SSRG International Journal of Electronics and Communication Engineering Volume 8 Issue 5, 1-5, May, 2021
ISSN: 2348 – 8549 /doi:10.14445/23488549/IJECE-V8I5P101

Ship Detection in Medium-Resolution SAR Images using Deep learning

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Received Date: 26 March 2021
Revised Date: 06 May 2021
Accepted Date:08 May 2021

***Abstract** — Due to its noticeable advantages of working, Synthetic aperture radar (SAR) has become a significant device for many remote sensing applications. The Existing methods for SAR images perform well under some constraints. In this work, a ship detection method based on CNN (Convolutional Neural Network) called VGG net (Visual Geometry Group) is proposed. To improve the performance of ship detection by adopting multi-level features produced by the convolution layers, which fits ships with different sizes. The Simulation results of the proposed method are compared with the existing method*

***Keywords** — Synthetic aperture radar, Convolutional Neural Network.*

I. INTRODUCTION

As a core component in the scientific field of earth observation (EO), ship detection has been an attractive and necessary contribution. Object detection and also ship detection has made remarkable progress in recent years through the adoption of deep learning. Analyzing EO images using deep learning for detecting ships is state-of-the-art.

Ship detection in high-resolution optical satellite imagery is a modern field at KSAT. Convolutional neural networks (CNNs) are the quintessential deep learning models, the main cause of tremendous progress, and can be adapted to fit various problems. When a CNN is trained on appropriate training data, it has proved to perform better than traditional algorithms in a variety of computer vision and image analysis problems. Knowledge about the machine learning architecture and how it responds to different data is a necessity and allows the opportunity of analyzing possible sources of errors. Enlightenment of underlying challenges in the system and data is desired. One possible challenge in optical EO data is the appearance of small clouds. These may look very similar to ships and hence cause false alarms. Again, this risk can be mitigated by using a large amount of precise training data for optimization. The CNN can then learn to ignore these false alarms

In this work, a ship detection method based on CNN (Convolutional Neural Network) called VGGnet (Visual Geometry Group) is proposed. To improve the performance of ship detection by adopting multi-level features produced by the convolution layers, which fits ships with different sizes. The Simulation results of the proposed method are compared with the existing method.

II. RELATED WORK

Yinghua Wang introduced another various leveled plot for distinguishing ships from high-goal engineered opening radar (SAR) pictures. The plan comprises two phases: identification and discrimination. Almost all the boat targets can be recognized from the test picture under a suitable bogus alert rate. In the meantime, an extraordinary number of bogus discoveries happen.

G.Margarit introduced a boat checking framework imagined to arrive at the past objective, SIMONS(Ship Monitoring with SAR). It is normal that information with an improved goal and polarimetric abilities would allow building classification confidence, to identify a wide scope of boats.

Zou et al. (2020) built up an improved SSD calculation dependent on MobilenetV2 convolutional neural network for transport picture target location and identification.

Wang et al. (2019) showed an improved Faster R-CNN dependent on the MSER choice rule for SAR transport recognition in the harbor in this paper. It is a boat discovery strategy dependent on the mix of highlight-based technique and pixel-based technique. First and foremost, Faster R-CNN is utilized to create locale recommendations. At that point, supplant the edge choice standard of Faster R-CNN with the greatest dependability extremal locale (MSER) technique to reconsider the created district recommendations with higher scores, targeting improving the discovery rate and diminishing the bogus caution rate at the same time.

Tao et al. (2018) executed another worldview for engineered gap radar (SAR) perception of boat focuses adrift. The proposed metric is contrasted, and two exemplary polarimetric measurements and the exploratory outcomes directed on C-band RADARSAT-2 polarimetric SAR (Pol-SAR) information show the plausibility of the proposed metric and relating approach.

ZHANG et al. (2019) tested a fast SAR transport discovery approach by improved your're just look once form 3 (YOLOv3). They probed a public SAR transport identification dataset (SSDD) which has been utilized by numerous different researchers.

III. PROPOSED WORK

This task embraces the possibility of profound networks and presents a quick VGG-based convolutional neural network (VGG-CNN) strategy to recognize ships from high-goal far off detecting symbolism. This part is partitioned into three phases. Initially, profound learning is portrayed with its applications. The second stage is the CNN which is the best illustration of profound learning, and the third stage is the VGGnet of CNN, which is the proposed model of boat location.

A. VGG MODEL

VGG Net is a neural network that performed very well in the Image net Large Scale Visual Recognition Challenge (ILSVRC) in 2014. It scored ahead of everyone else on the picture confinement undertaking and second put on the picture arrangement task. A limitation is discovering wherein the picture in a specific article is portrayed by a jumping box. Order is depicting what the item in the picture is. This predicts a classification mark, for example, "feline" or "cabinet." Picture Net is a tremendous data set of pictures for scholastic scientists. Consistently individuals who run Image Net host a picture acknowledgment rivalry. The objective is to compose a piece of programming nowadays, normally a neural network or some likeness thereof, that can effectively foresee the classification for a bunch of test pictures. Obviously, the right classifications are known uniquely to the challenge coordinators. (This keeps the neural networks genuine.)

The pictures utilized in the opposition are separated into 1000 unique classifications. Given a test picture, the neural network will yield a likelihood conveyance for that picture. This implies it computes a likelihood a worth somewhere in the range of 0 and 1 for every one of those 1000 classes, at that point picks the classification with the most noteworthy likelihood. Assuming the neural network is exceptionally sure about a forecast, its top decision has a high likelihood, for example, 77.78% for the bookshelf.

In the Image Net order challenge, you really get five opportunities to anticipate the correct classification, which is the reason the demo application shows the 5 most elevated probabilities the network processed. As the network additionally figures, the picture might have been a library, bookshop, or comic book — yet the probabilities show that it isn't as sure about those decisions.

Among the best performing CNN models, VGG is striking for its effortlessness. How about we investigate its engineering.

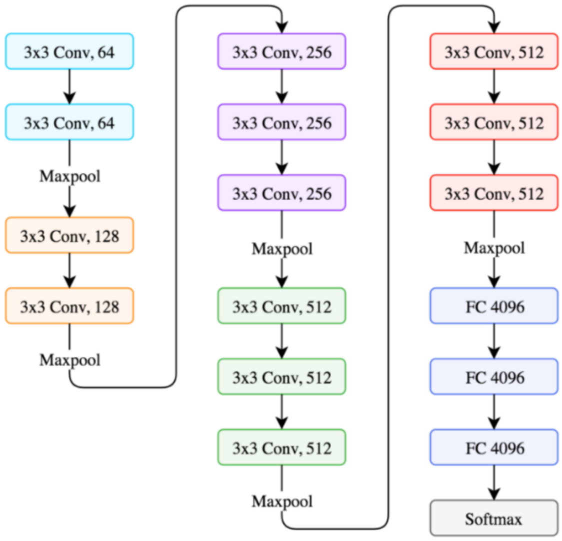

Fig. 1. VGG architecture

VGG is a 16 layer neural net, not including the max pool layers and the softmax toward the end. It's additionally alluded to as VGG16. The design is the one we worked with above. Stacked convolution + pooling layers followed by completely associated ANN. A couple of perceptions about the architecture: It just uses 3x3 convolutions all through the network. Note that two consecutive 3x3 convolutions have the compelling responsive field of a solitary 5x5 convolution. Furthermore, three stacked 3x3 convolutions have the open field of a solitary 7x7 one. Here's the visualization of two stacked 3x3 convolutions coming about in 5x5.

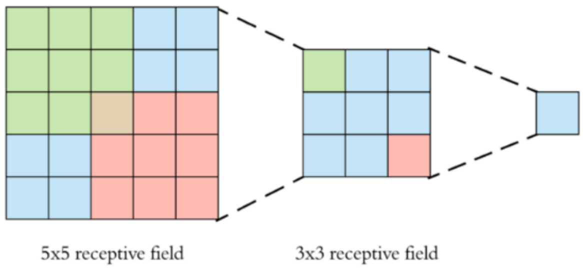

Fig.2. two stacked 3x3 convolutions visualization

Another benefit of stacking two convolutions rather than one is that we utilize two relu tasks, and more non-linearity gives more capacity to the model. The quantity of channels increases as we go further into the network. The spatial size of the element maps declines since we do pooling, yet the profundity of the volumes increment as we utilize more channels.

VGG is an essential CNN model. It's the first that strikes a chord in the event that you need to utilize an off-the-rack model for a specific assignment. There are substantially more confounded models which perform better. For instance, Microsoft's ResNet model was the champ of the 2015 Image Net test with a 3.6% blunder rate, yet the model has 152 layers!

IV. IMPLEMENTATION RESULTS

The broad investigations are done to confirm the adequacy of the proposed technique. In the first place, pictures with pixels containing ships, seawater, islands, and without ships are set up to check the exhibition of the proposed transport competitor extraction technique. We tried our strategy on taking the boat and no boat pictures on various occasions and areas and containing seaside scenes. The public SAR Ship Detection Dataset (SSDD) is utilized in this work. The SSDD incorporates SAR pictures gathered from Radarsat-2, TerraSar-x, and Sentinel-1 with goals going from 1 to 15 m and polar metric methods of HH, HV, VV, and VH. The insights regarding SAR pictures are recorded in table 1.

Table 1 Data Description

Sensors	Resolution	Size(pixel)
Sentinel-1	20m	1024x1024
RadarSat-2	1-100m	8192x8192
TerraSAR-X	10m	8891x8676

In this work, accuracy is widely used to quantitatively evaluate ship detection performance.

Accuracy = TP+TN/TN+FP+FN+TP

Herein, TP, FN, and FP denote true positive, false negative, and false positive, respectively. The accuracy for the input images is presented in Table .2.

Table.2.The accuracy of the proposed algorithm for various data set

Name of the Image	Accuracy (in %)
Image1	93.5
Image2	94.2
Image3	93.6
Image4	94.1
Image5	92.3
Image6	90.5
Image7	93.7
Image8	94.4
Image9	95.1
Image10	93.5
Image11	91.8
Image12	92.7
Image13	90.2
Image14	92.1
Image15	92.4

The simulation results of ship detection are given below

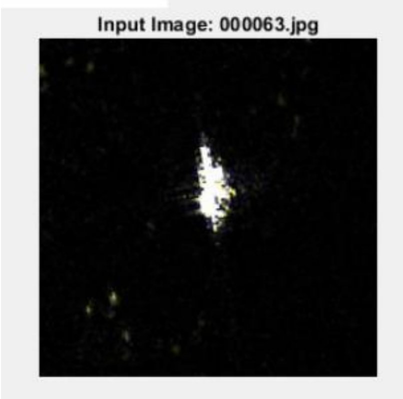

Fig.3. Input image

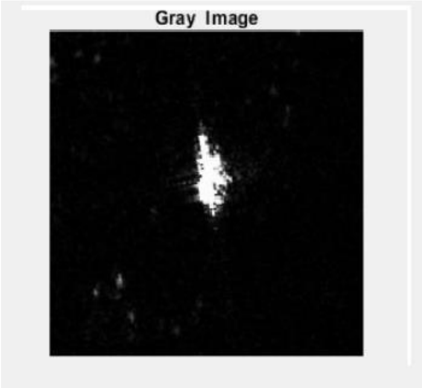

Fig.4.Gray image

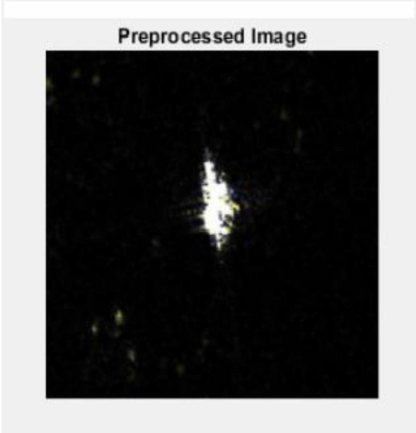

Fig.5. Preprocessed image

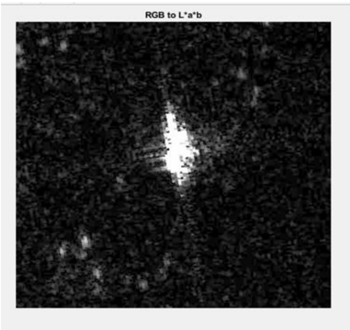

Fig.6.RGB to L*a*b

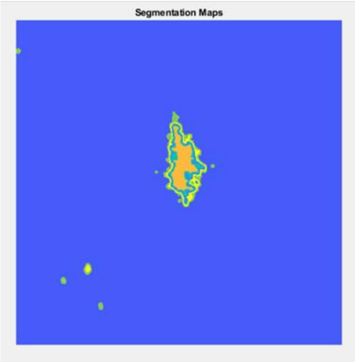

Fig.7. Segmentation maps

Fig.8.Layer processing

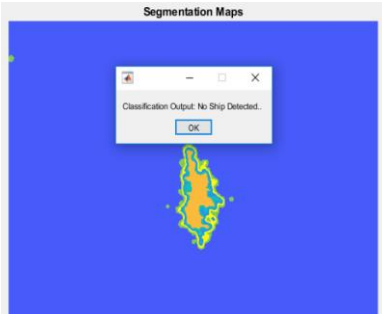

Fig.9 .Classification result

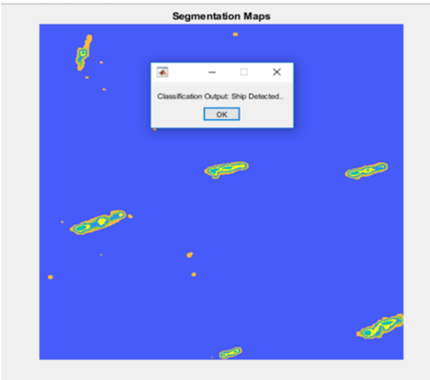

Fig.10. Classification result

A. Accuracy Comparison

The accuracy of the proposed method is compared with the existing method and is illustrated in Table

Table 3 Performance comparison of the proposed method with the existing method

S.No	Method	Average Accuracy (in percentage)
1	CNN	89
2	RNet	92
3	Proposed VGG Net	92.94

From table 3, it is observed that the proposed method provides better average accuracy than the existing methods.

V. CONCLUSION

This undertaking proposed a perform various tasks learning system for transport recognition in multi-goal SAR pictures. To investigate more powerful element extractors, an assignment explicit planned spine network is created motivated by the VGG-Nets. The recreation results demonstrate that the proposed network is incredible to separate discriminative portrayals for powerful SAR transport order. The acknowledgment execution is improved by consolidating the trio closeness imperative joined with the softmax grouping blunder punishment framing the perform various tasks learning model, which can accomplish great characterization execution by pulling the profound portrayals coming from a similar class nearer to one another and pushing those of various classes far separated in the mastered inserting space. To improve the speculation execution of trio CNNs in the DML, the Fisher regularization term is forced on the profound embeddings to exploit the trios in a preparation group. Henceforth, the worldwide data of the pairwise distances of the profound inserting is completely mined, and more powerful models learned are gotten.

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