Leveraging Deep Learning Techniques for Ship Detection in Satellite Imagery

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Abstract: In this rapidly advancing modern world and its technologies, Satellite imagery is one of the finest innovations that is playing a crucial role in numerous diverse industries, whether it be marketing, geo locating, banking or defence. Thus, it is understandable that satellite imagery does play a huge responsibility in making the world a better place to live in. Here, as satellite imagery is contributing to the daily routinary functions of the society, there is a noticeable increase in the use of this techniques, it has become very hard to manually analyse all the high-resolution images that are being captured. Hence, it is already high time to recognize the need of automating this technology. So, our project emphasizes on using deep learning techniques, CNN model to be precise and use it for the challenging task of ship detection from satellite images. We will be using "Ships in satellite imagery" dataset from Kaggle for this study, which will help and provide us with imagery data of ships from satellite images. Through this project, our aim is to contribute to a system which can improve maritime security and its related search and rescue operations, environmental surveillance and most importantly, improving shipping route system by developing an effective system to detect the ships.

KEYWORDS – *Ship detection, deep learning, maritime security, satellite imagery.*

1. INTRODUCTION

In this dynamic and innovative world, each and every technology seems to rapidly evolve as the time is progressing. One of the finest technologies that humans discovered was satellite imagery which is used by diverse industries around the world and has become one of the prominent factors for the world to function smooth and effective. The satellite imagery system captures high resolution images of the different things that happens on the earth's surface. The accessing of these images was done manually and were used for different purposes.

But as the time evolved, the number of industries that are using satellite imagery function has also increased in big numbers. Because of this factor, capture of these vast amounts of data has become a very big burden for humans to analyse manually. As a result, this system as every other system realised the need to be automated very soon.

Research question - Our project will be working on the automation of detection of ships in satellite images. And the Research question we will be focusing on will be *"How can the utilization of deep learning techniques improve the efficiency and accuracy of ship detection in high-resolution satellite imagery."*

Motivation – Our motivation and goal for the project is to explore the efficiency of deep learning techniques to build an effective system that can automate the challenging task of detecting ship images from satellite imagery. With the help of this, we aim to provide effective and valuable results and insights which can improve the decision making in various industries which are using this system.

We are using CNN model for this study which is well known for its effectiveness in Image detection tasks. Hence, we expect this model to provide us with the best accurate insights from detecting ship images. Our dynamic imagery dataset from Kaggle will provide valuable data for our study.

The effective completion of this study will be contributing to maritime security, efficient port operations, efficient search, and rescue operations, and also making a perfect ship routing and automated tracking algorithm for safe journey and operations. This will also help to make immediate response to ship accidents.

The study will be emphasising following sections in the coming pages starting from Related works, which will delve into the existing literatures and articles on ship image detection. After that, Methodology section deals with describing the working process of CNN model and other technical details. After this, Evaluation and Results will be discussed focusing on the impact of parameter choice.

Later, Conclusion and future works will be delving into summarizing our overall approach to this research study, findings, and insights we developed from this study and also the limitations we had and the future improvements that can be implemented. So, in overall, we will be providing valid results from an efficient system for automated ship detection and suggest the potential of this system to the real-world challenges.

2. LITERATURE REVIEW

This section will be utilized to portray a deeper understanding of the reasons behind choosing this topic of interest and an in-depth information of numerous research papers based on this topic which actively hone and influence this study.

The technique used most widely is CNN where the processing of the data, the classification and the detection is considered to be of great efficiency as described in the papers [12] and [13] where a model is developed with more than one convolution layer. Similarly, being a new approach to deep learning world, transfer learning technique was made of use in [15].

One such published paper that was related to this study is [1], where an appropriate model that can be employed on most of the public datasets was developed to successfully identify images with ships remotely. The idea for the application of this approach on a large dataset was to generate results in a progressive manner to accurately detect the ships and accordingly perform analysis. But the major downfall of this research is that this model may not be accurate enough for cases that are more challenging and not just straightforward.

The paper [2] suggests and develops a model that uses CNN model's single shot multi-box detector that takes in high resolution pictures as input and helps in identifying agricultural greenhouses within them. This model was implemented using the transfer learning concept, but it was noticed that while it works well for high resolution pictures, this model did not deem well for low resolution images. The accuracy was comparatively very low.

Another paper [3] and its study revolves around deep learning techniques and how it can be useful for the detection of airplanes in satellites imagery. This paper has majorly influenced our study as it focuses on images that overlap with each other, which is a challenging factor that could not be solved by previously mentioned papers. The use of non-suppressing algorithms helps in clarifying this situation. Even so, this paper has drawbacks as there is a lack in the detection of land interfaces.

The detection of ships in SAR images is depicted in paper [4]. By the use of K-means clustering, the model was developed and tested on numerous datasets. The limitation that was come across in this model is that any disturbances in the environment could cause a defect in the accuracy. In [5] two deep learning models namely, Yolov3 and R-CNN were utilized for detection of ships in remote sensing high resolution pictures and an efficient model was developed with accuracy levels recording up to 90.06% and 85.90%. Although the accuracy was high on detecting ships in remote sensing images, it was still difficult to detect them with images with differently angled sea conditions causing faulty results.

In [6] is also a study in which low-resolution images are taken as input and ships are detected within them. [7] generates model to detect aircraft using a public dataset. It was noticed that the error rate was reduced as the yolov3 loss function was employed. An extensive use of feature extraction can be seen in [8] where a model is developed to detect ships.

[9] has depicted a concern over the issues of hijacking and other criminal activities related to fisheries in maritime. And hence that induced the researchers of [9] to detect ships using CNN. Machine learning was used in [10] for detection of airplanes in high-resolution pictures. This model was found to be more accurate, and the speed of detection is higher in comparison to other models. But the complexity of background could have been handled properly.

Several techniques have been explained in [11] that focus on detection of objects like ships in satellite imagery. This paper can form good base for our study as it contains enough information to perform this project. Also, in optical images, the detection of ships using APIs that employ Tensorflow [14] have been spread globally by many researchers.

In [15], sliding window detection algorithm has been used to do classification of images and the use of this has an added advantage of being simple. But a disadvantage is that it has a lower speed when compared to other algorithms. Although in [16], a model that has better speed is depicted as it uses a selective search technique.

For higher accuracy in classification, an ensemble of CNNs [17] can be used instead of the classification CNN. Faster R-CNN is compared with the sliding window algorithm [18] to understand the accuracy of each model and which is better. [19] proposed a technique to detect smaller targets like ships by performing a combination of various resolution features. Whereas, in [20] a much more complicated and convolutional network was generated to amplify ship detection mechanisms intensively.

All these studies have contributed majorly to this project and an incorporation of it all has led to our research question.

3. METHODOLOGY

This section will highlight on the techniques that have been taken to detect the location of large ships in satellite images. The section describes in detail the step-by-step procedure used to build a CNN model using the TensorFlow framework.

4.1. Data Collection

The dataset used in this study was obtained from Kaggle. This dataset contains images extracted from Satellite collected over the San Francisco Bay and San Pedro areas of California. The data includes the images labelled with either a ship or no-ship classification. Authenticity and importance of the dataset was confirmed through accurate quality tests and verification.

4.2. Exploratory Data Analysis

EDA of data helps in understanding the characteristics of the dataset to acquire insights that helps in further modelling process. In this study, bar plots and pie chart are used to visualize the data.

Class-Label	Count
no-ship	3000
ship	1000

Fig. 1 Count of classes

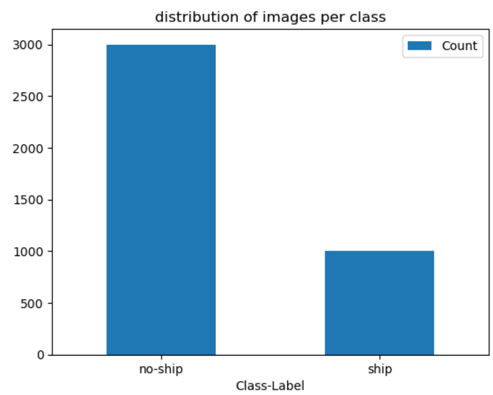


Fig. 2 Bar chart of classes

The Fig. 2 shows a bar plot depicting the count of images of no-ship and ship class, where no-ship has 3000 counts.

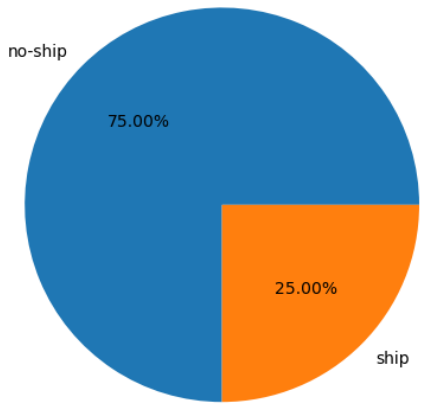


Fig. 3 Pie Chart of classes

Fig. 3 shows a pie chart illustrating the percentage distribution of classes, where 25% is of ship class.

These visualizations help in identifying the class imbalances or biases. The EDA process makes us understand the basic properties of dataset and helps in further data preprocessing and modelling steps.

4.3. Data Preprocessing

After the exploratory data analysis, the data is pre-processed as its important to furbish the quality of data. It applies alterations and manipulations to the raw dataset, preparing it for modelling.

In this study, the dataset exhibited class imbalance, with a difference in count between the ship and no-ship classes. Augmentation method is applied to the dataset to make the ship class balanced, so that there is an equal distribution of classes.

In the dataset, the ratio of classes is 1:3, where every image present in the ship class there are 3 images present in the no-ship class. To make the dataset balanced, augmentation is applied on the dataset producing 2 augmented images per original image of the ship class.

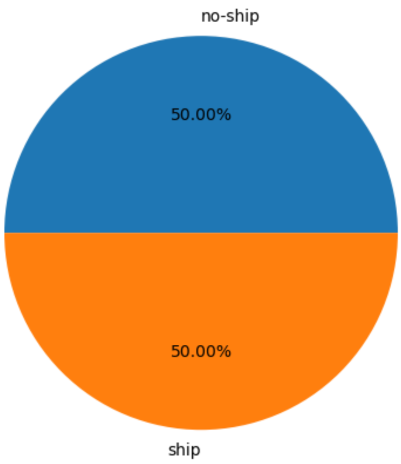


Fig. 4 Pie chart of Balanced dataset

The Fig. 4 depicts the pie chart of balanced classes after the application of augmentation method.

After augmenting the images, one-hot encoding is done to “labels” NumPy array which stores the data of classes. The array is encoded using “to_categorical” from keras, to ensure that model does not treat class labels as different categories and interprets them as ordinal values. It keeps the class at equal footing with respect to labels by removing redundant bias in the dataset.

4.4. Splitting of Data

After the preprocessing stage, it is important to split the datasets into subsets for training, testing and validation. This avoids overfitting and evaluate the performance of the model on unobserved data.

The data assigned arrays, such as images and labels are randomly shuffled using the seed value set at 42, this sets the images and labels to remain linked even after shuffling. This method splits the total count of data into 70% of training data, 20% of validation, and 10% of testing data. The training and validation dataset is used for training the model and testing data is used to test the model on unseen data. Exploring the unseen data allows the developers to see how robust the developing model is, as the model has not seen the data prior.

```
((4200, 48, 48, 3), (1200, 48, 48, 3), (600, 48, 48, 3))
```

Fig. 5 Training, Validation and Testing data

Fig. 5 shows the count of Training, Validation and Testing data. This step is important for making sure that the model can generalize and works well with unseen data.

4.5. Model Building

Detection of large ships in satellite image is the main goal of our study. A multi-stage process is followed to develop an image detection model using CNN. The architecture of our model consists of convolutional blocks, max-pooling layers, and fully connected layers. Accurate object detection is done on each stage by extracting relevant visual feature from the image.

```
Model: "Feature_Extraction_and_FC"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 48, 48, 3)]       0

 zero_padding2d (ZeroPaddin  (None, 58, 58, 3)         0
 g2D)

 conv1 (Conv2D)              (None, 29, 29, 16)        448

 bn_conv1 (BatchNormalizati  (None, 29, 29, 16)        64
 on)

 conv_2A_branch2a (Conv2D)   (None, 29, 29, 32)        4640

 bn_2A_branch2a (BatchNorma  (None, 29, 29, 32)        128
 lization)

 activation (Activation)     (None, 29, 29, 32)        0

 max_pooling2d (MaxPooling2  (None, 14, 14, 32)        0
 D)

 dropout (Dropout)           (None, 14, 14, 32)        0
...
Trainable params: 62242 (243.13 KB)
Non-trainable params: 288 (1.12 KB)
```

Fig. 6 Summary of the model

The Fig. 6 depicts the summary of the model, it describes the overview of the network’s layers, their types, output shapes and the number of parameters each layer needs.

Model Compiling is done using the binary cross-entropy loss function and Adam optimizer with a learning rate of 1e-3.

TensorBoard is used to visualise the training results, and during training, the weights of model are checkpointed throughout training process to track the validation correctness. Model is trained using the training datasets for a predetermined number of epochs, and callbacks are used to guard against overfitting.

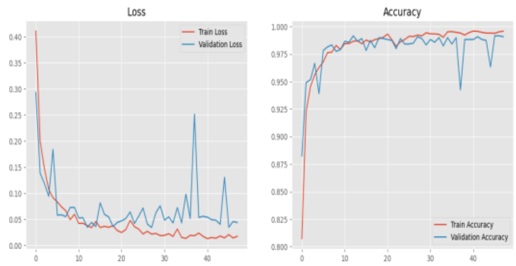


Fig. 7 Plotting loss and Accuracy for the dataset

The Fig. 7 shows the model training and validation progress. The loss plot shows the progress of the training and validation failures, whereas the accuracy chart displays the accuracy values. This provides an insight into the model's performance trends, helping in the evaluation of overfitting or underfitting issues.

4.6. Confusion Matrix Analysis

The trained model's performance is evaluated and visualised using confusion matrices. The model after training is used to forecast labels for the validation and test datasets. Confusion matrices is generated to evaluate the model's overall classification accuracy by comparing the predicted labels with the actual labels.

In order to evaluate the model's overall effectiveness, the confusion matrices for the validation and test data provided information on how well the model was able to classify cases from various categories.

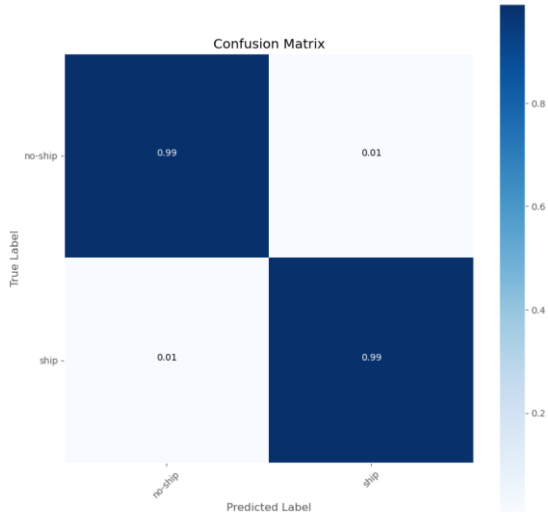


Fig. 8 Confusion matrix for validation dataset

Fig. 8 depicts the validation data's confusion matrix and Fig. 9 displays the confusion matrix for testing dataset.

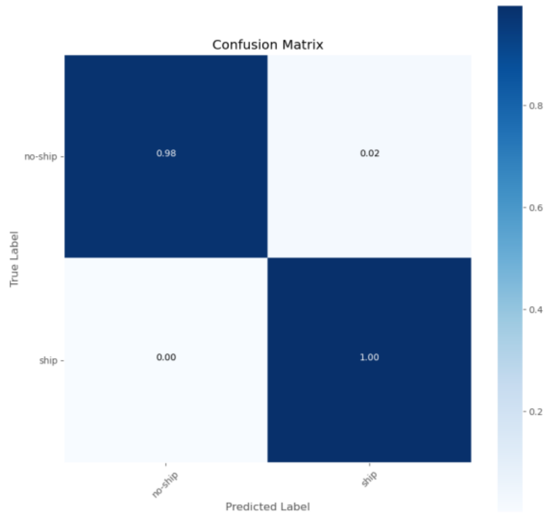
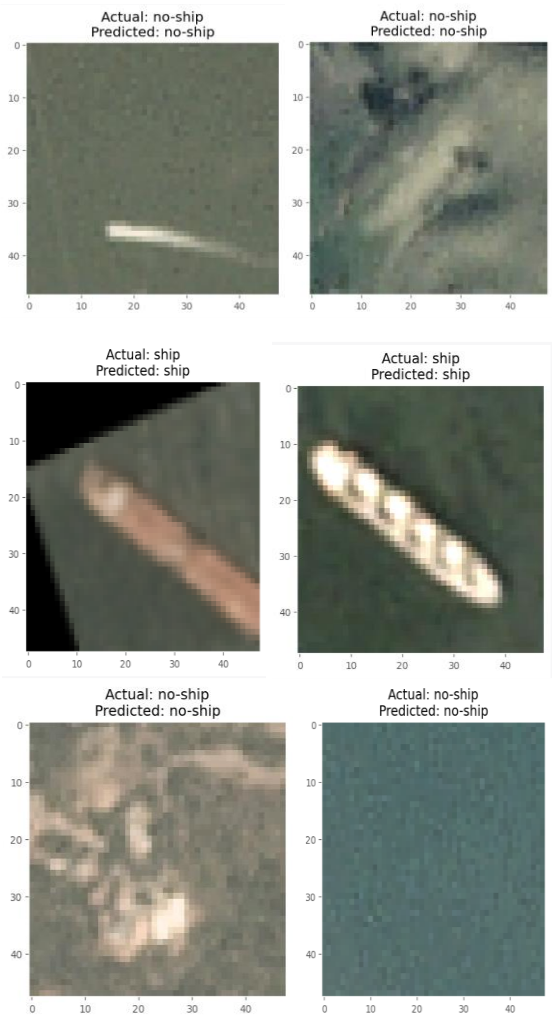


Fig. 9 Confusion matrix for testing dataset

Model is evaluated and checked after the training and validation process and displaying of confusion matrices. The results will be mentioned under the results and evaluation section.

4. Results And Evaluation

The developed model went through a rigorous training process to understand the distinguishes between “ship” and “no-ship” classes. A random selection of 10 images from the dataset is chosen for the qualitative analysis of the model’s performance. Each image detected is displayed it with corresponding actual and predicted class label, which emphasizes the model’s ability to accurately classify the classes as “ship” or “no-ship”.



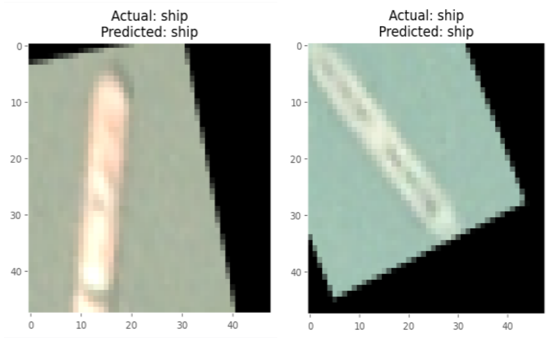


Fig. 10 Detection of ships in Satellite Imagery

5. Conclusion

In conclusion, our project has presented a very detailed report showing the potential of deep learning techniques, particularly the Faster R-CNN model. For this, we used “Ships in Satellite imagery” dataset which provided us with the data for this project.

Here, our goal was to build an effective system which will rewrite the manual accessing system of the satellite imagery and replace it with an automated ship image detection system which have the potential to create a breakthrough in the rapidly advancing satellite imagery system which is already used by tons of companies in various industries.

The evaluation of our studies has provided us with promising results. Our system was well able to categorize between images that had ship in it and that did not have any. The model shows the effective accuracy in detecting the ships from satellite images.

Also, this can give valuable contributions for costal management, shipping logistics and other maritime operations. This study also reveals the potential of deep learning methods to address complex challenges and data driven decision making.

6. LIMITATIONS

We should also mention some limitations that our model would possibly face:

1. The system was well able to detect large ship images easily and accurately, but models' performance with smaller ships and vessels images should be further investigated.

2. For the better performance of the model, it needs to be fed with almost equal images of distinct cases to get effective results.

3. The accuracy of the model must investigate during the times of very harsh weather or more poor lighting system which may make it hard for the system to detect the ships.

7. FUTURE WORK

Building on the findings of our studies, there are certain suggestions that can make the future studies regarding this subject more effective and efficient.

1. Classification for scenarios – Classifying the model for different scenarios such as defence system or ship navigation can enhance system capabilities and applicability.

2. multi-class detection – The model must be trained to detect more things in the same sea surface, such as small boats, submarines, fishing boats which will bring more effective results.

3. Real time integration with other sources- combining this satellite imagery with other data sources could help in enhancing the accuracy of the system and improve real time tracking of the ships.

8. REFERENCES

[1] Su-Ching Lin, Wei-De Chen, "Automatic aircraft detection in very high-resolution satellite imagery using a YOLOv3-based process," J. Appl. Rem. Sens. Vol. 15, No. 1, 2021

[2] Li, M.; Zhang, Z.; Lei, L.; Wang, X.; Guo, X. Agricultural Greenhouses Detection in High-Resolution Satellite Images Based on Convolutional Neural Networks: Comparison of Faster R-CNN, YOLO v3 and SSD.", Sensor, Vol. 20, 2020.

[3] Alganci, U.; Soydas, M.; Sertel, E. "Comparative Research on Deep Learning Approaches for Airplane Detection from Very High Resolution Satellite Images", Remote Sens, Vol. 12, No. 458, 2020

[4] Bo LI, Xiaoyang XIE, Xingxing WEI, Wenting TANG, Ship detection and classification from optical remote sensing images: A survey, Chinese Journal of Aeronautics,Vol. 34, No. 3,2021

[5] L. Lei, Y. She, X. Feng, R. Xiong and S. Liu, "Aircraft Detection of Remote Sensing Images Based on Faster R-CNN and Yolov3," 2020 International Conference on Culture-oriented Science & Technology (ICCST), pp. 166-170, 2020

[6] G. Mutreja, A. Aggarwal, R. Thakur, S. S. Tiwari and S. Deshpande, "Comparative Assessment of Different Deep Learning Models for Aircraft Detection," 2020 International Conference for Emerging Technology (INCET), pp. 1-6, 2020.

[7] Y. Yang, Y. Liao, L. Cheng, K. Zhang, H. Wang and S. Chen, "Remote Sensing Image Aircraft Target Detection Based on GIoU□YOLO v3," 2021 6th International Conference on Intelligent Computing and Signal Processing (ICSP), pp. 474-478, 2021.

[8] K. Wu, C. Bai, D. Wang, Z. Liu, T. Huang and H. Zheng, "Improved Object Detection Algorithm of YOLOv3 Remote Sensing Image," in IEEE Access, vol. 9, pp. 113889-113900, 2021

[9] J. Alghazo, A. Bashar, G. Latif and M. Zikria, "Maritime Ship Detection using Convolutional Neural Networks from Satellite Images," 2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT), 2021, pp. 432-437

[10] Al Mansoori, S., Kunhu, A., & AlHammadi, A. (2021, November). Effective Airplane Detection in High Resolution Satellite Images using YOLOv3

Model. In 2021 4th International Conference on Signal Processing and Information Security (ICSPIS) (pp. 57-60). IEEE.

[11] Urška Kanjir, Harm Greidanus, Krištof Oštir, “Vessel detection and classification from spaceborne optical images: A literature survey”, Remote Sensing of Environment, Volume 207, 2018, Pages 1-26, ISSN 0034-4257

[12] Ship Detection and Classification on Optical Remote Sensing Images Using Deep Learning (researchgate.net)

[13] S. Voinov, F. Heymann, R. Bill and E. Schwarz, "Multiclass Vessel Detection From High Resolution Optical Satellite Images Based On Deep Neural Networks," IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, 2019, pp. 166-169, doi: 10.1109/IGARSS.2019.8900506.

[14] M. Kartal and O. Duman, "Ship Detection from Optical Satellite Images with Deep Learning," 2019 9th International Conference on Recent Advances in Space Technologies (RAST), 2019, pp. 479-484, doi: 10.1109/RAST.2019.8767844.

[15] R. Praneetha, T. Dhipu and R. Rajesh, "SAR Image Classification using Transfer Learning," 2021 2nd International Conference on Range Technology (ICORT), 2021, pp. 1-6, doi: 10.1109/ICORT52730.2021.9581609.

[16] J. Uijlings, K. Sande, T. Gevers and A. Smeulders, “Selective search for object recognition,” Int. J. Computer Vision, vol. 104, pp. 154-171, 2013.

[17] M. Pritt and G. Chern, “Satellite image classification with deep learning,” IEEE Workshop Applied Imagery Pattern Recognition (AIPR), Oct 2017

[18] S. Ren, K. He, R. Girshick and J. Sun, “Faster R-CNN: towards real□time object detection with region proposal networks,” arXiv 1506.01497v3 [cs.CV], 6 Jan 2016.

[19] S. Zhang, R. Wu, K. Xu, J. Wang, and W. Sun, “R-CNN-based ship detection from high resolution remote sensing imagery,” Remote Sens., vol. 11, 2019, Art. no. 631, doi: 10.3390/rs11060631.

[20] H. Guo, H. Bai, Y. Yuan, and W. Qin, “Fully deformable convolutional network for ship detection in remote sensing imagery,” Remote Sens., vol. 14, 2022, Art. no. 1850