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# A Deep Learning Approach for Ship Detection Using Satellite Imagery

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## Abstract

INTRODUCTION: This paper addresses ship detection in satellite imagery through a deep learning approach, vital for maritime applications. Traditional methods face challenges with large datasets, motivating the adoption of deep learning techniques.

OBJECTIVES: The primary objective is to present an algorithmic methodology for U-Net model training, focusing on achieving accuracy, efficiency, and robust ship detection. Overcoming manual limitations and enhancing real-time monitoring capabilities are key objectives.

METHOD: The methodology involves dataset collection from Copernicus Open Hub, employing run-length encoding for efficient preprocessing, and utilizing a U-Net model trained on Sentinel-2 images. Data manipulation includes run-length encoding, masking, and balanced dataset preprocessing.

RESULT: Results demonstrate the proposed deep learning model's effectiveness in handling diverse datasets, ensuring accuracy through U-Net architecture, and addressing imbalances. The algorithmic process showcases proficiency in ship detection.

CONCLUSION: In conclusion, this paper contributes a comprehensive methodology for ship detection, significantly advancing accuracy, efficiency, and robustness in maritime applications. The U-Net-based model successfully automates ship detection, promising real-time monitoring enhancements and improved maritime security.

**Keywords:** Satellite imagery, Maritime Security, Copernicus Open Hub, Run Length Encoding

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## 1. Introduction

In the recently revolutionized years, there has been a growing interest in using satellite imagery for a lot of detection activities. Ship detection is one of the crucial tasks that lies under this category and is used for various maritime applications. These applications include vessel traffic management, environmental monitoring, and maritime security. This ship detection field has wide coverage and high resolution and can capture information in different spectral brands. However, these real-time detection applications include large quantitative input and are hindered by the impracticality of manual analysis of vast amounts of satellite imagery. This results in a lot of time consumption and demands extensive human effort, limiting real-time applications. To address this challenge, deep learning techniques have been implemented in satellite imagery for ship detection.

### 1.1 Deep Learning Approach

Deep learning is a specialized sub-field of machine learning that leverages artificial neural networks consisting of various interconnected multiple layers to generate and derive meaningful patterns and features. Deep learning has undeniably shown remarkable success in various computer vision tasks, demonstrating its potential in object detection, classification, and segmentation. Researchers have made significant progress utilizing deep-learning techniques for developing automated ship detection systems. As these systems use deep learning techniques, therefore, can process the vast amount of Sentinel imagery data in real-time. By leveraging deep learning algorithms, we can effectively analyze satellite images and accurately detect the ship. These algorithms allow the ship detection system to perform the detection based on large labeled datasets. It makes it feasible for applications that require quick response timing. The development of a model using a deep learning algorithm which offers the benefits of increasing efficiency and response time and reducing human error. The proposed deep learning approach will involve the training of the U-Net model. The dataset consists of Sentinel-2 images to train the data. The data collection was collected from the Copernicus Open Hub and Google Earth Engine data catalog. The open and free policy of these sites made it easy to extract the most optimal data.The collected data is obtained in an encoded format. To make the data comfortable, the data is pre-processed using pre-processing techniques. The data is masked and reconstructed through the lossless compression or run-length encoding process to reduce the complexity of the data. Finally, the data is divided into the train and validation datasets. The masked dataset is compressed but in an imbalanced form that is formatted and balanced by under-sampling the data, which is finally sent as input for the deep learning model. This paper proposes the algorithmic-based methodology presentation for the training and evaluation of the deep learning model (U-Net), which contributes to the advancement of ship detection techniques in terms of accuracy, efficiency, and robustness.

## 2. Background and Motivation

Ship detection in satellite imagery is a crucial task with implications for maritime security, traffic management, and environmental monitoring. Traditional techniques reliant on manual inputs face limitations in adapting to diverse conditions. This motivates researchers to explore advanced methods, particularly leveraging deep learning techniques such as Convolutional Neural Networks (CNNs), which have revolutionized object detection. CNNs enable automatic learning of relevant features from raw data, enhancing ship detection accuracy and efficiency. The shift from traditional manual methods to deep learning models addresses challenges, offering opportunities to automate processes and achieve real-time monitoring. This motivation stems from the desire to overcome obstacles, improve accuracy, and streamline ship detection, impacting various applications in the field.

### 2.2 Research Background

Ship detection in satellite imagery is a very crucial and important task with multifaceted implications across various areas such as maritime security, maritime traffic management, and environmental monitoring. Traditional ship detection techniques typically rely on manual inputs, which limit their ability to adapt to large, diverse, and environmental conditions. These challenges let the researchers explore advanced techniques that can effectively address the existing constraints and improve the accuracy and efficiency of ship detection systems.

### 2.3 Motivation

In the developing era in the field of detection, recognition, and classification, with the help of deep learning techniques, particularly through (CNNs), have revolutionized computer vision tasks and have shown tremendous change and advancement in the field of object detection. Similarly, in the field of Ship Detection, CNNs can automatically learn the pertinent features from the raw data and make them suitable for detecting the ship in the present satellite imagery. By using the power of deep learning, the researchers can increase the accuracy and the robustness of the deep learning model, which reduces manual effort and saves a lot of time. The model's background mainly works on using traditional and manual methods to locate and detect the ship, which was a huge challenge for the scientists. The motivation for researchers in this area is to overcome these challenges and give them an opportunity to enhance ship detection accuracy, automate the process, and enable real-time monitoring. The impact of this extends to developing and increasing the efficiency of various applications in the domain.

## 3. Literature Review

Various Contributions have been made to ship detection over the years by researchers incorporating different techniques and models. Some of their prestigious work has been discussed.

We have noticed a significant optimization and improvement in the field of Ship detection throughout the reviewed works, The key advancements that have been noticed include:

- Evolution of new algorithms, such as adaptive CFAR methods, dual-polarization analysis, and fusion techniques using polarimetric features.
- Utilization of convolutional neural networks (CNNs) for Ship detection and localization.
- Improvement in accuracy, robustness, and error using multiple algorithms and adopting a combination of various Deep Learning models together providing a comparison among the best-fit models for their research.
- Exploring the potential of SAR and PolSAR data for accurate and promising results.

Vachon et al. 1997, the author contributed to developing ship detection techniques using RADARSAT SAR data using microwave pulses.The final design is the result of an iterative procedure, balancing performance characteristics among subsystems to achieve the optimal design [1]
Chong and Zhu. 2003 concluded a survey on ship and wake detection using SAR imagery highlighting the key challenges and approach.Different methods for the improvement of the original image are applied as a preprocessing technique for the Radon transformation [2]
Xi et al. 2016 This paper introduced a PolSAR Ship detection model by combining polarimetric similarity and the third eigenvalue of the coherency matrix.To improve the detection performance of ship targets, this paper mainly develops the ship detection method based on the contrast enhancement utilizing the polarimetric scattering difference [6]
"Sea-Land Segmentation With Res-UNet And Fully Connected CRF" by Z. Chu et al. (2019): In this research paper, the authors have proposed a segmentation method that fuses the Res-UNet model with Conditional Random Fields (CRF) for semantic segmentation of Sea-Land which is a key step for ship detection. It leverages the results of the previous models based on the Res-UNet Model. Then it
employs the CRF method to refine and improve the accuracy of ship segmentation results, enabling precise ship identification and delineation [14]
"Comparison of CNN and SVM for Ship Detection in Satellite Imagery" by A. Kurniawardhani et al. (2020): Published in 2020, this paper puts forward the approach of selecting the better-suited models, in this paper the author has compared the Support vector machine(SVM) algorithm to Convolution Neural Network (CNN) based deep learning algorithm which concludes that CNN outperforms SVM in ship detection with an average training accuracy of 99.12% [18]
"Ship Detection in Sentinel 2 Multispectral Images with Self-Supervised Learning." by A. Ciocarlan et al. (2021): The author proposes a deep learning-based ship detection approach that enforces a self-supervised learning model designed for Sentinel-2 multispectral imagery. The model incorporates spectral information in the satellite images to attain better results [19]
"Ship Detection and Segmentation using Unet" by S. Karki et al. (2021): Introduces us to a ship detection method that uses the U-Net architecture. The U-Net model is utilized for ship region segmentation and classification, allowing for accurate identification of ships in the images [22]

## 4. Problem Statement

The detection of ships using satellite imagery faces significant challenges that impede the development of accurate and robust algorithms. One critical obstacle is the presence of occlusions, where ships are partially obscured by landmasses, adverse weather conditions, or other maritime objects, leading to difficulties in achieving precise identifications. The diversity in ship sizes further complicates the task, requiring the development of models capable of consistently recognizing both small vessels and large maritime structures. The complex backgrounds often found in satellite imagery, such as coastlines and buildings, introduce noise and create a fertile ground for false positives and negatives during ship detection. Cloud cover obstructs visibility in satellite images, impacting the reliability of ship detection algorithms, and necessitating the development of techniques to handle obscured regions. Atmospheric conditions, including haze and fog, pose additional challenges, affecting image quality and thereby challenging the accuracy of ship detection models. Noise introduced by satellite sensors presents another hurdle, requiring strategies for noise reduction to ensure the clarity and precision of imagery. Accurate labeling of ships in densely populated maritime areas adds complexities, potentially introducing inaccuracies in model training and performance. Generalizing ship detection models across diverse geographic regions proves challenging, as models trained on specific datasets may struggle to adapt to different environmental characteristics and ship types. Furthermore, anomalies within satellite imagery, such as artifacts or distortions, impact the reliability and generalization capabilities of ship detection models. Finally, the need for real-time ship detection in dynamic maritime environments imposes constraints on algorithm efficiency and speed, emphasizing the necessity for rapid and accurate detection methods to meet operational requirements. Addressing these challenges is crucial for advancing the field of ship detection using satellite imagery, with implications for maritime surveillance, safety, and environmental monitoring.

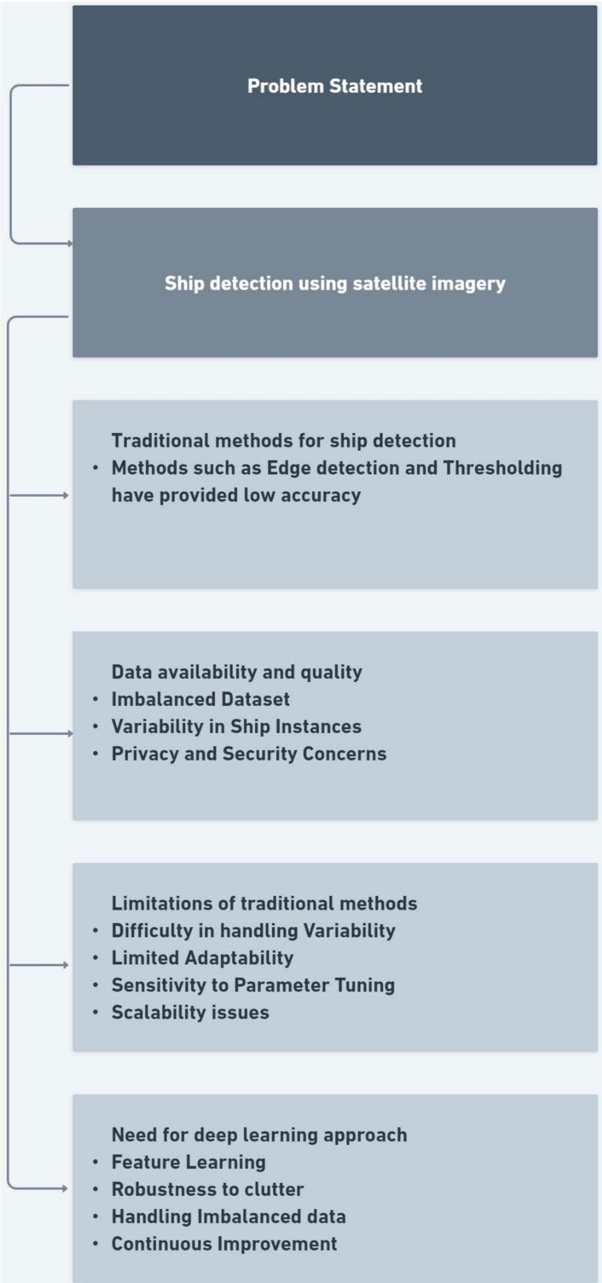


**Fig. 1.** Problem faced by the traditional method for detection and localization of ship and the need for Deep Learning approach

## 5. Study Definition and Dataset

This research paper utilizes the Google Earth Engine Data Catalog and Copernicus Open Hub Sentinel-2 Dataset for ship detection, relying on high-resolution, hyperspectral images captured by Sentinel-2 satellites. The dataset, sourced from Copernicus Open Hub and Google Earth Engine, contains labeled images with dimensions of 768x768x3 pixels, showcasing diverse scenes including coastlines, buildings, plateaus, and ships. Split into training and validation sets, the dataset encompasses instances of one or more ships, or none, each labeled with EncodedPixel information.

### 5.1 Study Definition

Satellite images are digital images of the Earth's surface captured by satellites that are orbiting the Earth. These images can provide very important information about the Earth's surface, weather patterns, land properties, atmosphere, and different environmental changes. Satellites are equipped with different types of cameras and sensors that help to transmit electromagnetic waves to create images. Images captured by the satellite are used for various purposes like weather forecasting, disaster management, environment monitoring, remote sensing, etc.

### 5.2 Sentinel-2 Dataset

This research paper focuses on the use of the Google Earth Engine Data Catalog and Copernicus Copernicus Open Hub Sentinel-2 Data for ship detection. Both are the main source for dataset collection for the image file. Sentinel-2 is a wide-range band in a specific range of wavelengths within the electromagnetic spectrum captured and recorded by sensors or different instruments.

It is a high-resolution, hyperspectral imaging mission that supports the Copernicus land monitoring program. It is a part of the European Union's Copernicus earth observation program that aims to provide accurate and up-to-date information about the planet. Its assets contain 12 UINT16 spectral bands that represent rescale pixel values by 1000; this rescaling is commonly done to convert the values from the original reflectance range (0-1) to a more convenient range for analysis and visualization.

Sentinel-2 L2 assets have the following format: COPERNICUS/S2_SR/20151128T002653_20151128T102149_T56MNN. Here the first numeric part represents the sensing date and time, the second numeric part represents the product generation date and time, and the final 6-character string is a unique granule identifier indicating its UTM grid reference. Dense clouds and foggy weather on the sentinel-2 images can be removed using the following extension COPERNICUS/S2_CLOUD_PROBABILITY.

### 5.3 Dataset

The dataset is extracted from the Copernicus Open Hub database and Google Earth Engine data catalog which is an open-source data collection area for satellite imagery. The dataset consists of images of one ship, more than one ship, or no ship in each image. The dimension of each image is 768* 768* 3. The dataset is divided into two parts that are for training and validation. The dataset consists of different coastlines, buildings, plateaus, and ships. The dataset is labeled with EncodedPixel.

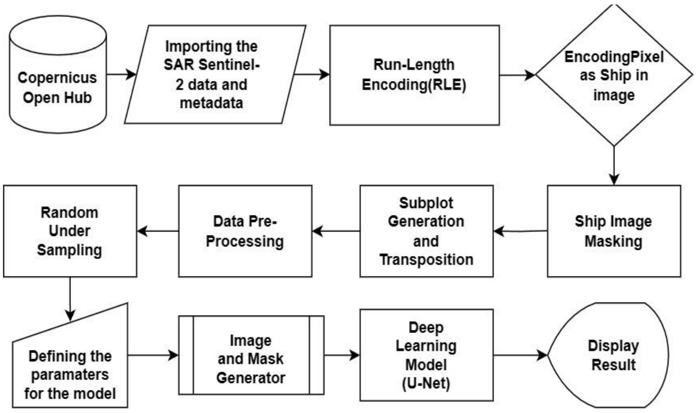


**Fig. 2.** The Flow Diagram explains how to detect the ship with the satellite images. This includes step-by-step methods to localize the ship by using U-Net Deep Learning techniques

## 6. Methodology

The methodology of this paper explains the start-to-end procedure for developing the Deep Learning model and the data regulating process.

### 6.1 Data Overview

Data extraction is a pivotal step in this research, conducted from the openly accessible Copernicus Open Hub database and the Google Earth Engine data catalog. Both repositories serve as rich sources for satellite imagery, aligning with the principles of open-source data sharing. Dataset encompasses a diverse array of images, featuring instances with localized ships, images showcasing single or multiple ships, and those devoid of any ship presence.To facilitate a structured dataset, ship labels are assigned using the concept of EncodedPixels. This involves assigning ship-segmented IDs and providing a detailed output of ship locations within each image. Notably, for images without any ship presence, a NaN (Not a Number) ID is allocated. This supervised labeling process allows for a better understanding of ship distribution patterns within the dataset. The utilization of Copernicus Open Hub (Open source) and Google Earth Engine aligns with the ethos of open-source data, fostering collaboration and accessibility in the realm of satellite imagery.

**Fig. 3.** These sets of images are the data overview of the previously derived satellite images from Copernicus Open Hub.Data consist of images with one ship, more than one ship or no ship

### 6.2 Data Manipulation

Data manipulation was required as IDs were repeated for many labels (EncodedPixels) because they are segmented from a single image. For further computation, we need to make data comfortable to use.

#### 6.2.1 Run Length Encoding (RLE) & Decoding

Run-length encoding (lossless compression) allows the original data to be perfectly reconstructed in the form of compressed data. The procedure involves running through the data and counting how many times each point is repeated without any breaks. RLE compresses the data points, and the conversion is restored as the original data frame input. RLE works on the principle of lossless compression, where the data is compressed from a large input with multiple values for each special data value to a concise and compressed output for that given data value. With reference to the given (Fig. 4.), we can analyze the multiple data frequencies to be converted into the compressed form using RLE operation.

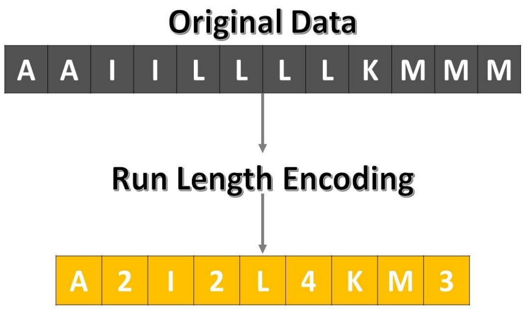


**Fig. 4.** The procedure involves running through the image and counting different times each point is repeated without any breaks in the data set

### 6.2.2 Data Masking

The converted dataset consists of a datatype (EncodedPixels) which explicitly shows the segmented location of the ship. Mask Query is used to filter out all the image IDs in the respected encoded pixels for a particular label of the image or the image ID for that specific column and obtain all RLE Masks for the given image. These masks are converted and split into strings of masked lists. Further, all the starting, ending, and lengths are stored in an array. Using these points, a formula is generated for creating an array for taking the valuable pixel values as 1 (only the ship will be represented) and remaining as 0 (the background except the ship is termed as negligible). Re-shaping of an array is also necessary for combining the ship masks and generating the final mask. The equation for constructing the masking array is:

$$E = S + L - 1 \quad \textbf{(1)}$$

$E$ : Pixels located at the ends

$S$ : Pixels located a the start

$L$ : Length where a ship can exist in the original image

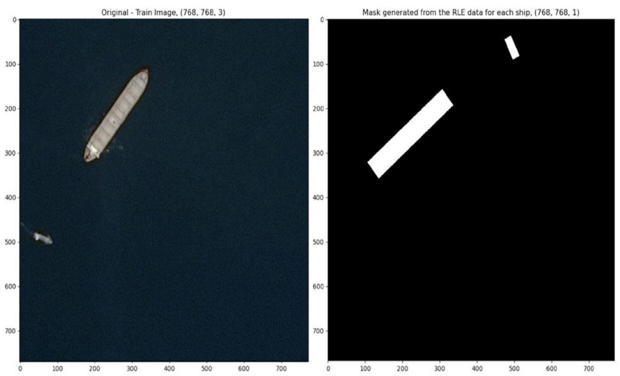


**Fig. 5.** Mask-generated image from the RLE Data.Re-shaping of an array is also necessary for combining the ship masks and generating the final mask that is inverted in nature.

### 6.2.3 Subplot Generation & Transposition

The Original image and the mask created from the RLE data for each ship are visualized and plotted as the output. The image generated after the RLE operation is in the lateral inverse of their actual orientation. The output for the image must be transposed to be in its original position for better extraction for further pre-processing.

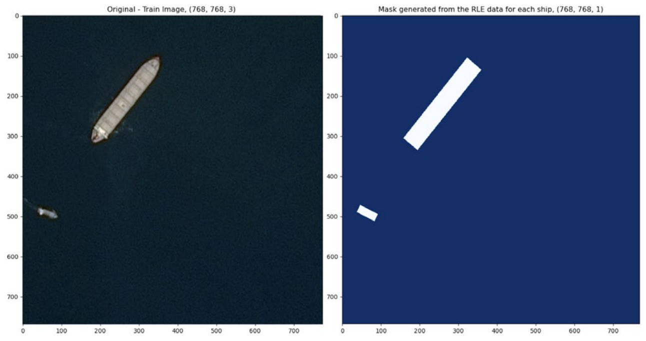


**Fig. 6.** Transposed image after masking from RLE Data.After transposition, inverted images need to be transposed.

## 6.3 Data Pre-processing

RLE data is successfully manipulated into the masked outputs hence the data is split into the Train and the validation data. The bool function will distribute the EncodedPixels, NaN value would be termed as 0 and the remaining image IDs as 1 just to extract the unique image IDs in the masked data frame. The train validation split is a stratified split that preserves the proportions of examples in each class as observed in the original data frame. The ratio of the train validation split is [25:17].

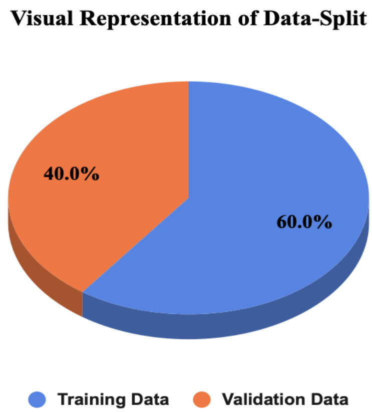


**Fig. 7.** Pie Chart showing the amount of data split for training and testing. The train and validation split are in ratio of [25:17]

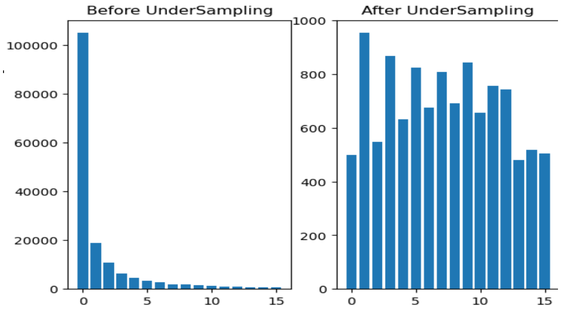


**Fig. 8.** Effect of statistical undersampling technique on images

The train data extracted in the split is still unbalanced and is processed into the balanced data using means of Undersampling by grouping the random ship counts together and creating a data frame for grouped ship counts.

## 6.4 Algorithm Used

**TABLE. 1.** Ship Detection Algorithm

**Algorithm: Deep Learning Approach for Ship Detection Using Satellite Imagery**

```
Copernicus open hub ← CollectDataset()
for each image in Dataset
    EncodedShips ← RunLengthEncoding(image)
    ShipMask ← ShipImageMasking(image, EncodedShips)
CreateSubplots(Dataset, ShipMasks)
for each image, mask in Dataset
    TransposedImage, Masks ← ImageTransposition(image, mask)
    TrainingSet, TestingSet ← TrainTestSplit(Dataset)
if Dataset is imbalanced
    TrainingSet ← RandomUndersampling(TrainingSet)
ModelParameters ← DefineModelParameters()
AugmentedImages, Masks ← ImageMaskGeneration(TrainingSet)
UNetModel ← TrainUNetModel(AugmentedImages, Masks)
for each image in TestingSet
    ShipDetectionResult ← ShipDetection(UNetModel, image)
DisplayResults(ShipDetectionResults)
```

The algorithm for ship detection using satellite imagery begins by collecting a dataset from the Copernicus Open Hub. For each image in the dataset, a run-length encoding (RLE) is applied to compress consecutive elements with the same value. The encoded ship information is then utilized to create a ship mask, highlighting ship locations in the image. Visualization of the original images alongside their respective ship masks is facilitated through subplot creation. Subsequently, image transposition is performed for each image and mask pair, possibly involving flipping or rotating to augment the dataset. The dataset is split into training and testing sets, and in cases of imbalance, random undersampling is applied to the training set. Model parameters are defined, and an augmented training set is generated through image mask generation. A U-Net model is trained using the augmented images and masks. Finally, the trained model is employed to detect ships in the testing set, and the results are displayed in such a way that it will create a yellow-bounding box around the ship in the image providing a comprehensive approach to ship detection in satellite imagery through a deep learning framework. Deep learning, specifically leveraging the U-Net architecture, is chosen for ship detection in satellite imagery due to its inherent strengths in handling large datasets and automating feature extraction.

## 6.5 Architecture of the model

To achieve the development process, the established model of Convolutional Neural Network (CNN), namely U-Net, was chosen for image segmentation. This predefined model does pixel-wise binary classification by assigning 1 to the pixel with a mask and 0 to the pixel with no mask.

The U-Net is a deep learning model used in image segmentation to extract relevant information from an image. U-Net stands out for its specialization in image segmentation, making it particularly well-suited for tasks requiring detailed delineation of object boundaries, such as ship detection in satellite imagery. The U-Net model's superior accuracy and segmentation capabilities position it as a robust choice for maritime applications.The U-Net architecture consists of an encoder and decoder Neural Network with a skip connection that helps preserve spatial information and improve the gradient flow during training. Skip connection helps capture an image's local and global information. U-Net has a Convolutional layer consisting of a different filter matrix that is rotated on the image to extract the relevant information. The activation function used is Sigmoid and then rectified linear unit (ReLU) due to its computational simplicity, faster convergence, and ability to avoid vanishing gradient problems.The decoder section employs Upsampling layers to restore image resolution, and Concatenation merges detailed encoder features with the decoder's high-level features.

$$\sigma(x) = \frac{1}{1+e^{-x}} \text{ (sigmoid function)} \quad \textbf{(2)}$$

$$\boldsymbol{f(x) = max(0, x)} \text{ (ReLU function)} \quad \textbf{(3)}$$

The pooling layer helps to reduce the irrelevant parameter of the feature matrix and computation in the network. The pooling layer often uses the max pooling operation to perform the downsampling process.Max Pooling is strategically utilized to maintain crucial information related to ship presence while gradually reducing the resolution of the feature map. This process is integral in the overall functioning of U-Net, as it contributes to the model strength to discern significant patterns and features in satellite imagery, leading to accurate ship detection results.

$$f^{(m)} = [f_1^{(m)} \dots f_k^{(m)} \dots f_K^{(m)}]^T, \; f_K^{(m)} = max_{x \epsilon X_K}(x) \quad \textbf{(4)}$$

Training the selected model using a preprocessed dataset, typically using a training and validation set. The training of the model uses a backpropagation algorithm. After every epoch, The gradient of the loss function with respect to the weight function is calculated to measure the error caused by the learning parameter due to a different weight initialization method. The calculated error is then backpropagated in the network to adjust the value of the learning parameter that will train the model.

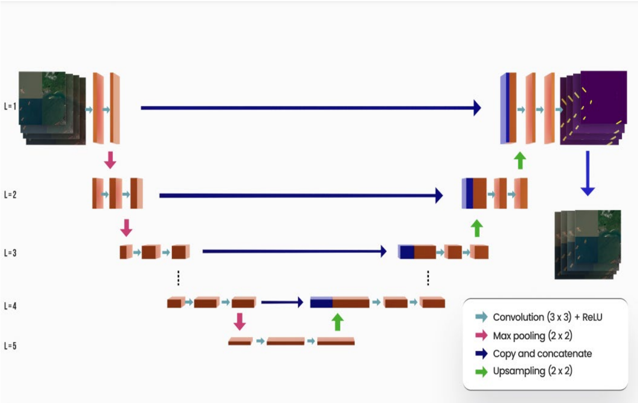


**Fig. 9.** This image showcases the U-Net architecture with its different layer along with ship images in 3-D

## 6.6 Model Summary

The ship detection model processes 768x768-pixel, three-channel satellite images, incorporating Gaussian Noise for variability and Batch Normalization for stable training. Key features are extracted by Convolutional layers (Conv2d_76 to Conv2d_85), while Max Pooling reduces spatial dimensions, streamlining computations. Upsampling layers restore image resolution, and Concatenation merges detailed and high-level features, fostering a holistic understanding of satellite imagery. The output, (192, 192, 32), indicates ship presence. With 491,149 parameters (491,143 trainable), Batch Normalization and Concatenation optimize the model for accurate ship detection in complex satellite data, showcasing its efficacy in maritime applications.

**TABLE. 2.** Model Summary of U-Net

| **Layers** | **Output Shape** | **Parameter** | **Connected to** |
|---|---|---|---|
| RGB_Input | (None,768,768, 3) | 0 | [] |
| Gaussian_Noise_4 | (None, 768,768,3) | 0 | [‘RGB_Input[0][0]’] |
| Batch_Normalization_4 | (None, 768,768,3) | 12 | ['gaussian_noise_4[0]0]' ] |
| Conv2d_76 | (None, 768,768,3) | 224 | ['batch_normalization_4[0][0]'] |
| Conv2d_77 | (None, 768,768,3) | 584 | ['conv2d_76[0][0]'] |
| Max_Pooling2d_16 | (None, 384,384,8) | 0 | ['conv2d_77[0][0]'] |
| Conv2d_78 | (None, 384,384,8) | 1168 | ['max_pooling2d_16[0][0]' ] |
| Conv2d_79 | (None, 384,384,8) | 2320 | ['conv2d_78[0][0]'] |
| Max_Pooling2d_17 | (None,192,192,16) | 0 | ['conv2d_79[0][0]'] |
| Conv2d_80 | (None,192,192,32) | 4640 | ['max_pooling2d_17[0][0]' ] |
| Conv2d_81 | (None,192,192,32) | 9248 | ['conv2d_80[0][0]'] |
| Max_Pooling2d_18 | (None,96,96,32) | 0 | ['conv2d_81[0][0]'] |
| Conv2d_82 | (None,96,96,64) | 18496 | ['max_pooling2d_18[0][0]' ] |
| Conv2d_83 | (None,96,96,64) | 36928 | [‘conv2d_82[0][0]’] |
| Max_Pooling2d_19 | (None,48,48,64) | 0 | ['conv2d_83[0][0]'] |
| Conv2d_84 | (None,48,48,128) | 73856 | [‘max_pooling2d_19[0][0]’] |
| Conv2d_85 | (None,48,48,128) | 147584 | ['conv2d_84[0][0]'] |
| Up_Sampling2d_16 | (None,96,96,128) | 0 | ['conv2d_85[0][0]'] |
| Concatenate_16 | (None,96,96,192) | 0 | ['up_sampling2d_16[0][0]' ] |

·Total params: 491,149

Trainable params: 491,143

Non-trainable params: 6

## 7. Result and Discussion

The U-Net model employed in this research paper for ship detection using satellite imagery has demonstrated notable accuracy, efficiency, and robustness. As we delve into a comparative analysis with other prominent object detection models such as RCNN, Masked RCNN, and YOLO, it becomes evident that the U-Net model exhibits distinct advantages in the context of ship detection.

U-Net, specifically designed for image segmentation tasks, showcases a unique architecture with encoder and decoder components connected by skip connections. This design allows U-Net to effectively capture both local and global features, preserving spatial information crucial for accurate segmentation. In contrast, RCNN (Region-based Convolutional Neural Network) relies on region proposals and lacks the direct pixel-wise segmentation capabilities inherent in U-Net.

Masked RCNN, an extension of RCNN, introduces a mask branch for segmentation, making it more adept at instance segmentation tasks. However, the computational complexity of the mask branch can be higher than that of U-Net, which may impact real-time performance, especially in resource-constrained scenarios.

YOLO (You Only Look Once), known for its real-time object detection capabilities, divides the image into a grid and predicts bounding boxes and class probabilities directly. While YOLO is efficient, it may face challenges in precisely delineating complex object boundaries, potentially affecting segmentation accuracy.

In the context of ship detection, U-Net's pixel-wise segmentation approach proves advantageous. The U-Net model, as demonstrated in the presented research, achieves a training accuracy of 99.45% and a validation accuracy of 99.50%, indicating its proficiency in capturing intricate details in satellite imagery. The loss values for training (0.0118) and validation (0.0182) further affirm the model's precision in predicting ship segmentation masks.In summary, while RCNN, Masked RCNN, and YOLO excel in object detection, U-Net stands out for its specialization in image segmentation, making it particularly well-suited for tasks requiring detailed delineation of object boundaries, such as ship detection in satellite imagery. The U-Net model's superior accuracy and segmentation capabilities position it as a robust choice for maritime applications.

### 7.1 Result

#### 7.1.1Accuracy


**Fig.10.** Proposed U-Net Model performance for the training and the validation accuracy.
Training Accuracy = 99.45%.
Validation Accuracy = 99.50%

#### 7.1.2 Loss

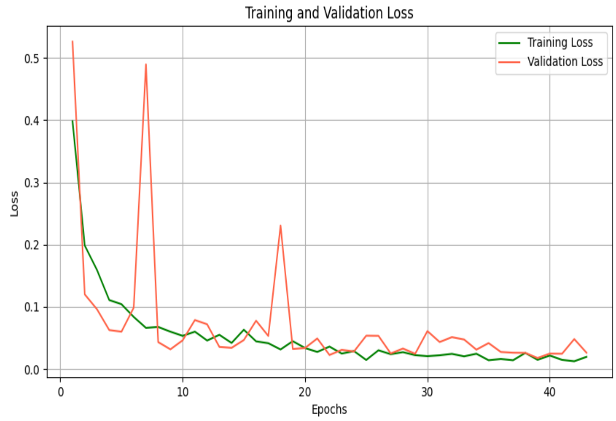


**Fig. 11.** Proposed U-Net Model performance for the training and the validation loss:
Training Loss = 0.0118
Validation Loss = 0.0182

### 7.2 Discussion

#### 7.2.1 Accuracy Analysis

Accuracy is the measure that quantifies the model's performance ability to classify pixels into their respective classes. The higher accuracy indicates that the model captures the underlying patterns and features from the data.

With reference to our model results (Fig. 10.), the training accuracy of 99.45% depicts that the model is correctly classified for 99.45% of pixels in the training dataset.

Similarly, the validation accuracy of 99.50% indicates that the model accurately detects 99.50% of the pixels in the validation dataset. Mathematically, the number of correctly classified pixels in the training set (N_correct_training) and validation set (N_correct_validation) can be calculated as follows:

$$N_{Correct\_training} = Training\ Accuracy \times \text{Total number of pixels in training set} \quad \textbf{(5)}$$

$$N_{Correct\_validation} = Validation\ Accuracy \times \text{Total number of pixels in validation set} \quad \textbf{(6)}$$

### 7.2.2 Loss Analysis

Loss function is a mathematical function that is used to calculate the difference between target segmentation mask and predicted segmentation mask. In this project, the training loss is 0.0118 and the validation loss is 0.0182 showing that the U-Net model had achieved high precision in predicting the segmentation mask of ships. In ship detection using satellite imagery, cross-entropy loss is a critical measure that evaluates the disparity between the predicted and actual distributions of ship and background classes. It is particularly useful in handling imbalanced datasets, penalizing misclassifications more for the minority class (ships). Operating on a logarithmic scale, the loss ensures efficient optimization of decision boundaries between ship and background, enhancing the model's ability to discern details accurately. By facilitating parameter optimization during training, cross-entropy loss contributes to the overall accuracy, efficiency, and robustness of the U-Net model in ship detection tasks.

$$\text{Cross-Entropy Loss} = -\frac{1}{N}\sum_{i=1}^{N} \sum_{j=1}^{C} y_{ij} log\left(p_{ij}\right) \quad \textbf{(7)}$$

where:

- N is the total number of pixels in the dataset.
- C is the number of classes (segmentation classes).
- $\boldsymbol{y_{ij}}$ is the binary indicator (0 or 1) if pixel $i$ belongs to class $j$in the ground truth.
- $\boldsymbol{p_{ij}}$is the predicted probability of pixel $i$ belongs to class $j$ as output by the U-Net model..

### 7.2.3 Generalization & Overfitting

The insignificant distinction between the preparation and approval exactness/shortfall values demonstrates that the proposed U-Net model sums up well to new, unremarkable information. Overfitting happens when a model performs well on the preparation information but ineffectively on inconspicuous information. In any case, our model's high approval exactness and low approval misfortune show that it really figured out how to sum up and didn't overfit the preparation information.

## 8. Conclusion and Future Work

### 8.1 Conclusion

As an aspect of Ship Detection, the focus of this paper was to collect, analyze, and manipulate the Sentinel-2 images dataset further using the data-preprocessing techniques and develop a deep learning model to detect the ship in the used satellite imagery dataset. The U-Net model was tested to determine the accuracy of 99.50%, and the validation loss for the model is 0.0182, leveraging the U-Net's ability to encode and decode structure.The model detection can be concluded by detecting the specific ships (unique-ids) on the images. The detected ships are marked with a bounding box that is being detected by the model. The bounding boxes are marked using specific unique mask IDs and depend on the model's calculated accuracy. Furthermore, the model results show (Fig.12.) that the model is robust and powerful for the ship detection task using satellite images. Applying this deep learning approach can help in maritime surveillance and decision-making and is also used as an asset to provide security.

**Fig. 12.** The image illustrates three different ships with marked boundaries

### 8.2 Future Work

In the upcoming phases of investigation, researchers will direct their attention toward advancing the classification and detection capabilities of ship recognition systems, particularly in challenging weather conditions. This endeavor becomes crucial when conventional visibility spectrum imagery is inaccessible, such as during nighttime, foggy scenarios, or under cloudy and rainy conditions. The overarching objective is to bolster the model's efficacy amid adverse weather, and this aspiration may materialize through the incorporation of a cutting-edge multi-modal data fusion technique. The envisioned trajectory involves synergizing various types of data into a unified model to amplify performance and surmount the hurdles presented by extreme weather conditions. As researchers traverse this path, they anticipate a paradigm shift in the methodology, foreseeing a future where the model's architecture becomes a focal point of exploration. This could manifest in the generation of diverse sensor-integrated inputs, and the integration of sophisticated fine-tuning and transfer learning methods. Additionally, these technologies play a pivotal role in environmental monitoring, aiding in the identification and tracking of vessels for a prompt response to potential environmental hazards. The streamlined port management facilitated by advanced ship detection systems offers economic and operational benefits, reducing congestion and enhancing overall efficiency. Furthermore, the precision in ship detection supports customs and border control activities, enhancing national security efforts. The heightened accuracy of ship detection models is a boon for the insurance industry, enabling more reliable risk assessments and minimizing financial losses in maritime emergencies. Overall, the far-reaching applications of ship detection technologies promise to transform various industries and address critical challenges in maritime operations. The future promises not just incremental advancements but a transformative leap in the realm of ship detection technologies.

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