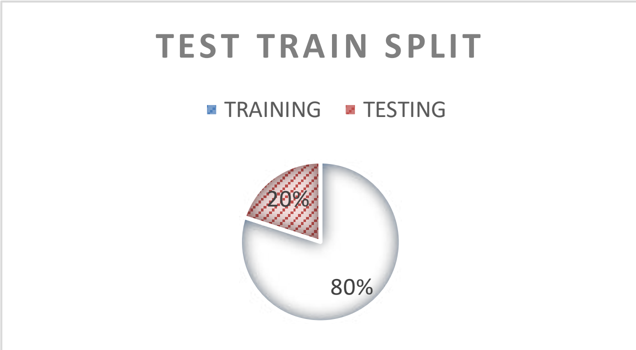

Figure 6: Train Test Split

Detection model: the detection model has a mean average precision (mAP) of 0.6460 or 64.6% which is considerably high mask R-CNN model. The mathematical representation of mean average precision (mAP) is shown in equation 3 given below:

$$mAP = 1/\text{n}\sum_{k=1}^{n}(AP_k) \quad \text{…………… [Equation 3]}$$

Here AP is the average precision of class 'k' and 'n' is the number of classes

Figure 7: Detection test cases

The figure 7, shows that the model is perfectly capable of identifying ships of different sizes and shape within the same image with a much greater efficiency.

Clustering result:

The clustering test cases of the model were able to group the ships into clusters based on their position and direction of movement.

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Figure 8: Test Case 1

Figure 9: test case 2

From the figure 8 it can be see that the ships color coded yellow, red and purple are moving different to others ships which are color coded green. And from the figure 9 it can see that the ships in the center which are color coded blue and are in vertical orientation are behaving abnormally while the other ships color coded green and red are moving correctly.

Figure 10: test case 3

From the figure, 10 the model correctly identifies the ships ignoring smaller boats in the image and it can be seen that there are two big clusters, which show ships moving in same way and are color-coded red and yellow and thus no irregular ship movements are present among the detected ships.

Discussion:

During the research work the authors found out that the model was localized in its extend to predict clusters based on the area covered by the image. The detection model in itself is not completely accurate and there have been instances of wrong detections.

Despite the preliminary stage of the model, the research work is promising in its visualization of ships moving abnormally and with continuous monitoring of the ships the results will improve due to change in number of clusters over time providing additional insight about the ship movement.

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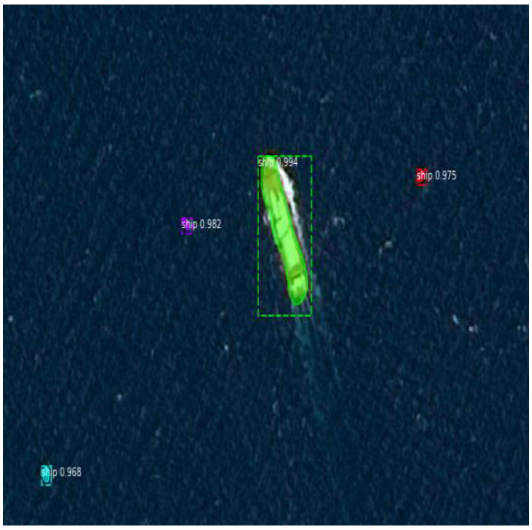

Figure 11: test case 4

From the figure 11 it can see that the model is perfectly capable of identifying ships of different sizes and shape within the same image with a much greater efficiency.

Figure 12: test case 5

The figure 12 shows that the model has failed to recognize the ship as it found that the second ship attached to the main cruise ship had more prominent shape of the ship than the cruise ship itself.

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Figure 13: test case 6

From figure 13 it can be observed some instances the ships dumped on the land and containers showing similar color schemes to an actual ship have been wrongfully detected as the ship in water.

VI. CONCLUSİON

There have been numerous works demonstrating ways and techniques for ship detection from images but none has been brought to a real life working product which can easily be modified and optimised to work with existing system without any trouble. If the computation is less and the performance is not compromised this can be implemented in various maritime applications. In this model the work has been majorly focused on the power of the python machine learning libraries that can filter out the background and extract the foreground as the ship itself and then work on several mathematical formulae to cluster the ships and thus help us to identify the outliers in a single end to end pipeline. There are numerous ways for both the ship detection as well as clustering and implementing the best one could offer a decent performance and computational speed to develop a pipeline where the application of this research work is in use. It has been seen how feature maps from images are extracted and how these feature maps can be optimised to save computational power of the CPU. As the steps are interlinked like a chain any one of the bead being broken can lead to failure of entire system hence itis noted that the model works efficiently and smoothly at each level of operation.

There had been several attempts made to make a system that is capable of performing using different image formats like images from SAR satellite and optical sensor satellite. Need for upgrades to match the feed that is being processed by the camera that could be compared with the training set images to identify ships of various shapes and sizes based on use artificial intelligence concepts to make the system capable enough to perform the above task on its own without human intervention.

Finally to conclude ,the authors would like to add that when talking about a fast paced filed like machine learning and artificial intelligence there will be discoveries and breakthroughs at regular interval of time so effort should be made to appreciate these efforts and further improve then thereby contribution to this growing community of young developers worldwide.

VII. FUTURE WORK

Although this work is very new and basic right now and limited too. The authors have some future plans for it. In future, they intend to implement a model which will show the mathematical work done by the algorithms. The performance of the algorithms will then be evaluated using various evaluation metrics. The authors are working on mixing the algorithms used in this work and are trying to make a hybrid algorithm model, which will show more

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accuracy. In the ground of machine learning, the work for the future involves the usage of all the machine learning techniques in each possible way. The software used in maritime industry is to keep track of ships, maintaining logs as well as monitoring relative position and orientation of ships, the Navy can use the software for tracking enemy movements along the international borders. The software can be further developed to detect ships carrying immigrants to the mainland and also to detect any cases of smuggling by cross checking the data for irregular movements and unverified vessels.

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