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SHIP DETECTION FROM SATELLITE IMAGES USING DEEP LEARNING

N.M Bhagya Sree [1] & S. Subhash Kumar [2]
[1] PG Scholar, Department of CSE, B.I.T Institute of Technology, Hindupur, Andhra Pradesh, India.
[2] Assistant Professor, Department of CSE, B.I.T Institute of Technology, Hindupur, Andhra Pradesh, India.

Abstract: On both detection and ranging (SAR) and optical satellite imaging, the detection of marine and onshore river ships has been examined. Traditional ship recognition techniques usually on SAR photos, on the other hand, might have a high false alarm rate and be impacted by the sea level model, particularly in streams and offshore places. On tiny and accumulating ships, traditional detection techniques based on optical pictures do not function well. The idea of neural architectures is used in this research to provide a rapid geographic deep convolution network (R-CNN) technique for detecting ships in high-resolution satellite data. To begin, we select GaoFen-2 optical satellite photos with a horizontal resolution m and use a R-R-CNN to partition the large image region The area is divided into discrete fields of interest (ROI) that could contain ships. The ROI photographs are then subjected to ship recognition techniques rely on a geographical area deep neural network (R-CNN). We use an effective option approach to detect, Faster-RCNN, and keep improving the architecture of its previous convolutional (CNN), VGG16, while using delivery is available feature representations and having to perform ROI consolidation on a larger previous layer in a proposed method to achieve more accurate result of comparatively tiny and collecting ships (RPN). Finally, we make a comparison the element (fe model (DPM), a further two widely used target recognition architectures, the bolt action fully convolutional analyzer , the previous VGG16-based Faster-RCNN, and our enhanced Faster-RCNN to one of the most impactful classic ship detection technique, the active shape model . Experiments show that our revised Faster-RCNN approach outperforms the competition.

Keywords: Ship detection, RCNN, CNN

1. INTRODUCTION

Ship detection on remote sensing photos has a wide range of applications in civil and defence security. In shore surface, inland river surface Ship identification using satellite images can give realtime 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 harbors, 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 requires 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 DCNN-based methods make it possible to detect ships with a variety of different sizes, shapes, and colors and achieve a better result than traditional target detection methods. However, most of the studies combine a CNN with SAR images that have no colorful 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.

1.2 OBJECTIVE

Objective of this work is to develop a deep learning algorithm for detection of ships and no ships from the given image. This is done by applying best algorithm which can detect ships from given input image in short time compared to existing machine learning methods.
To perform this operation each step is performed on dataset and a model is generated which is used for predicting from given input image.

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2. OVERVIEW OF THE SYSTEM

2.1 Existing System:

First, the sea-land image is segmented using texture, shape data and extract the sea region as the selected area (ROI). The potential object location is then determined using an algorithm such as the contrast box technique or moderately hierarchical segmentation 2 of 14. Finally, after post-processing, erroneous boxes are filtered to obtain the final detection findings.
Previously, various image processing approaches identified important features from visible spectrum images, which were then input into supervised classifiers. We present a technique for determining whether or not a visible spectra aerial photograph a ship. The proposed design was based on Convolutional (CNN), and it increases performance by merging neural codes generated by a CNN with other types of neural codes.
The k-Nearest Neighbor method is used. The results of the KNN and the CNN SoftMax output are compared.
Two VGG genes are VGG-16 and VGG-19. VGG-16 has thirteen fully associated networks and three pooling layers, whereas VGG-19 has sixteen final fully connected and three pooling layers. In both architectures, washout and max-pooling methods, as well as Relu algorithms, are applied.

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2.1.2 Disadvantages of Existing System

Although these strategies have demonstrated promising performance, their applicability in complicated circumstances is limited.

- High fidelity and high-resolution satellite images pose processing challenges and critical time challenges for manual human-based efforts. One way of tackling the problems mentioned above is using Computer Vision techniques to automate the detection process. Deep Learning techniques have proved to be quite popular for Computer Vision detection tasks.
- Models like CNNs and RCNNs have proved very favorable for object detection tasks. Extra performance-enhancing techniques have been proposed for Deep Neural Networks such as CBAMs. A CBAM is a generalize-able module for CNNs that has little-to-no overhead on functioning and resources and has noticeably improved performance on classification tasks. So it is to be investigated if implementing CBAMs on various CNNs selected (CNN, RCNN,

RRCNN, Mask RCNN) in detecting ships in satellite images can positively impact performance or not.

2.2 Proposed System

In maritime surveillance, automatic ship detection of synthetic aperture radar (SAR) images is commonly utilized. SAR images have the ability to detect in all weather conditions and at all times of day. As a result, a variety of object detection algorithms have been presented, spanning from classical to deep learning techniques.

Seagoing boats are susceptible to current ship detecting technologies. In order to address these issues, this project proposes a unique multi-scale ship detection approach in SAR images based on a Multi-scale Faster R-CNN network.

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.

2.2.1 Advantages of the Proposed System

A ship detection method that is effective for small ships and gathering ships based on high-resolution remote sensing imagery.

Experimental results indicate that the proposed method can effectively detect the ship targets from various circumstances without any prior knowledge.

2.3 Proposed System Design

In this project work, I used five modules and each module has own functions, such as: Dataset Collection

Pre-processing

Training R-CNN

Training Model

2.3.1 Dataset Collection:

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.

2.3.2 Preprocessing

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.

2.3.3 Training Using R-CNN Model

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.

2.3.4 Training 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.

3. ARCHITECTURE

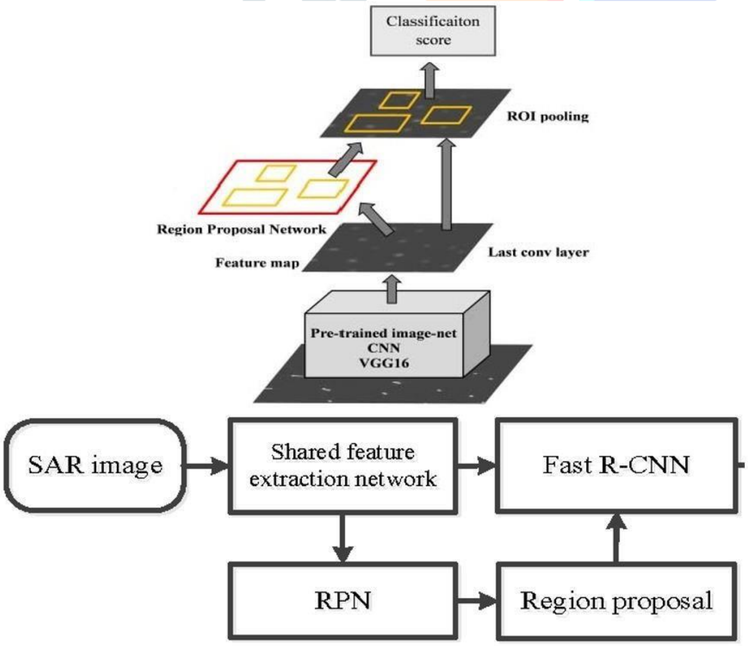

Fig 1: Architecture diagram

4. RESULTS SCREEN SHOTS

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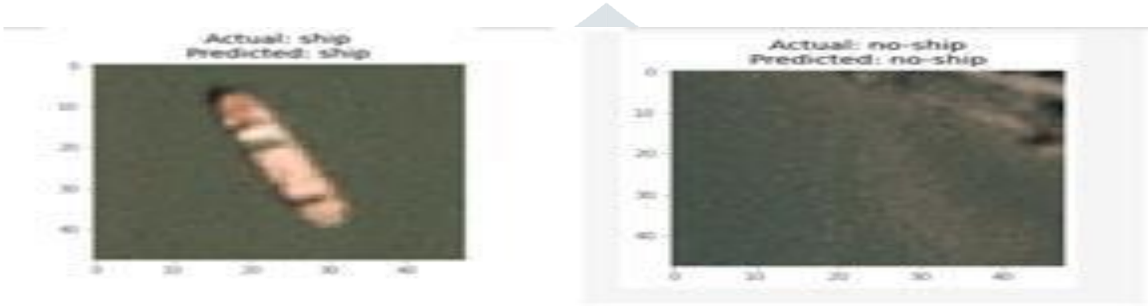

Accuracy of trained model is displayed in graph.

Predicted Result

CONCLUSION

Based on high-resolution remote sensing photos, we devised a ship detection algorithm that is suitable for small ships and large ships. The approach used a coarse-to-fine strategy, in which the nonwatery area was segmented from the water area first, followed by the identification of potential areas that could contain ships. Furthermore, the R-CNN algorithm is used to detect ships in photos with high accuracy.

Future Enhancement

In future work image segmentation and detection of specific location inside image can be improved with better detection. Algorithms like Faster R-CNN can be implemented for improving accuracy

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