

Towards a Reliable and Sensitive Deep Learning Based Approach for Multi-Ship Detection in SAR Imagery

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Abstract

Synthetic Aperture Radar (SAR) images show promising results in monitoring maritime activities. Recently, Deep learning-based object detection techniques have impressive results in most detection applications but unfortunately there are challenging problems such as difficulty of detecting multiple ships, especially inshore ones. In this paper, a three-step ship detection process is described and a reliable and sensitive hybrid deep learning model is proposed as an efficient classifier in the middle step. The proposed model combines the finetuned Inception-Resnet-V2 model and the Long Short Term Memory model in two different approaches: parallel approach and cascaded approach. In experiments, the region proposal algorithm and the Non-Maxima suppression algorithm are applied in the first and last step in the three-step detection process. The comparative results show that the proposed approach in cascaded form outperforms the competitive recent state-of-the-art approaches by enhancement up to 16.3%, 16.5%, and 18.9% in terms of recall, precision and mean average precision, respectively. Moreover, the proposed approach shows high relative sensitivity for challenged cases of both inshore and offshore scenes by enhancement ratios up to 81.88% and 24.58%, respectively in recall perspective.

1. Introduction and Related Work

Synthetic Aperture Radar (SAR) system is considered a perfect source of images (Chaturvedi, 2019 and Cui et al., 2021) specially for military applications, environmental monitor, marine monitoring, or any other application that requires a relatively high accuracy due to the fact that neither weather nor light can affect the imaging process of the SAR. With the increasing count of launching satellites, such as Sentinel-1, Gafon-3 and Terra SAR-X, the availability of SAR images has been increased. Maritime transport has an essential role in growth and sustainable development that leads to a significant increase in the currently ships count. The management of marine traffic is one of the most important applications of SAR images, from which ships can be detected easily due to their bright intensity (Cui et al., 2021 and Arivazhagan et al., 2019). Meanwhile, in real scenario, a SAR image contains other objects besides ships, which are not interested in, such as sea ice and coastline structure, and even speckle noise that may negatively affect the ship detection process (Song et al., 2017).

During the past decades, researchers were interested in the field of SAR ship detection and many researches have been published. In (Liang et al., 2020) Constant False-Alarm Rate (CFAR)

algorithm is presented that is able to identify targets statistically by setting a threshold while maintaining a constant false alarm rate. In (Ai et al., 2010) a 2-D joint lognormal distribution algorithm, which uses the correlation of the gray intensity to model the ship targets is demonstrated. A new hierarchical scheme for detecting ships in SAR images is proposed in (Wang and Liu, 2012), which consists of detection and discrimination modules, such that ship candidates are obtained by applying CFAR, while ship discrimination is performed by using one-class classification. Another method in (Hou et al., 2013) is proposed to detect ship targets by measuring the visual conspicuity of each water region and the k-means clustering algorithm. In (Zhang et al., 2018) a ship segmentation scheme with non-local processing is proposed in order to handle the speckle noise and the complicated backscattering phenomenology in SAR images. These ship detection approaches are based on manually extracted features, experienced statistic model and traditional image processing methods. A prior knowledge is required, and optimization difficulty is another challenge.

In recent years, deep learning, which is able to automatically extract features, has encountered

another revival especially with the rapid development of hardware computing (Fouad et al., 2020). An impressive work has been done to highlight the superiority of methods based on deep learning over traditional methods (Wang et al., 2018 and Carman and Kolhatkar, 2020). A lot of Convolutional Neural Network (CNN) architectures has already achieved great success for image features extraction, classification tasks in computer vision field and region proposal-based object detectors. For instance, the transfer learning and single shot multibox detector (SSD) are combined, in (Wang et al., 2018), for ship detection. However, the SSD provides a relatively low accuracy. In (Kang et al., 2017), a faster region-based convolution neural network (R-CNN) is adapted to solve the ship detection problem with higher accuracy. However, the multi-scale characteristics of the SAR ship images are not considered. For instance, the approach in (Wang et al., 2019) based on RetinaNet (Lin et al., 2017), shows higher accuracy for large size ships, however with a small detection rate for small size ships. As well, in (Zhou et al., 2020), a multi-scale version of the Faster R-CNN (Ren et al., 2016) is presented to solve the detection problem of multi scaled images and small sized ships, however, with a small detection rate for ships near the port, i.e., complex background. The problem of multi scale problem in SAR imagery are solved by proposed methods in (Liu et al., 2019) based on merging the strong scattering components and super-pixel grouping. These methods can achieve 0.85 of recall metric. In (Zhao et al., 2020), an attention-based model, is proposed to construct fine-grained feature pyramid. The proposed model can handle ships of various sizes with complex backgrounds based on combination of receptive filed and attention blocks.

In this paper, a hybrid Deep Learning (DL) approach, based on Convolution Neural Network (CNN) model and Long Short Term Memory (LSTM) model, is presented as a reliable and sensitive classifier to enhance the detection accuracy of the multi scaled small sized ships in the SAR images. In work, both the bagging method and boosting method, for obtaining more efficient DL hybrid approach, are discussed. By the bagging method, a proposed parallel approach is generated,

while a proposed cascaded approach is generated by the boosting method. The two proposed approaches are evaluated and compared with recent state-of-the approaches. The paper is organized in 4 main sections. Section 2 explains, in detail, the three-step ship detection process, including the proposed hybrid DL approach. Experimental work and comparative analysis are illustrated in Section 3. Finally, conclusions and suggested future work are drawn in Section 4.

2. Methodology

Ship detection process, in SAR images, is a complex problem that has three main issues to be considered: i) the nature of multi-scale characteristics of ships in SAR images, ii) the difficulty of detecting ships in complex backgrounds, and iii) the challenge of detecting small ships. This section presents the detailed stages towards the proposed approach to deal with such issues and perform the detection task with a relatively high accuracy and reliability.

In order to perform ship detection, the input SAR image should pass through a three-step process, as shown in Figure 1. In the first step, a Regions of Interest (ROI) generation process is applied that accepts an input image and results proposals for the locations (ROIs) of the detected objects in the image. In the second step, the generated ROIs are classified using an efficient classifier to decide if the detected object in each ROI is a ship or not. In the last step, a process for eliminating overlapped bounding-boxes (if any) of the classified ships is applied to form a single detection bounding box (Pang et al., 2019).

2.1 Region Proposal Algorithm for ROI Generation

The most traditional methods that are commonly used to detect objects in an image are image pyramids (Pang et al., 2019) and sliding windows (Blue and Brindha, 2020). On the other hand, they have two main drawbacks: i) time consuming due to the looping process and ii) different detection rates as a result of applying parameters with different values. The main idea of the region proposal algorithm (RPA) (Taghizadeh and Chalechale, 2020) is that it can inspect the image to define the regions, where an object is most likely to be located.

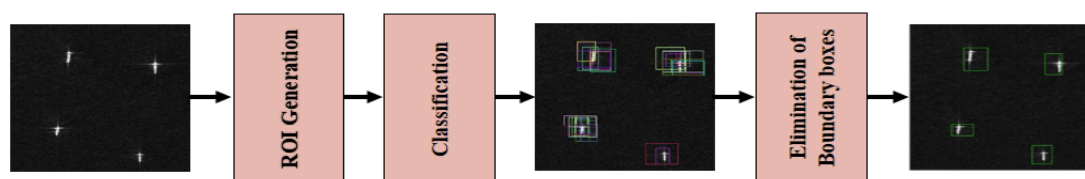


Figure 1: General flowchart of ship detection process in SAR images (Pang et al., 2019)

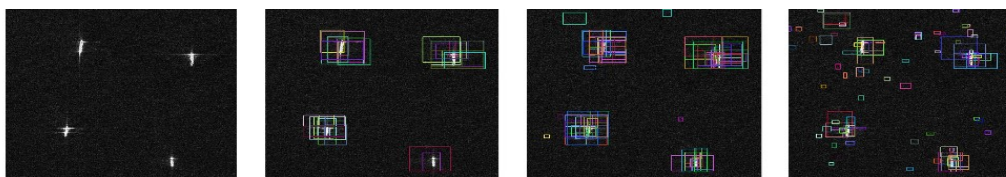


Figure 2: Sample generated ROIs using RPA

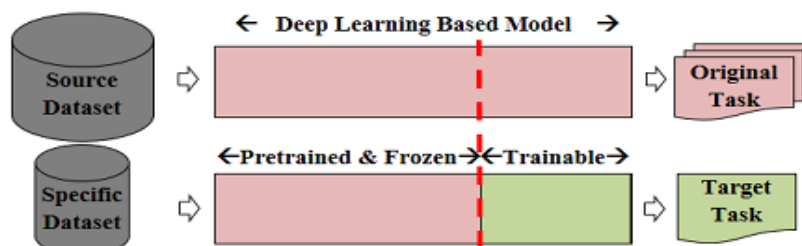


Figure 3: A typical transfer learning technique (Zhuang et al., 2020)

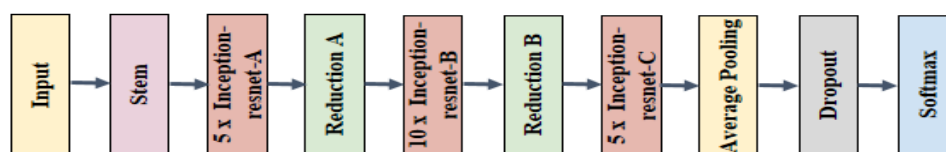


Figure 4: The basic network architecture of Inception-Resnet-v2 (Szegedy et al., 2017)

This can be achieved by using superpixel algorithm (Shang et al., 2020) for over-segmenting the input image. The RPA is considered to be more efficient than the traditional object detection techniques, i.e., image pyramids and sliding windows for some reasons as: i) the count of generated ROIs is few, ii) it is faster than exhaustively examining every scale/location of the input image, and iii) the amount of accuracy lost is minimal. In Figure 2, some samples, of the generated ROIs using the RPA, are shown, where white pixels represents the objects that may be classified as ships and colored boxes represent objects detected with different spatial resolutions that should be classified later as ships or not.

2.2 The Proposed Hybrid DL Approach for Classification Step

2.2.1 The transfer learning technique

In the scope of DL, transfer learning is performed by training a CNN classification model for a certain task using a large enough dataset or applying fine-tuning process to a pre-trained model, i.e., base model, using the new dataset targeted to the new task (Zhuang et al., 2020), as illustrated in Figure 3.

2.2.2 Using the LSTM model

The Long Short-Term Memory (LSTM) model is introduced as a special type and an enhanced version of recurrent neural networks (RNNs) to

There are a variety set of state-of-the-art CNN models that can be implemented as base-models for transfer learning such as VGG16 (Simonyan, and Zisserman, 2014), VGG19 (Wen et al., 2019), MobileNet V2 (Sandler et al., 2018), Xception (Chollet, 2017), Inception V2 (Alamsyah and Fachrurrozi, 2019), Inception-Resnet-V2 (Szegedy et al., 2017) and more.

In the proposed DL approach, Inception-Resnet-V2 (Szegedy et al., 2017 and Wang et al., 2019), is utilized as the base model for transfer learning. InceptionResnet-V2 (Szegedy et al., 2017) is a CNN-based classification model trained on a large scale and available ImageNet dataset (Deng et al., 2009). InceptionResnet-V2, shown in Figure 4, is a combined structure of both Inception networks and ResNet networks. Inception networks have their own structure, that depends on convolutional filters of different sizes with pooling process within one layer, while ResNet networks utilize a shortcut connection structure which is flexible and dependent on the tasks due to its ability to skip one or more layers to avoid degradation as a result of deep structure and accelerate the training process as well.

solve the vanishing and exploding gradient problem (Wang et al., 2019). The LSTM model utilizes base memory cells (mc) with a cell state and three gates: input, output, and forget gate, in each mc inside the hidden layer. These applied gates allow the LSTM

model to efficiently remember and learn patterns in long-term dependencies. While CNN-based model has the ability to extract important features from the internal representation of the image, the LSTM model has the capacity to selectively remember patterns for a long duration of time in the target image. The LSTM models support different schemes, i.e., many-to-many scheme, in which a sequence of predicted output values can be generated by a sequence of input at a time. Moreover, stacking LSTM hidden layers are supposed to enhance the prediction efficiency and a count of two-layer stacked LSTM, as shown in Figure 5, is recommended to avoid the degradation problem (Deng et al., 2009).

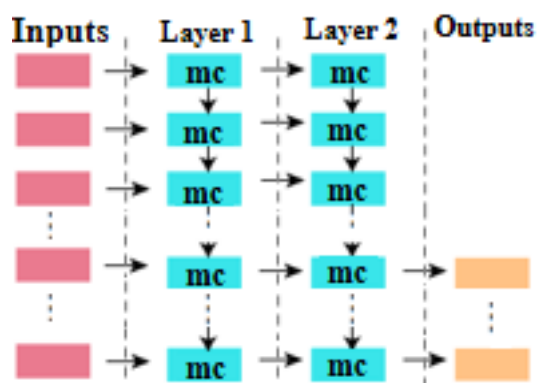


Figure 5: General structure of a two-layer stacked LSTM (Mahmoud et al., 2021)

In the classification step of the ship detection process, the LSTM model based on many-to-many scheme, in a two-layer stacked version, is combined with the fine-tuned Inception Resnet-V2-base model, in a hybrid classification DL-based model. The extracted features, from the Inception-Resnet-V2- base model, will be enhanced with those predictions generated from the LSTM model in order to ultimately improve the classification accuracy, hence the whole detection process.

2.2.3 Approaches of CNN and LSTM in a hybrid model

This study proposes the pre-trained Inception-Resnet-V2 as a base model for classification step. Two different approaches are suggested for combining the two-layer stacked LSTM model with the Inception-Resnet-V2 base model in a proposed hybrid model. The first hybrid model implements the pre-trained Inception-Resnet-V2 and the two-

layer stacked LSTM in a parallel form, while the second approach implements them in a cascaded one. The input size for all approaches are $224 \times 224 \times 3$ that accommodates all ship sizes in the data set, as shown in Table 1, which are ranged from 7×7 to 211×298 in SAR images of size 500×500 in average spatial resolution.

In the first suggested hybrid model, i.e., the proposed parallel model as shown in Figure 6, the input to the LSTM branch is first transferred to a gray scale, i.e., 224×224 . Then, each gray scale input is reshaped into 28 batches, each is of size 1792, and fed to the LSTM branch batch by batch. The extracted features from the pre-trained Inception-Resnet-V2 of dimension $5 \times 5 \times 1536$ are merged by those predictions form the two-layer stacked LSTM of dimension 1536 through element-wise multiplication with each batch of the 25 batches output from Inception-ResnetV2. The output of the 25 element-wise multiplications with the batch of dimension 1536 from LSTM is flattened in a merge layer of enhanced extracted features of dimension 38400. The enhanced extracted features, from the merged layer, are fed as input to a classification phase consisting of two cascaded fully connected layers of size 256 and 128, respectively followed by a Softmax output layer, as shown in Figure 7.

In the second hybrid model, i.e., the proposed cascaded model shown in Figure 8, the extracted features, from the pretrained Inception-Resnet-V2 of dimension $5 \times 5 \times 1536$, are reshaped to form 25 timed series batches, each batch of size 1536. The reshaped batches are then fed as 25 input sequences to the LSTM model that generates 25 batches of predicted values, each batch of size 512. The 25 predicted batches are reshaped to form enhanced extracted features of dimension 12800 in the merge layer. The merged enhanced features are directed to two fully connected layers of size 256 and 128, respectively, followed by the Softmax function as illustrated in Figure 9.

2.3.4 Overlapped bounding-boxes elimination using non-maxima suppression

Extra bounding-boxes around the same detected object can be eliminated by applying a Non-Maxima Suppression (NMS) (Hosang et al., 2017) that can collapse those weak bounding-boxes based on a given confidence.

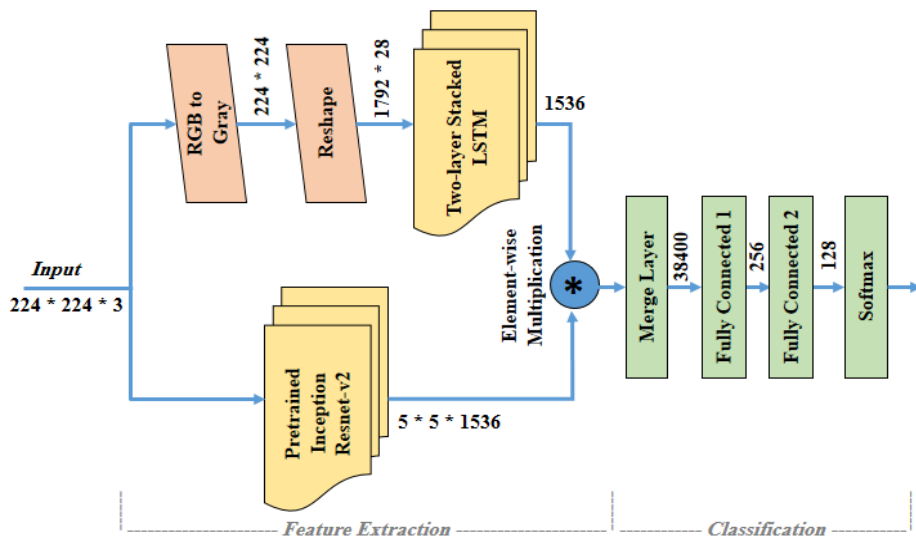


Figure 6: The parallel form structure of the proposed hybrid model

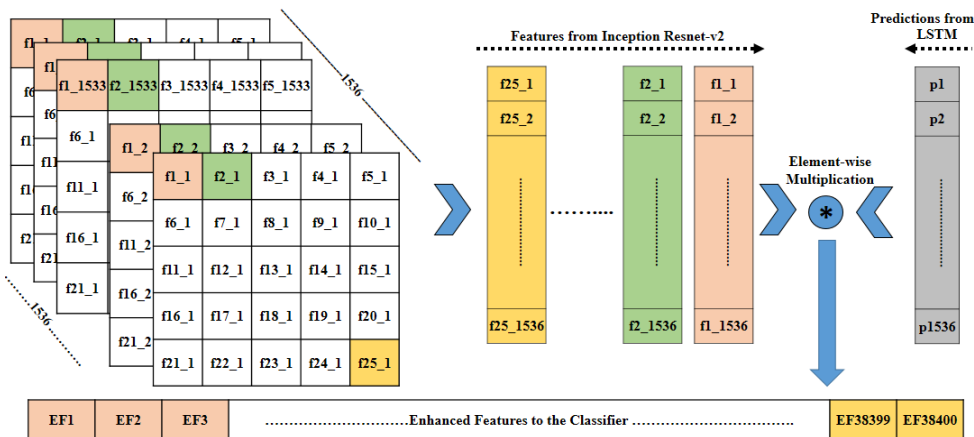


Figure 7: Enhancing the extracted features in the proposed parallel model

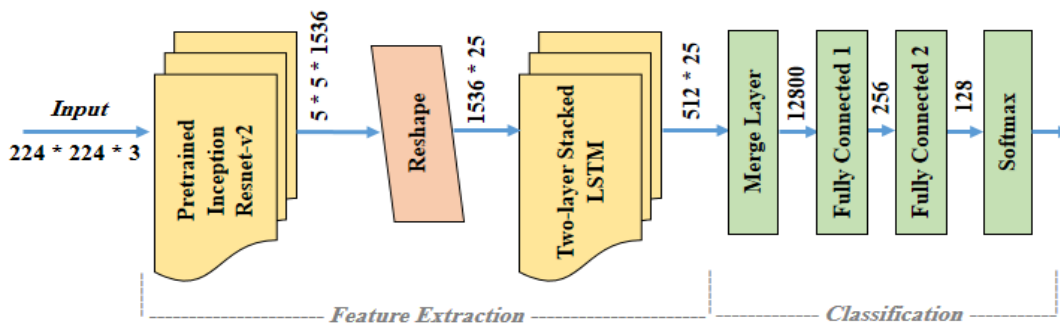


Figure 8: The cascaded form structure of the proposed hybrid model

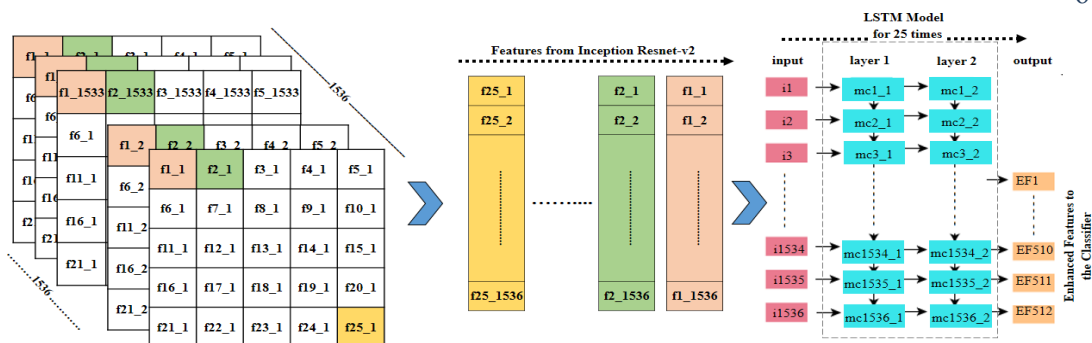


Figure 9: Enhancing extracted features in the cascaded form

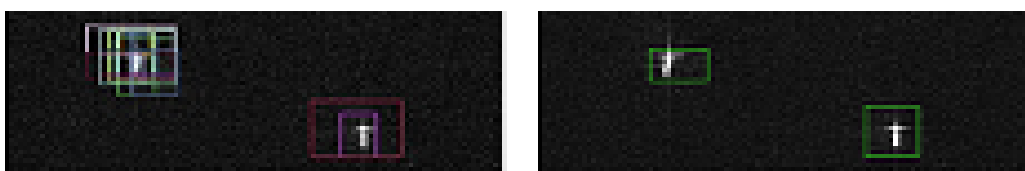


Figure 10: Bounding-boxes (a) before and (b) after applying NMS on the overlapped boxes

Table 1: Full description of the open (SSDD) (Li et al., 2017)

Sensors	Sentinel-1, RadarSat-2, TerraSAR-X
Place	Visakhapatnam, India; Yantai, China
Polarization	HH, VV, HV, VH
Resolution	1 m–10 m
Scene	Inshore, offshore
Num. of images	1,160
Avg. size of Images	500 × 500
Num. of ships	2,358
Avg. Num. of Ships per image	2.03
Smallest ships size	7 × 7
Biggest ships size	211 × 298

The benefit of using NMS is to remove all the overlapped boxes except only one that perfectly surrounds the detected object hence; obtain only one detection per object. NMS algorithm starts by choosing the boundary box with the highest confidence score and suggests that it perfectly bounds the object, while the other boundary boxes, for that object, are suppressed. For the rest boundary boxes the next one with the highest confidence score is selected again and the whole process is repeated till finishing all the remaining boundary boxes. Figure 10 shows the difference between the output image before and after using the NMS algorithm.

3. Experimental Work

3.1 Dataset Description

The open SAR Ship Detection Dataset (SSDD) (Li et al., 2017) is used to verify the effectiveness of the proposed model for ship detection through training, validation and testing phases. SSDD is proposed in 2017 and already has been widely used in researches

as in (Cui et al., 2019, Chang et al., 2019, Zhang et al., 2019(a), Zhang and Zhang, 2019 and Zhang et al., 2019(b)). SSDD contains 1160 SAR images with a total of 2358 ships. Images of SSDD have different resolutions and polarization modes that effectively allows to evaluate the robustness of the proposed ship detection approach. A full description of SSDD is shown in Table 1.

3.2 Training Strategy

SSDD is randomly divided into 70% for training, 10% for validation and 20% for testing. The training and validation sets are pre-processed by count of 9 augmentation techniques: 1) horizontal shift, 2) vertical shift, 3) horizontal-vertical shift, 4) horizontal flip, 5) vertical flip, 6) random rotation, 7) random brightness, 8) random zoom, and 9) Gaussian noise, to generate new image patches that is divided into two classes ship and scene. In experiments, the learning rate used is 0.0001 and the number of epochs is 100. The batch size used is 32

and the model utilizes Adam optimizer (Ogaltsov and Tyurin, 2019). The workstation used has 10th generation Intel core I7-10700T processor with 16 GB RAM and an ASUS Geforce GTX 1650, 1733 MHz, 2560 CUDA cores with 6 GB dedicated memory GPU. The environmental software includes Python 3.6.3, Tensorflow 1.7.0, Keras 2.1.2, CUDA 9.1 and cudnn 7.1.2. After the training and validation phases, i.e., in the test phase, the proposed DL model is fed with ROIs generated from test images using the RPA for classification purposes. Finally, the NMS algorithm will be applied to eliminate the unnecessary overlapped bounding-boxes in the ROIs of classified ships and then generates the final output SAR image from the input one, with non-overlapped bounding-boxes around the detected ships.

3.3 Evaluation Metrics

The most commonly used metrics for evaluating deep learning-based object detectors are Recall, Precision and mean Average Precision (*mAP*). These metrics are defined by:

$$\text{Recall} = TP / (TP + FN) \quad \text{Equation 1}$$

$$\text{Precision} = TP / (TP + FP) \quad \text{Equation 2}$$

$$mAP = \int_0^1 P(R) dR \quad \text{Equation 3}$$

where *TP* is True Positive rate, *TN* is True Negative rate, *FN* is False Negative rate, *FP* is False Positive

rate, *P* is Precision, *R* is the Recall, *P(R)* is Precision–Recall (*P-R*) curve, by which *mAP* is used to represent detection accuracy. Precision is the ratio between the True Positives and all the Positives. For the target problem statement, it is a measure of correctly identified objects as ships out of all detected ships. It reflects how reproducible predictions are, even if they are far from the accepted value, i.e., the reliability of the system. Recall is the measure of the proposed model correctly identifying True Positives. Thus, for all existing ships in the scene, recall reflects how many of them are correctly identified as ships, i.e., it gives a measure of how accurately the model is able to identify the relevant data. Recall reflects the sensitivity of the model. So, the model with higher recall is more sensitive to ships and can accurately detect most of ships in the input scenes regardless its scale or location. Precision-Recall Curve *P(R)*, is a direct representation of the Precision(y-axis) and the Recall(x-axis). Precision-Recall curves summarize the trade-off between the true positive rate and the positive predictive value for a predictive model using different probability thresholds.

4. Results and Discussion

Experimental results of the proposed parallel model shows an accuracy of 94 %, while the proposed cascaded model shows an accuracy of 97 %, as shown in their ROC curves and the associated AUCs in Figure 11. It is concluded that the cascaded form of the proposed hybrid model outperforms the parallel form in terms of classification accuracy by a ratio of 3.19%.

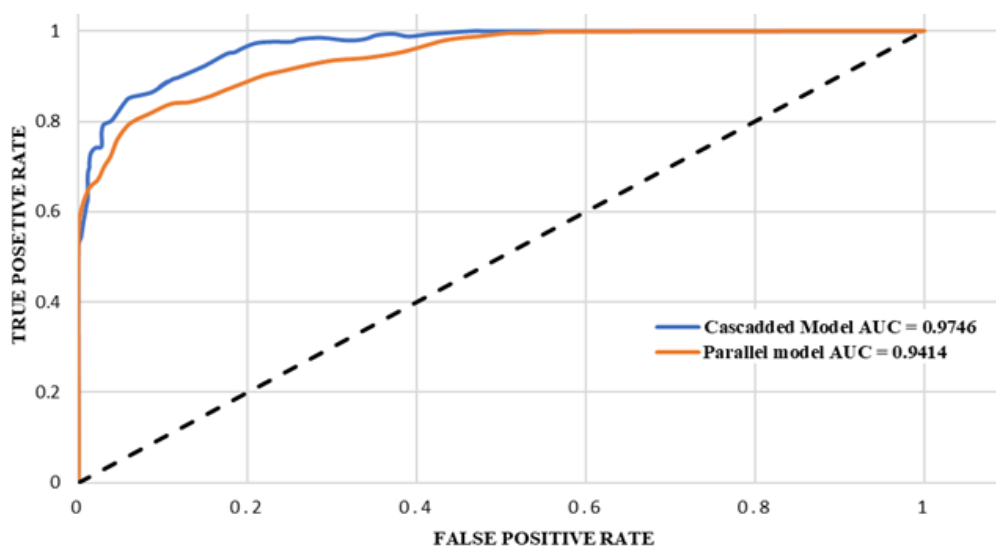


Figure 11: The ROC curve of the classification module

Table 2: Evaluation metrics of competitive approaches on SSDD

Method	Recall(%)	Precision(%)	mAP(%)
Faster R-CNN	85.16	81.15	82.66
RetinaNet	96.70	93.12	95.68
R-FCN	95.65	92.63	95.15
SSD	94.51	85.15	92.67
YOLOv3	96.70	93.62	95.34
YOLOv1	84.07	84.53	81.24
YOLOv2	92.86	84.92	90.09
HyperLi-Net	96.74	90.36	96.08
Proposed Parallel Model	93.20	87.63	93.71
Proposed Cascaded Model	97.81	94.57	96.59

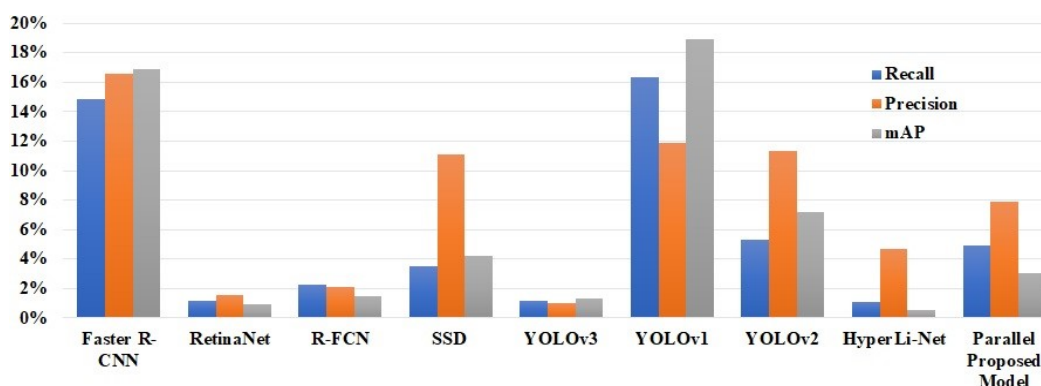


Figure 12: Improvement ratios (%) in recall, precision and mAP of the proposed cascaded model as opposed to the competing approaches

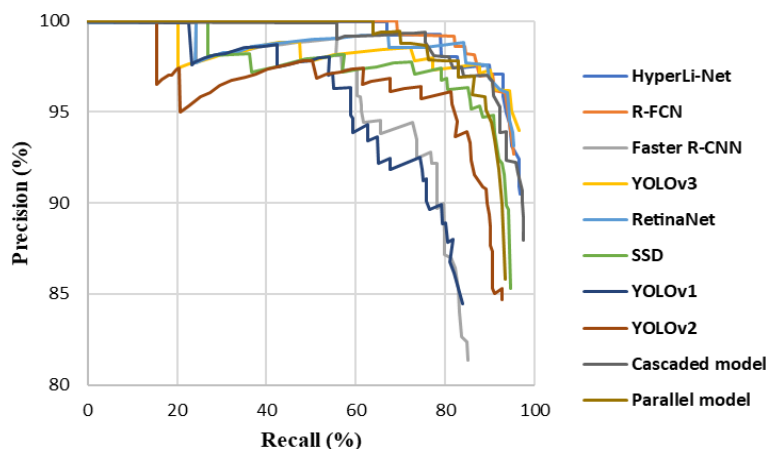


Figure 13: Precision-Recall (P-R) curves of all competing approaches

The two proposed hybrid models, in parallel and cascaded form separately, are compared with the most recent state-of-the-art approaches that utilize the same dataset for system training and evaluation (SSDD). The competitive approaches are YOLOv1 (Redmon et al., Wang), YOLOv3 (Redmon and Farhadi, 2018), YOLOv2 (Redmon and Farhadi, 2017), R-FCN (Dai et al., 2016), RetinaNet (Lin et al., 2017), Faster R-CNN (Ren et al., 2016), SSD (Liu et al., 2016) and HyperLi-Net (Zhang et al.,

2020). The comparative results, as shown in Table 2, show an outstanding performance of the cascaded form of the proposed hybrid model in comparison with the competitive approaches by ratios up to 16.3%, 16.5%, and 18.9% in terms of Recall, Precision, and mAP, respectively as shown Figure 12. The Precision-Recall (P-R) curves for the proposed cascaded model and the competitive approaches are shown in Figure 13.

Table 3: Evaluation metrics of competitive approaches on inshore and offshore scenes of SSDD

Method	Inshore			Offshore		
	Recall	Precision	mAP	Recall	Precision	mAP
Faster R-CNN	70.35	62.05	66.22	98.12	94.32	97.68
SSD	47.67	87.23	46.52	79.57	99.33	79.38
RetinaNet	48.26	83.00	45.66	83.60	97.80	83.35
Attention RPN	85.40	73.30	84.10	96.40	96.40	98.20
Proposed Parallel Model	66.71	79.30	43.28	80.07	98.34	81.815
Proposed Cascaded Model	86.70	88.55	85.51	99.13	99.57	99.36

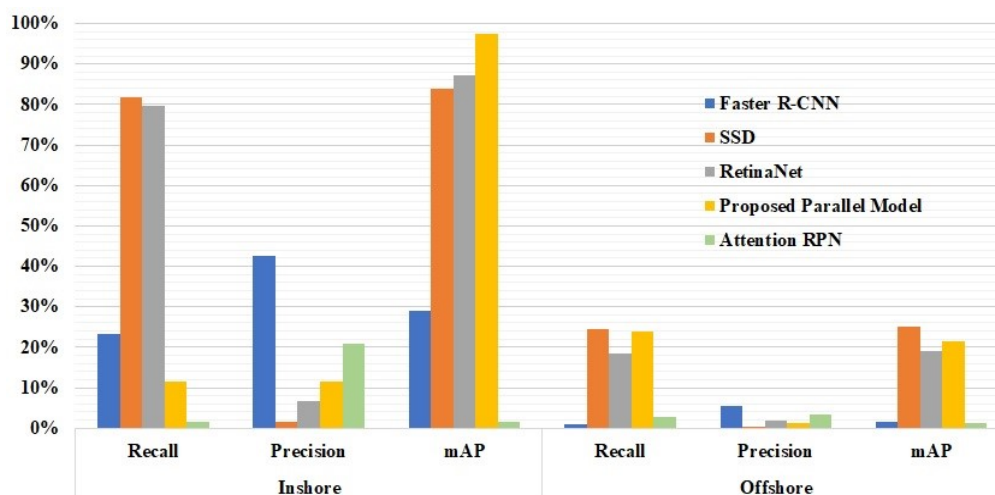


Figure 14: Improvement ratios (%) in recall, precision and mAP of the proposed cascaded model for inshore and offshore cases

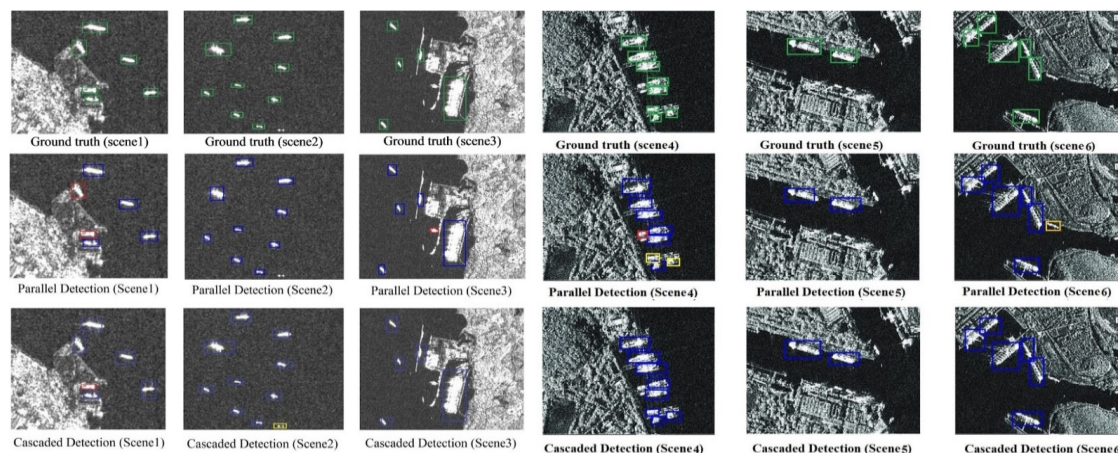


Figure 15: Different test scenes for both the proposed parallel and cascaded models, where blue bounding-boxes means correct detection, red means missed detection, and yellow means false-alarms

A more challenged capability of any ship detection process is its ability to reliably detect ships in the SAR images regardless their sizes or locations, i.e., inshore or offshore. Table 3 presents the performance of the proposed cascaded model in detecting ships in both inshore and offshore scenes. As shown in Figure 14, for the inshore cases, the

proposed cascaded model shows high efficiency by enhancement ratios up to 81.88%, 42.71% and 97.55% in terms of Recall, Precision and mAP, respectively relative to the competing state-of-the-art approaches. Meanwhile, for the offshore cases, the proposed cascaded model can achieve enhancements up to 24.58%, 5.57% and 25.17%,

respectively for the same metrics. The improvements achieved by the proposed cascaded model in the recall and precision metrics for both inshore and offshore denote a higher combination of sensitivity and reliability of the proposed model in the challenged cases, especially, i.e., inshore ones.

Different output samples (ground truth and detected ships) in different scenes, from both the proposed parallel model and the proposed cascaded model, are shown in Figure 15.

5. Conclusions and Future Work

This paper presents two deep learning hybrid approaches, combining the pre-trained Inception-Resnet-V2 and a two-layer stacked LSTM, for ship classification in a three-step detection process in SAR images. The first proposed approach, generated by the bagging method, combines them in parallel form, while the other, generated by the boosting method, combines them in the cascaded form. In detection process the region proposal algorithm is applied for ROI generations, while NonMaxima algorithm. is implemented for eliminating overlapped bounding-boxes.

Both models are trained using SSDD dataset and evaluated using Recall, Precision and mAP evaluation metrics. Experimental results show that the proposed cascaded model outperforms all competitive state-of-the-art approaches, including the parallel one, with ratios of 97.81%, 94.57%, and 96.59% for recall, precision, and mean average precision respectively. Moreover, the results shows an outstanding efficiency of the proposed cascaded model especially for inshore scenes as challenged cases, as it achieves 81.88%, 42.71% and 97.55% for the same metrics respectively. The outstanding results show that the proposed cascaded model capable of performing multiple ship detection in SAR images with relatively high reliability regardless their sizes or locations, i.e., high sensitivity model.

The future work is suggested to be an enhanced version of the proposed model that has a better ship detection accuracy for both inshore and offshore scenes. It is intended to apply attention-based techniques, which boost the model to higher detection accuracy. Relative to the practical implementation, the future work will be focused on studying practical implementation of such deep learning applications, as intensive codes, on embedded platforms, i.e., on-board computers of the aerospace vehicles such as Unmanned Aerial Vehicle (UAVs) and satellites (Elshazly et al., 2021). These implementations will be tested in different environments: as software on embedded

micro-controllers, or hardware implementation on FPGA and even on both as a hardware and software co-design. The future work will focus on optimizing these deep learning based models, as high computational applications, to work on different on-board embedded platforms including hardware and/or software partitioning, code analysis, code transformation, and code re-targeting heterogeneous computing platforms.

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