SHIP DETECTION FROM SATELLITE IMAGE USING DEEP LEARING

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ABSTRACT:

The detection of marine and onshore river ships has been investigated using optical satellite imaging and detection and ranging (SAR). Conventional boat acknowledgment methods normally on SAR photographs, then again, could have a high deception rate and be affected by the ocean level model, especially in streams and seaward places. Traditional optical picture-based detection methods are ineffective on small, accumulating ships. In this study, a rapid geographic deep convolution network (R-CNN) method for detecting ships in high-resolution satellite data is developed using the concept of neural architectures. To begin, we select optical satellite images from GaoFen-2 with a horizontal resolution of m and divide the vast image region into discrete fields of interest (ROI) that might contain ships using a RR-CNN. Ship recognition methods based on a geographical area deep neural network (RCNN) are then applied to the ROI images. Faster-RCNN is an efficient option for detection, and its predecessor, VGG16, continues to improve its architecture. In order to obtain a more accurate result from relatively small and collecting ships (RPN), we must perform ROI consolidation on a larger previous layer and make use of available feature representations. The bolt action fully convolutional analyzer, our improved Faster-RCNN, the previous VGG16-based Faster-RCNN, and one of the most influential classic ship detection techniques, the active shape model, are all compared to the element (fe model) (DPM). Our revised Faster-RCNN strategy outperforms the competition, as demonstrated by experiments.

1. INTRODUCTION:

Ship detection on remote sensing photos has a wide range of applications in civil and defence security. Inshore surface inland river surface Ship identification using satellite images can give real-time location information for navigation management and marine search and rescue, ensuring the efficacy and safety of activity at sea and on inland rivers, such as ocean transportation supplies. It also helps to supervise and build significant coastal zones and harbours, which helps to maintain the environment and sea health as well as offshore areas and inland rivers the majority of current research [1–11] is based on synthetic aperture radar (SAR) pictures. Nonetheless, developing and solving a proper statistical model for a complicated sea area is difficult.

In light of the aforementioned issues, another option is to employ an optical satellite image-based target detection technique. Optical satellite photos have supplied a wealth of structure outline color, and texture information during the last few generations, and vessel recognition employing 2D image detection methods in Landsat images has already been intensively researched [14–16]. The traditional methods of shipping recognition are based on segmentation algorithm [17], and require that the sea level be in great condition; however, the detection accuracy are not adequate. Many different researchers began to utilize physical facilities on custom elements such as the classification algorithm (SVM) Xgboost, decision trees, and so on [18,19] which are predicated on hand-engineered characteristics such as the svm classifier (SVM), Logistic regression, decision trees and so on. Convolutional neural network (DCNN) can extract semantic level image features that are robust to image noise and morphological changes and relative positions of targets [36–39]. The DCNNbased methods make it possible to detect ships with a variety of different sizes, shapes, and colours and achieve a better result than traditional target detection methods. However, most of the studies combine a CNN with SAR images that have no colourful features since it used in optical remote sensing images. Moreover, it is still a challenge to detect small ships and ships that are densely close to each other.

In this research, we offer an upgraded R-CNN method of ship detecting on optical remote sensing images to overcome the aforesaid difficulty, particularly for tiny warships and fleet clusters classification. With the advancement of remote sensing methods, a huge amount of remote sensing images with a spatial resolution greater than 1 m is now available. Quick Bird GeoEye, Worldview, GaoFen-2 (GF2) GaoFen-4, and others are examples of such images. Small ships can be detected and distinguished from groupings using these sub meter range spatial data photos. In this article, we emphasize on GF2 optical pictures, which have a 1-m resolution and were taken from China's first spatial and spectral satellites [40]. GF2 photos have a lot of colour and are good quality.

Additional relevant details are required to detect small ships and separate them from clusters. Images of greater definition, such as Quick Bird and GeoEye, should theoretically result in a better detecting result. In our study, however, GF2 is more cost-effective.

In this research, we offer an updated RCNN approach for vessel classification on optical satellite images to overcome the aforesaid difficulty, particularly for tiny warships and ship groupings recognition. With the advancement of multispectral sensors, a huge amount of remote sensing images with a granularity exceeding 1 m is now available. Quick Bird, GeoEye Worldview, GaoFen-2 (GF2), GaoFen-4 and others are examples of such images.

Small ships can be detected and distinguished from clusters using these sub meter sensitivity satellite images photos. In this article, we focus on GF2 optical pictures, which have a 1-m resolution and were taken from Korea's first spatial and spectral satellite [40]. The GF2 pictures 'high resolution provides a wealth of colour and texture information and features, which are critical for detecting small ships and distinguishing ships throughout clusters. Images of greater definition, such as Speedy Bird and GeoEye, should theoretically make for a better detecting result. In our study although, GF2 is more cost-effective

2. LITERATURE SURVEY:

These visual detection algorithms above are also widely used in remote sensing ship detection. Zhang R et al. [24] proposes a new method of ship detection based on convolution neural network (SCNN), combined with an improved saliency detection method. Kang M et al. [25] take the objects proposals generated by Faster R-CNN for the guard windows of CFAR algorithm, then pick up the small-sized targets, thus re-evaluating the bounding boxes which have relative low classification scores in detection network. Liu Y et al. [26] presents a framework of Sea-Land Segmentation based Convolutional Neural Network (SLSCNN) for ship detection that attempts to combine the SLS-CNN detector, saliency computation and corner features. These methods above are known as horizontal region detection. However, in real life, for a ship with a large aspect ratio, once the angle is inclined, the redundancy region will be relatively large, and it is un favorable to the operation of non-maximum suppression, often resulting in missing detection, as shown in Figure 1. In order to solve the same problem, Jiang Y et al. [27] proposed the Rotational Region CNN (R2CNN) and achieved outstanding results on scene text detection. However, since R2CNN still uses horizontal anchors at the first stage, the negative effects of non-maximum suppression still exist. RRPN [28] uses rotation anchors which effectively improve the quality of the proposal. However, it has a serious problem of information loss when processing the ROI, resulting in a much lower detection indicator than the R2CNN.

Many methods have been developed for detecting ship targets from SAR images during the last two decades, including direct ones and indirect ones. The direct methods detect ships directly. Of those methods, adaptive threshold way [2], probability neural network (PNN) model method [3]and distributed constant false alarm rate (CFAR) methods[4–6] are the generally used methods. The indirect meth-odds firstly detect ship wakes and then seek ships around wakes, which mainly include Radon transform, mathematical morphology and wavelet analysis [7]. Among these meth-ods, the distributed CFAR framework is the most widely accepted conceptual model. However, CFAR-like detectors involve parameter estimations of ships and sea/background clutters, and the threshold setting is essential so that a con-stand false alarm probability is guaranteed for all values of unknown clutter parameters. The strong dependence of theca schemes on prior knowledge about ships and back-ground observation limits their application. The variance weighted information entropy (WIE), recently being applied to the extraction of regions of interest (ROIs) from infrared and SAR images, has been proved to be a simple and effective quantitative description index for the complex degree of image background [8,9]. The variance WIE is particularly suitable for gray imagery to measure its non-uniformity. However, the existing researches mainly focus its applications on the rough extraction of ROIs. By relying on a simple central spot quarter scheme to subdivide image constantly, target is often segmented into different sub-blocks in searching for ROIs. Also, the involved image pre-treatment (for expanding the image boundary into 2M×2N) and the thresh

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3. PROPOSED SYSTEM:

Synthetic aperture radar (SAR) picture automatic ship detection is widely used in maritime surveillance. SAR pictures can be used for detection in any weather and at any time of day. This has led to the presentation of a wide range of object detection algorithms, from deep learning methods to classical ones.

Seagoing vessels are vulnerable to ship detection technology currently in use. This project suggests a novel multi-scale ship detection method based on a Multi-scale Faster R-CNN network using SAR images in order to overcome these problems. To begin, the SAR pictures are decomposed into a pyramid structure and the features are extracted using a multi-scale network. Then, utilizing the feature map for each layer, the region proposal network (RPN) is used to generate suggestions that include ship targets Finally, to acquire the final detection performance, these recommendations are fed into the classification network.

3.1 IMPLEMENTAION:

3.1.1 DATASET:

In this work, a public dataset from Kaggle on the Airbus Ship Detection Challenge is obtained. The dataset contains more than 100 thousand 768 × 768 images taken from satellite. The total size of the dataset is more than 1 Gb. Along with the images in the dataset, is a CSV file that lists all the images ids and their corresponding pixels coordinates. These coordinates represent segmentation bounding boxes of ships. Not having pixel coordinates for an image means that particular image doesn't have any ships.

In this project ship dataset is collected form Kaggle which has ship and non-ship images dataset with collection of images. Dataset has features and labels in which features are taken as content inside image and labels are taken as ship or non-ship.

3.1.2 PRE-PROCESSING:

Due to imbalance in dataset, up sampling is done on the minority class, by randomly duplicating images until the 2 classes have comparable distribution in the dataset. After this is done, the dataset will be split into the training, testing and validation sets by randomly shuffling them and then splitting.

Another way is to introduce class weights for each specific class. Each class is penalized with the specific class weight. Higher the class weight, greater the penalty. Classes with lower percentage have a higher penalty. This allows for the model to penalize itself heavily if class detected is incorrect.

In this step data analysis of ship and non-ship images is performed first to check if both the folders have equal dataset. As the dataset is not equally divided image augmenting is applied to check which folder has less images and ratio is matched by adding augmented images to the minority dataset. Graphic representation of both scenarios is analyzed using charts.

Then the dataset is split in to two parts training and validation dataset in 80:20 ratio. Each training and validation data has features and labels which are used for training model and testing accuracy of the model.

3.1.3 Training Validation:

R-CNN algorithm is initialized with these parameters

Features are explained.

* Conv2D - This is a two-dimensional Network layer wherein the filter size determines what the algorithm will take input. The higher the value of layer used, the more data is collected from input images.

* MaxPooling2D - This decreases the feature space of the neural layer's feature space without sacrificing any data from dataset. This permits a model to gain a little more sturdiness.

* Dropout - This eliminates a proportion of connections among neurons in successive levels that the user specifies. This makes the project more stable. It would be used in either fully linked and completely neural layers.

* Batch Normalization - This level generalizes the information in the neuronal program's hidden component. This is comparable to how artificial learning algorithms use Minmax/Standard scaling.

* Batch Normalization - This layer normalizes the values present in the hidden part of the neural network. This is similar to Minmax/Standard scaling applied in machine learning algorithms

*Padding- This replaces the decimal places in the featured map/input picture, permitting borders characteristics to remain.

Using fit function training data features and labels are given as input to the model which trains algorithm within given epochs and model data is saved in to history.

Accuracy of the Model:

In this step from the history variable accuracy of the model with validation and training data is taken and displayed in the form of graphs.

Augmenting Images of Minority Class:

The images present in the *ship* class are augmented and then stored in the dataset, so that there is an equal representation of the classes. The current ratio of classes is 1:3, meaning that for every image present in the *ship* class there are 3 images present in the *no-ship* class. This will be countered by producing 2 augmented images per original image of the *ship* class. This will make the dataset balanced.

If augmentation of dataset is required then set AUGMENTATION to *True*. This will balance the dataset via augmentation of minority classes. To train via class weights, then set AUGMENTATION to *False*.

- The dataset is split into training and validation set with 80 % and 20% images respectively. Function is created for encoding and decoding mask on top of every image then Mask R-CNN for segmenting the ships in image with a confidence score between 0 and 1 is set. The time required to mask out ships in the complete dataset was 9.82 second. Pre trained MS COCO weights are used for training the model. Since these weights have already been trained on a large variety of objects hence they provide a good place to start learning from.

3.1.4 TRAINING VALIDATION:

Training, Validation and Testing

Instead of using *train_test_split* the images and labels arrays are randomly shuffled using the same seed value set at *42*. This allows the images and their corresponding labels to remain linked even after shuffling.

This method allows the user to make all 3 datasets. The training and validation dataset is used for training the model while the testing dataset is used for testing the model on unseen data. Unseen data is used for simulating real-world prediction, as the model has not seen this data before. It allows the developers to see how robust the model is..

Split Data:

*** 70% - Training**

*** 20% - Validation**

*** 10% - Testing**

If AUGMENTATION is set true, then the number of images per class is balanced. If AUGMENTATION is set to False, then compute the class weights given below and accordingly change the fit function of the Keras API when training.

Creating Model:

Creation of model:

Conv_block - This function contains the convolutional layer, batch normalization and activation layers. The numbers of filters, kernel size, strides to be taken are defined by the developer. This allows a developer to make the model without having to repeat the same lines continuously many times. It also uses the OOPs concepts of Python which is recommended instead of coding like it is *C*.

Basic model - This function creates the model using the aforementioned function, max pooling layers and dropouts. After the specified number of convolutional layers, a flatten layer is introduced, along with dense layers so that the image can be classified. The flatten layer converts the feature map produced by the convolutional layers into a single column for classification.

For image detection in images using Faster R-CNN the feature map produced by the convolutional layers is used, i.e., the model drops the layers after the final convolutional block and passes the generated feature map to a Regional Proposal Network, which can either uses a vanilla CNN model containing fully connected layers or a Logistic Regression, Support Vector machines or Random forests. Advised to use vanilla CNN as it uses less CPU and memory, plus slightly faster and capable of giving multiple outputs if required.

Algorithm Parameters:

Explanation of features

* Conv2D - This is a 2-dimensional convolutional layer, the number of filters decide what the convolutional layer learns.

Greater the number of filters, greater the amount of information obtained.

* MaxPooling2D - This reduces the spatial dimensions of the feature map produced by the convolutional layer without losing any range information. This allows a model to become slightly more robust

* Dropout - This removes a user-defined percentage of links between neurons of consecutive layers. This allows the model to be robust. It can be used in both fully convolutional layers and fully connected layers.

* Batch Normalization - This layer normalizes the values present in the hidden part of the neural network. This is similar to Minmax/Standard scaling applied in machine learning algorithms

* Padding- This replaces the decimal places in the featured map/input picture, permitting borders characteristics to remain.

Model Training:

Block 1

* An input layer is initialized using the Input Ker slayer; this defines the number of neurons present in the input layer

* Zero Padding is applied to the input image, so that boundary features are not lost.

Block 2

* First Convolutional Layer, it starts with 16 filters and kernel size with (3, 3) and strides (2,2). Padding is maintained same, so the image does not change spatially, until the next block in which MaxPooling occurs

Block 3 - 4

* Similar structure in both with a convolutional layer followed by a MaxPooling and Dropout layers.

Output Block

* The feature map produced by the previous convolutional layers is converted into a single column using Flatten Layer and the classified using a Dense layer(output layer) with the number of classes present in the dataset, and *sigmoid* as activation function.

Compiling the Model

The model is compiled using the *Adam* optimizer with learning rate set at 1e-3. *Binary Cross entropy* is used as a loss function as there are only two classes.

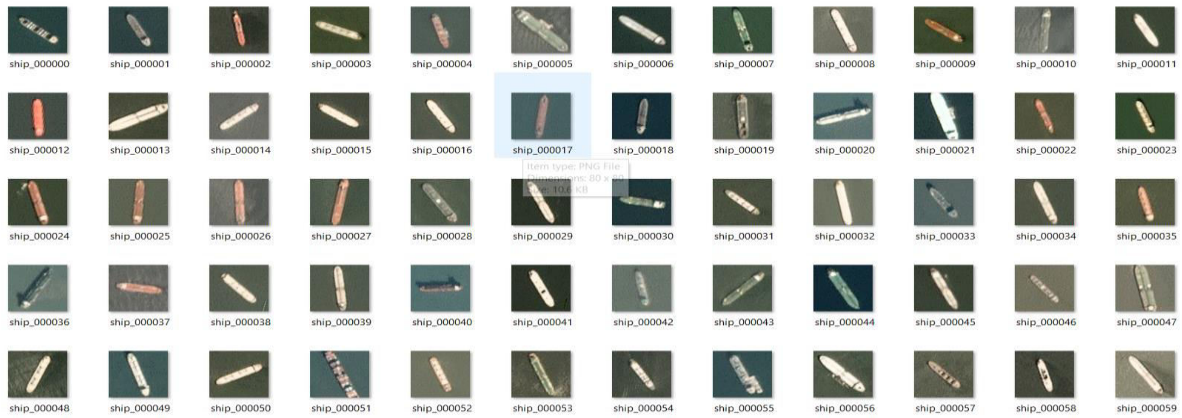
Training model:

The model is trained for 50 epochs with a batch size of 16. The best model weights are stored in the file *model_weight.h5* with Tensor Board logs being stored in the *logs* directory.

Prediction:

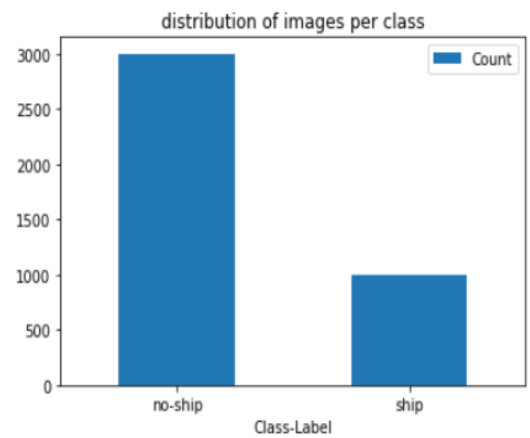
Input test images and verify ship is detected or not.

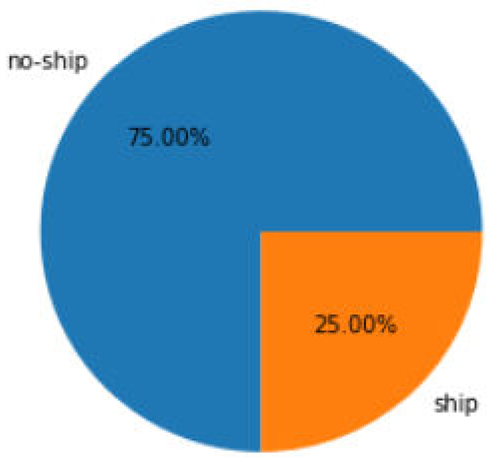
4. RESULTS AND DISCUSSION:



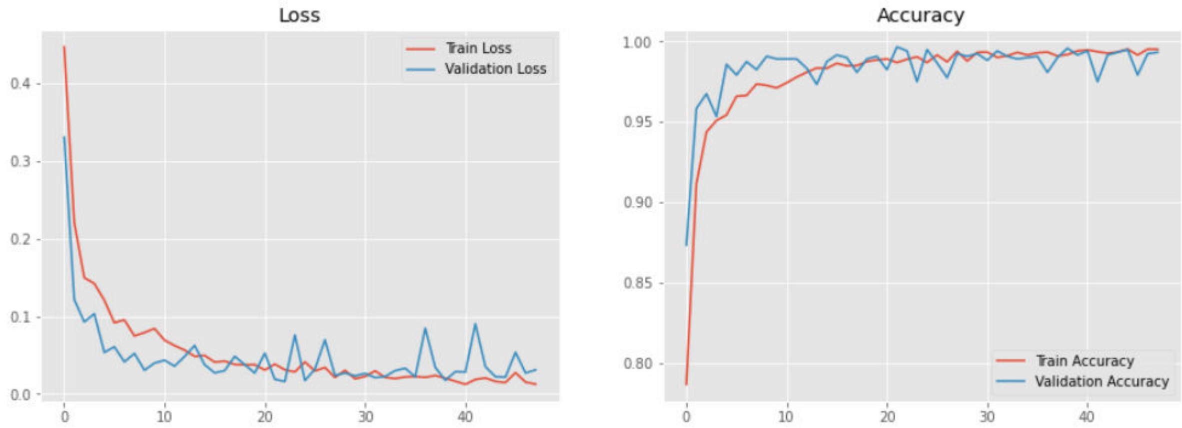

```
261/262 [===========================>.] - ETA: 0s - loss: 0.4457 - accuracy: 0.7867
Epoch 00001: val_accuracy improved from -inf to 0.87333, saving model to model_weights.h5
262/262 [============================] - 8s 29ms/step - loss: 0.4460 - accuracy: 0.7866 - val_loss: 0.3300 - val_accuracy: 0.8733
Epoch 2/50
262/262 [============================] - ETA: 0s - loss: 0.2204 - accuracy: 0.9114
Epoch 00002: val_accuracy improved from 0.87333 to 0.95833, saving model to model_weights.h5
262/262 [============================] - 7s 28ms/step - loss: 0.2204 - accuracy: 0.9114 - val_loss: 0.1214 - val_accuracy: 0.9583
Epoch 3/50
262/262 [============================] - ETA: 0s - loss: 0.1495 - accuracy: 0.9437
Epoch 00003: val_accuracy improved from 0.95833 to 0.96750, saving model to model_weights.h5
262/262 [============================] - 7s 28ms/step - loss: 0.1495 - accuracy: 0.9437 - val_loss: 0.0925 - val_accuracy: 0.9675
Epoch 4/50
261/262 [===========================>.] - ETA: 0s - loss: 0.1422 - accuracy: 0.9507
Epoch 00004: val_accuracy did not improve from 0.96750
262/262 [============================] - 7s 28ms/step - loss: 0.1420 - accuracy: 0.9509 - val_loss: 0.1032 - val_accuracy: 0.9533
Epoch 5/50
261/262 [===========================>.] - ETA: 0s - loss: 0.1206 - accuracy: 0.9543
Epoch 00005: val_accuracy improved from 0.96750 to 0.98583, saving model to model_weights.h5
262/262 [============================] - 8s 29ms/step - loss: 0.1205 - accuracy: 0.9543 - val_loss: 0.0534 - val_accuracy: 0.9858
Epoch 6/50
262/262 [============================] - ETA: 0s - loss: 0.0915 - accuracy: 0.9660
Epoch 00006: val_accuracy did not improve from 0.98583
262/262 [============================] - 8s 29ms/step - loss: 0.0915 - accuracy: 0.9660 - val_loss: 0.0607 - val_accuracy: 0.9792
Epoch 7/50
```

4.1 Graphs

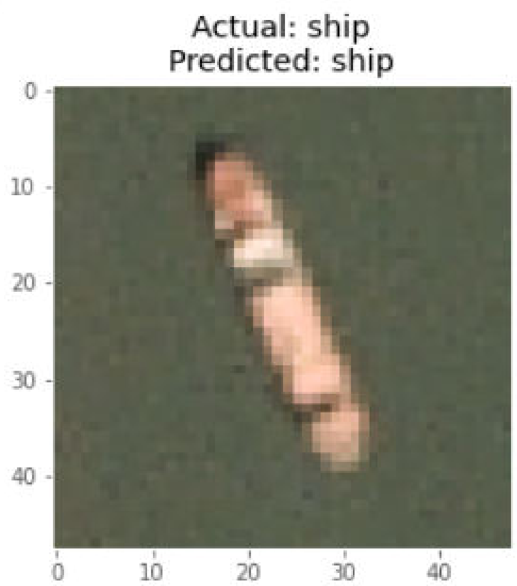




4.2 Evaluation:



4.3 PREDICTION:



5. CONCLUSION

Based on high-resolution remote sensing data, we suggested an efficient ship detection approach for small ships and gathering ships. The technique process used a coarse-to-fine strategy, whereby the candidate areas that may contain ships (ROI) are extracted first, followed by the segmentation of the non watery area from the water area. Second, to reliably identify ships in ROI photos, the R-CNN technique is used. Additionally, we advanced the detection of tiny ships and gathering ships and enhanced the RCNN framework's structure. Ultimately, our enhanced Faster-RCNN demonstrated superior recall and accuracy in comparison tests.. In future work, we will try more traditional methods in the preprocessing stage to increase the recall of ROI, such as the variation of LBP, Gaussian Local Descriptors, SML, and PCA classifier. It will be worthwhile to conduct further research on more sophisticated CNN and even RNN methods based on optical remote sensing imagery.

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