IMPLEMENTATION OF FAST-RCNN TO DETECT SHIPS FROM OPTICAL SATELLITE IMAGES

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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. The ships were detected by using Regional Convolution Neural Networks. But R-CNN takes more time to detect ships and accuracy is low. To overcome these limitations the proposed method is fast RCNN. Fast –RCNN detects the objects in very less amount of time and with more accuracy.

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

I. INTRODUCTION

Ship detection in remote sensing images has attracted wide attention for its broad applications. 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 are limited which results in low resolution and revisit cycle is also more. Hence, the ships were detected from the Optical satellite images with high resolution and no speckles at high frequencies. At this point Machine learning offers the great solution. Convolutional neural network is one of the neural networks which can be used to detect the objects in the image but doesn't localize the objects. In existing method Regional Convolutional Neural Network was implemented which can detects and localize the objects but with low accuracy and takes more time to detect ships. This work aims to propose an algorithm i.e. Fast-RCNN to detect ships with more accuracy and takes less time to detect. This was implemented in the MATLAB, since it is the easiest and most productive computing environment for engineers and scientists

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

Machine learning is a form of artificial intelligence (AI) that teaches computers to think in a similar way to how humans do: learning and improving upon past experiences.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. The Region of Interest was obtained from the images by using selective search approach method.
3. These region proposals are warped into a square and fed into a convolutional neural network.
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.

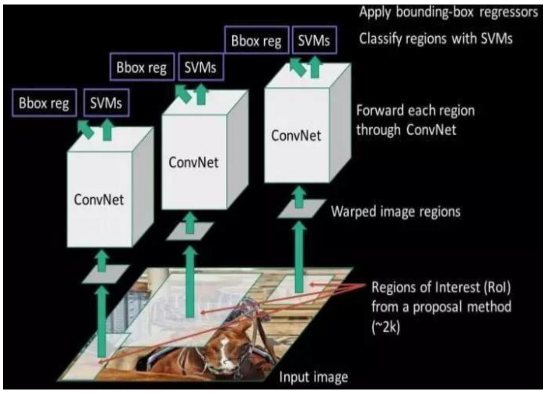

Figure 1: R-CNN architecture

LIMITATIONS OF EXISTING METHOD:

1. In R-CNN the input image is divided into many regions and then all those regions were given as input to convolutional layer. Applying convolution to all those regions individually takes more time and calculations were troublesome.
2. In R-CNN at the output SVM classifier was used to detect object. It doesn't perform well when there is large data set because the required training time is higher.
3. It also doesn't perform very well, when the data set has more noise i.e. target classes are overlapping.

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 ~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.

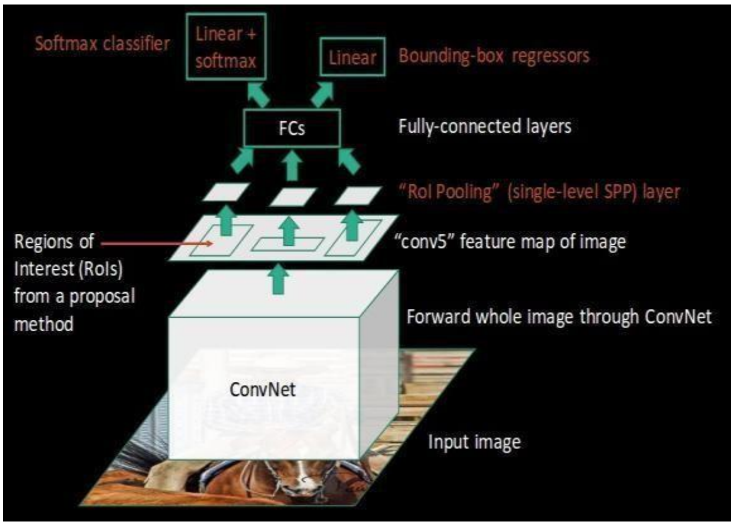

Figure 2: FRCNN architecture

V. RESULTS

FOR EXISTING METHOD:

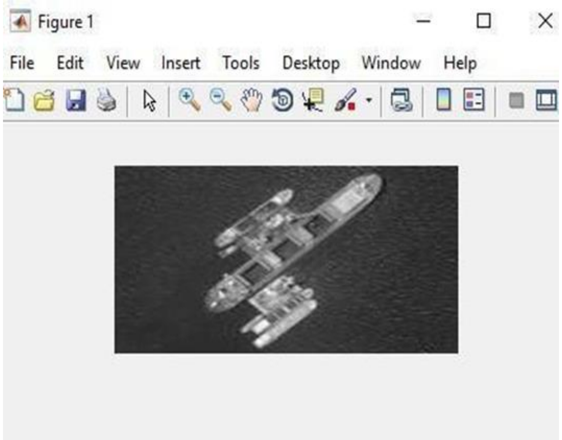

Figure 3 : Input image for RCNN

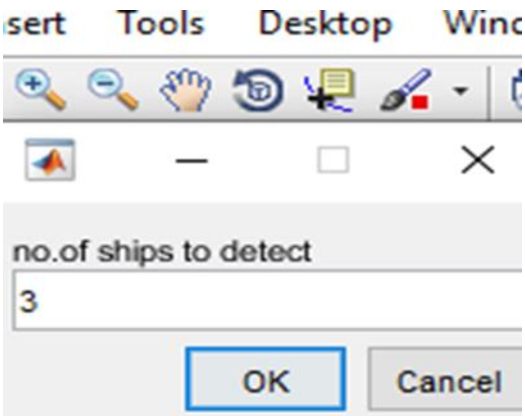

Figure 4: Number of ships to detect

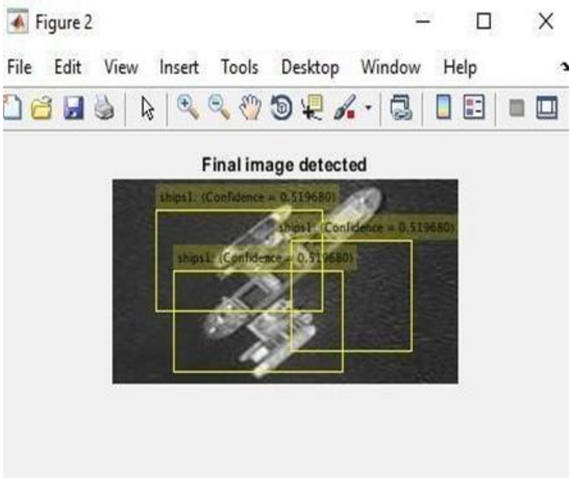

Figure 5: Final detected image using RCNN

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R-CNN training complete.
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Accuracy--
   78.9772

Precision--
   82.8063

Recall--
   99.4627
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Figure 6: Parameters obtained using RCNN

FOR PROPOSED METHOD

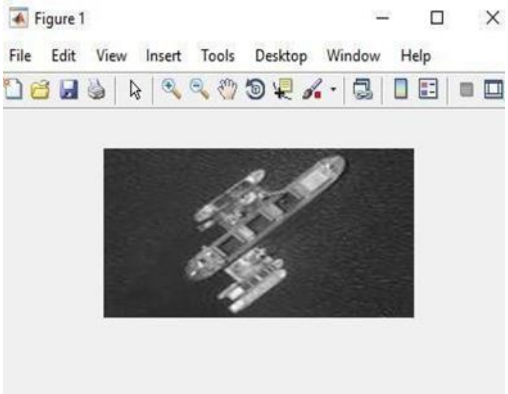

Figure 7: Input image for Fast-RCNN

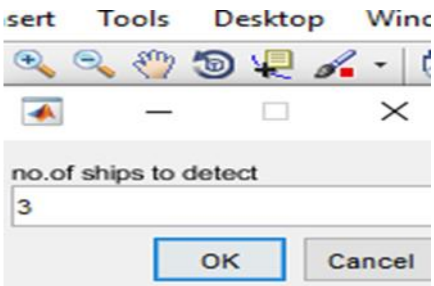

Figure 8: Number of ships to detect

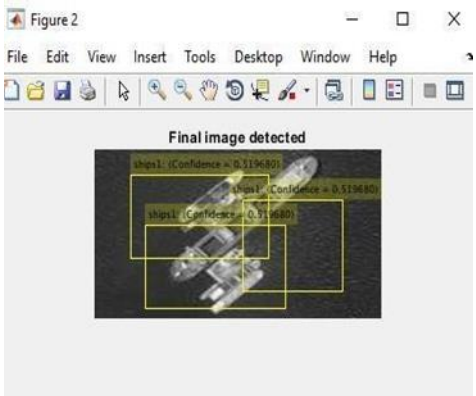

Figure 9: Final Detected image using Fast-RCNN

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Accuracy
   88.2271

Precision--
   93.3300

Recall--
   99.3151
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Figure 10: Parameters obtained from Fast-RCNN

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.

Table 1: Confusion matrix

Actual class	**Predicted class**	
	Posi tive	Negat ive
Positive	TP	FN
Negative	FP	TN

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.The detection of ships plays major role to avoid illegal fishing activities and controlling illegal transport. The success of deep learning gives rise to object detection. With the help of Regional Convolutional Neural Network the ships were detected in the image. In RCNN, at the output SVM classifier was used to detect object. It doesn't perform well when there is large data set because the required training time is higher and the accuracy is low.

Therefore in proposed method Fast-RCNN is used. Softmax classifier is used at the output which can differentiate objects even if there is large data set.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.

VII. 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 (BIGSARDATA), 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]. 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.