

SHIP DETECTION FROM OPTICAL SATELLITE IMAGES USING Fast-RCNN

D.SRAVYA¹, Dr. D.GOWRI SANKAR REDDY²

¹M.Tech, Department of Electronics and Communication Engineering, S.V.University, Tirupati.

²Assistant Professor, Department of Electronics and Communication Engineering, S.V.University,
Tirupati.

¹srisravya1996@gmail.com

ABSTRACT: Ship detection plays an important role in several applications like avoiding illegal fishing activities, controlling illegal transports, and to detect warships. The surface of the sea can be observed with satellite images rather than with radar and video cameras. The main objective is to focus on the detection and localization of ships from Fast RCNN applying for satellite images.

Keywords: Ship detection, optical satellite image, Deep learning-RCNN and Fast-RCNN

I.INTRODUCTION

Ship detection and classification is critical for national maritime and national defence. The surface of the ocean can be observed by video cameras, optical satellite imaging, or synthetic aperture radar. The field view of the video cameras is more limited and synthetic aperture radar images were usually with high-level speckles and also the number of SAR sensors is limited results in low resolution and revisit cycle is also more. Hence, Optical satellite images are preferable due to high resolution and no speckles at high frequencies. As massive optical remote sensing images become a promising technique and has attracted great attention to applications including maritime security and traffic control. This work aims to propose an algorithm i.e. Fast-RCNN to detect ships from optical satellite images with high resolution.

II.LITERATURE REVIEW

In [1] the ships were detected by simple shape analysis, image segmentation, and supervised hierarchical classification method. But the accuracy is low.

In [2] the ships were detected by using both IR band and visible band in the highly cluttered background video camera images of boats. But the range of video cameras is very limited.

In [3] the ships were detected by using the K-Nearest Neighbourhood method (KNN). But KNN is not robust to noisy data.

In [4] the ships were detected by Synthetic Aperture Radar (SAR). But images with SAR have high-level speckles and insensitive to wood materials.

In [5] the detection of ships from the video camera image via using Local Gabor Binary Pattern Histogram Sequence and implemented Multi-Layer Perceptron and Support Vector Machine (SVM) for classification. But LGBPHS takes more time for matching.

In [6] developed a ship detection method at the coastal zone via optical satellite image. An initial mask was created by thresholding the normalized difference water index (NDWI) using the zero level of the current global elevation data. But difficult to implement in complex scenarios.

III.EXISTING METHOD

Deep learning is one of the machine learning variations. It can learn information from existing pictures or texts. Deep learning has neural networks like ANN, CNN, R-CNN, and Fast-RCNN. RCNN uses selective search to extract objects in the image. The selective search identifies varying scales, colours, textures, and enclosure patterns in the image, and based on that various regions were extracted.

Steps involved in RCNN:

- 1 An image is given as input.
- 2 With the help of the selective search method Regions of Interest (RoI) were obtained.
3. All of these regions are then reshaped as per the input of CNN.
4. CNN then extract features for each region and SVMs was used to divide these regions into different classes.
5. Finally, a bounding box regression was used to predict the bounding boxes for each identified region

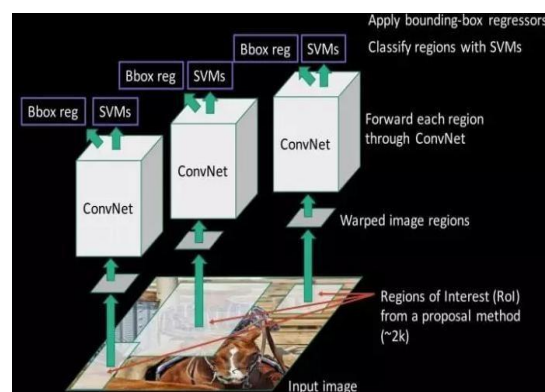


Figure 1: R-CNN architecture

LIMITATIONS OF EXISTING METHOD:

1. The accuracy and site of the object are poor.
2. Takes more time to detect the object.

IV. PROPOSED METHOD

In R-CNN the input image is split into more number of regions and for all of these regions convolution operation is performed individually which was time-consuming process. Therefore in this paper Fast-RCNN is proposed i.e. Fast Regional convolutional neural network.

Instead of applying convolution to all or any $\sim 2K$ regions, here the entire input image is given to ConvNet.

Steps involved in FRCNN:

1. An image is given as input.
2. This image is passed to ConvNet which in turn generates the region of interest using the selective search approach method.
3. The RoI pooling layer was applied to the extracted regions of interest to make sure all the regions are of the same size.
4. Finally, these regions were passed on to a fully connected network which classifies them, as well as returns the bounding boxes using softmax and linear regression layers simultaneously.

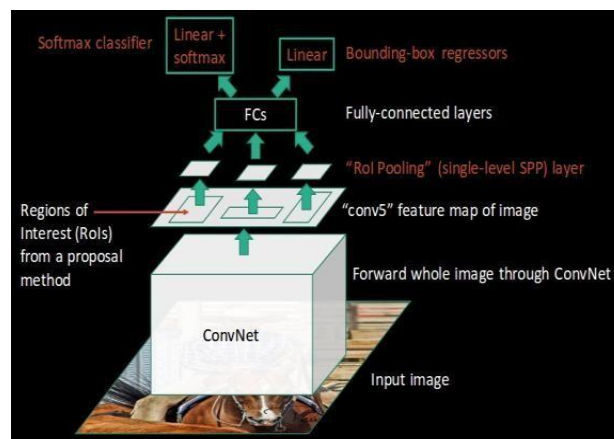
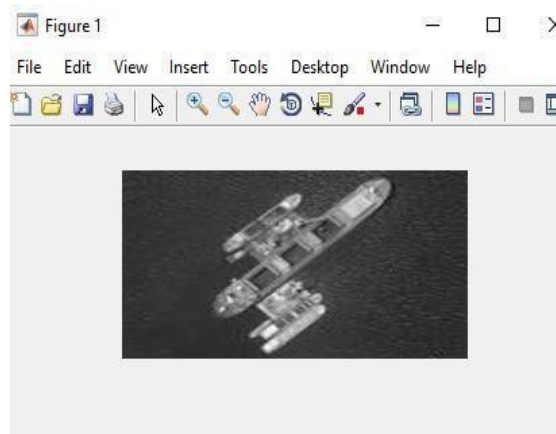
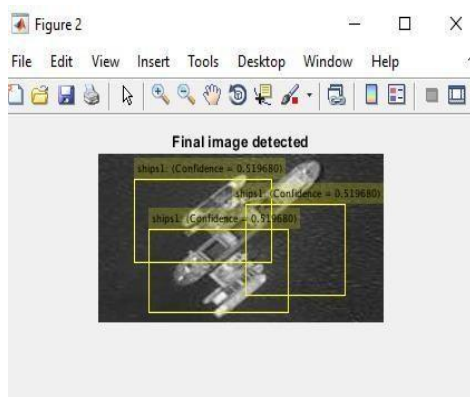
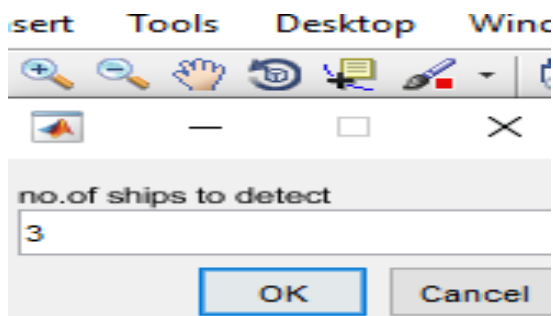


Figure 2: FRCNN architecture

V. RESULTS

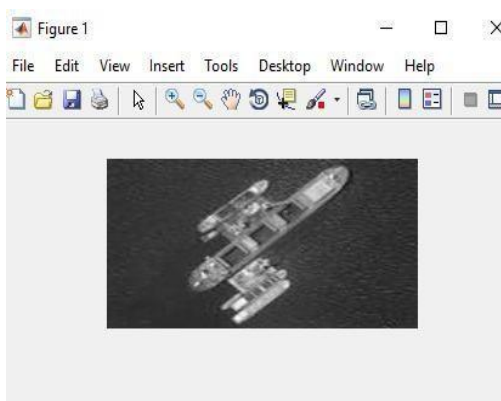
FOR EXISTING METHOD:

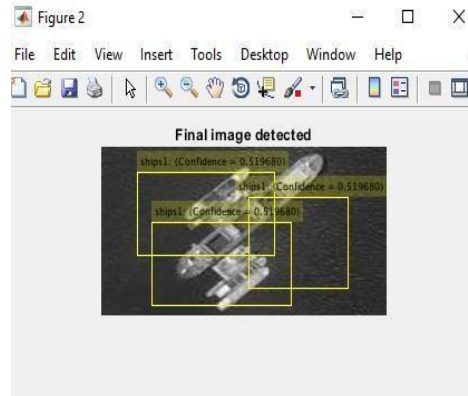
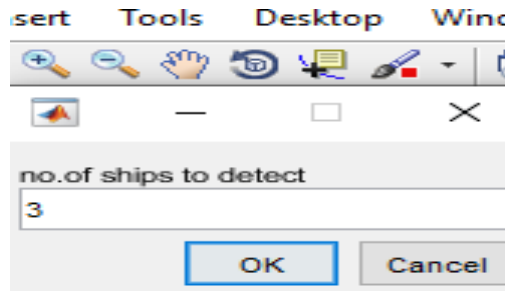




```
R-CNN training complete.  
*****  
  
Accuracy--  
    78.9772  
  
Precision--  
    82.8063  
  
Recall--  
    99.4627
```

FOR PROPOSED METHOD





```

Accuracy
      88.2271

Precision--
      93.3300

Recall--
      99.3151
    
```

PARAMETER	EXISTING METHOD	PROPOSED METHOD
1.ACCURACY	78.9772%	88.2271%
2.PRECISION	82.8063%	93.3300%
3.RECALL	99.4627%	99.3151%

Table 1: Comparison of results

The parameters Accuracy, Precision, and Recall were calculated with the help of the confusion matrix. The confusion matrix consists of predicted class and actual class as rows and columns respectively.

Actual class	Predicted class	
	Positive	Negative
Positive	TP	FN
Negative	FP	TN

Table 2: Confusion matrix

TP: True Positive

FN: False Negative

FP: False positive

TN: True Negative $N=TP+TN+FP+FN$

The resultant parameters were calculated by using the below formulae:

Accuracy= $(TP+TN)/N$

Precision= $TP/(TP+FP)$

Recall = $TP/(TP+FN)$

VI.CONCLUSIONS

This paper proposed an algorithm to detect the ships in oceans from optical satellite images.

With the help of Fast-RCNN, the accuracy is improved and the exact location of the object is possible which needs less time for computation.

REFERENCES:

- [1] C. Zhu, H. Zhou, R. Wang, and J.Guo, "A Novel Hierarchical Method of Ship Detection from Space-borne Optical Image Based on Shape and Texture Features," in IEEE Transactions on Geo-science and Remote Sensing, vol. 48, no.9,pp.3446-3456, Sept. 2010.
- [2].C.Yaman and V.Asari, "Long Range target classification during a cluttered environment using Multi-sensor image sequences," 2007 third International Conference on Recent Advances in space.
- [3] Q. Du, Y. Zhang, X. Yang and W. Liu, "Ship target classification based on Hu invariant moments and ART for maritime video surveillance," 2017 4th International Conference on Transportation Information and Safety (ICTIS), Banff, AB, 2017, pp. 414-419.
- [4]W. Li, B. Zou, and L. Zhang, "Ship detection in a large scene SAR image using image uniformity description factor," 2017 SAR in Big Data Era: Models, Methods and Applications (BIGSAR DATA), Beijing, 2017, pp. 1-5.
- [5] N. Rahmani and A. Behrad, "Automatic marine targets detection using features based on Local Gabor Binary Pattern Histogram Sequence," 2011 1st International eConference on Computer and Knowledge Engineering (ICKE), Mashhad, 2011, pp. 195-201.

- [6]B. Besbinar, A. Alatan, Inshore ship detection in high-resolution satellite images: approximation of harbours using sea-land segmentation, Proc. of SPIE Vol. 9643 96432D-9, 2015.
- [7]. V.F. Arguedas, "Texture-based vessel classifier for electro-optical satellite imagery," 2015 IEEE International Conference on Image Processing (ICIP), Quebec, QC, 2015 pp.3866-3870.
- [8] I. Karakaya and Y. Çemtay, "The effect of band selection to success of artificial neural network in hyper-spectral classification, "2017 25th Signal Processing and Communications Applications Conference (SIU), Antalya, 2017, pp. 1-4.
- [9] W. Shen and W. Wang, "Node Identification in Wireless Network Based on Convolutional Neural Network, "2018 14th International Conference on Computational Intelligence and Security (CIS), Hangzhou, 2018, pp. 238-241.
- [10]V. F. Arguedas, "Texture-based vessel classifier for electro-optical satellite imagery," 2015 IEEE International Conference on Image Processing (ICIP), Quebec City, QC, 2015, pp. 3866-3870.