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Oil Spill Detection Using Sentinel-1 SAR Data

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Anahtar Kelimeler
Oil Spill Detection,
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Abstract: Oil spills present a substantial threat to marine ecosystems and coastal economies, necessitating efficient and accurate detection methods. Driven by the necessity for dependable monitoring in a variety of environmental conditions, this study utilizes Sentinel-1 Synthetic Aperture Radar (SAR) data and the Mask R-CNN deep learning model to detect and delineate oil spills. Sentinel-1 was selected for its capacity to acquire data irrespective of weather conditions or time of day, thereby ensuring consistent monitoring. The Mask R-CNN model was selected for its ability to perform precise, pixel-level segmentation, enabling accurate spill boundary detection. The model's performance was evaluated using a dataset comprising 381 Sentinel-1 images from diverse geographic and environmental contexts. The model demonstrated an overall accuracy of 80% for MV Wakashio and 81% for MK Princess Empress, with an Intersection over Union (IoU) of 76% and 74.8%, respectively. These results underscore the model's efficacy in discerning oil spills from false positives, such as algal blooms and sediment patterns. The proposed methodology demonstrates a clear advantage over traditional techniques and exhibits scalability for real-time applications.

Sentinel-1 SAR Verileri Kullanılarak Petrol Sızıntısı Tespiti

Keywords
Petrol Sızıntısı Tespiti,
Sentinel-1,
Çevresel Koruma,
Afet Yönetimi,
Sentetik Açıklıklı Radar

Öz: Petrol sızıntıları, deniz ekosistemleri ve kıyı ekonomileri için önemli bir tehdit oluşturmakta ve etkili ve doğru tespit yöntemleri gerektirmektedir. Çeşitli çevresel koşullarda güvenilir izleme gerekliliğinden hareketle, bu çalışmada petrol sızıntılarını tespit etmek ve tanımlamak için Sentinel-1 Sentetik Açıklıklı Radar (SAR) verileri ve Mask R-CNN derin öğrenme modeli kullanılmıştır. Sentinel-1, hava koşullarından veya günün saatinden bağımsız olarak veri elde etme kapasitesi nedeniyle seçilmiştir, böylece tutarlı bir izleme sağlanmıştır. Mask R-CNN modeli, hassas, piksel düzeyinde segmentasyon yapabilmesi ve doğru sızıntı alanı tespitine olanak sağlaması nedeniyle seçilmiştir. Modelin performansı, farklı coğrafi ve çevresel bağlamlardan alınan 381 Sentinel-1 görüntüsünden oluşan bir veri seti kullanılarak değerlendirilmiştir. Model, MV Wakashio için %80 ve MK Princess Empress için %81 genel doğruluk gösterirken, IoU sırasıyla %76 ve %74,8 olmuştur. Bu sonuçlar, modelin petrol sızıntılarını alg patlamaları ve tortu örüntüleri gibi yanlış pozitiflerden ayırt etmedeki etkinliğinin altını çizmektedir. Önerilen metodoloji, geleneksel tekniklere göre açık bir avantaj sağlamakta ve gerçek zamanlı uygulamalar için ölçeklenebilirlik sergilemektedir.

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1. Introduction

The management and logistics of oil, a critical natural energy resource, represents a significant global concern [1,2]. The intricate nature of guaranteeing the secure and effective conveyance of oil, particularly via maritime routes, highlights the necessity for comprehensive tracking and monitoring systems [3]. The global transportation and logistics of oil, a vital natural resource, present significant challenges, particularly in mitigating the environmental risks associated with oil spills [4,5]. Oil spills, whether the result of tanker accidents or natural disasters, present a significant threat to marine ecosystems and coastal communities. Therefore, it is imperative that they are rapidly detected and responded to effectively [6,7]. It can be argued that the effective management of oil spills, from the initial detection stage through to the subsequent clean-up operation, is of paramount importance for the dual purposes of environmental protection and the continued efficiency of oil logistics [3]. This necessitates not only the identification of potential problem areas but also the deployment of advanced ground and Earth observation techniques for the real-time monitoring of events [7].

The current methods for monitoring and managing oil spills rely significantly on satellite-based remote sensing technologies, including radar and optical imagery [5]. Recent studies have highlighted the effectiveness of Sentinel-1 SAR data in detecting marine oil spills. For instance, Caporusso et al. [4] employed Sentinel-1 and Google Earth Engine to monitor oil spills in Venezuelan waters, showcasing its ability to analyze spill extents rapidly in diverse conditions. Similarly, Ahmed et al. [5] utilized deep neural networks with Sentinel-1 imagery to successfully identify spills along the Egyptian coastline, emphasizing the model's robustness in varying environmental scenarios. Cheng et al. [3] proposed a framework incorporating Sentinel-1 data to address special disturbances in oil spill detection along the Suez Canal, achieving high accuracy in complex maritime settings. Houali et al. [7] implemented a semi-automated approach for oil slick extraction in the Moroccan exclusive economic zone, demonstrating the potential of radar imagery in diverse environmental conditions. These studies demonstrate the growing reliance on radar-based technologies for environmental monitoring.

Earth observation, primarily through satellite technology, has been an indispensable tool for monitoring global environmental phenomena, offering a comprehensive overview of terrestrial and maritime activities [8,9]. Although satellite capabilities have undergone considerable advancement, particularly in terms of resolution and functionality, the fundamental premise of utilising satellite imagery for the observation and monitoring of processes on Earth [10] remains unchanged. One of the most crucial applications of this technology is in the monitoring of oil spills, which may be the result of natural disasters such as storms or incidents involving oil tankers [4]. Oil spills present a significant threat to marine ecosystems and coastal environments, necessitating prompt detection and intervention to mitigate their detrimental impacts [11,12]. Given the potential for oil spills to cause significant harm to natural habitats, particularly those of marine and coastal species, the ability to rapidly detect such incidents is of paramount importance [13]. This enables the prompt initiation of cleanup operations, which is essential for limiting the environmental damage caused by these events [9]. Remote sensing has emerged as one of the most effective technologies for tracking oil spills, providing essential data for understanding the spill's spatial extent and rate of spread.

However, the limitations of temporal and spatial resolution of these satellite systems, when considered alongside the complexities of accurately detecting oil on water surfaces, serve to hinder the effectiveness of existing monitoring solutions [14]. The proposed method addresses several key limitations of existing oil spill detection techniques. By utilizing radar-based Sentinel-1 data, it overcomes challenges associated with cloud cover and weather conditions that frequently hinder optical imagery. The application of the Mask R-CNN model significantly improves object segmentation accuracy, enabling the detection of smaller spills that are often missed by traditional methods. Furthermore, the high temporal resolution of Sentinel-1 ensures timely data availability, allowing for rapid response in disaster scenarios. These features collectively enhance the efficiency and reliability of oil spill monitoring.

Furthermore, while deep learning and AI-driven object detection techniques have enhanced spill detection capabilities, they remain constrained by the quality and diversity of training data, which may result in potential inaccuracies in real-world spill scenarios [4]. To ensure effective oil spill monitoring, it is essential to have high temporal and spatial resolutions. Temporal resolution refers to the frequency of data collection, while spatial resolution pertains to the detail and accuracy of the spatial data [5]. This dual focus enables the expeditious identification of the spill's propagation and the estimation of the area necessitating remediation [15]. Optical satellites, which are widely used for object detection, play a pivotal role in remote sensing. However, their performance on water surfaces, where subsurface elements may interfere with detection, can be constrained [16]. In contrast, radar technology has demonstrated greater efficacy in maritime settings, particularly for the detection of oil spills, as it can penetrate cloud cover and distinguish between oil slicks and water surfaces. Nevertheless, the utility of radar data remains contingent upon its temporal and spatial resolution, which can vary considerably between different satellite systems [17-19].

In recent years, the European Space Agency's Sentinel-1 satellite has emerged as a leading resource for oil spill monitoring due to its open-access data policy and its ability to provide high temporal and spatial resolution radar imagery [3]. Sentinel-1 offers unique advantages over other satellite systems [20-22]. These advantages include high temporal and spatial resolution, C-band radar technology, and dual polarization capabilities [21]. Notably, the C-band radar technology ensures reliable data collection, even in adverse weather conditions such as cloud cover and nocturnal periods [22-24]. The satellite's open access policy ensures affordability and ease of access, making it a valuable resource for developing countries and research institutions with limited financial resources [23]. Additionally, its dual polarization capacity facilitates the distinction between oil spills and other sea surface features, enhancing the precision of analysis [22-26]. An increasing number of studies have focused on the Sentinel-1 platform for environmental monitoring, as it offers consistent and reliable data at no cost to users. This makes it particularly well-suited for developing nations and research institutions with limited resources. Furthermore, advancements in technology, particularly in artificial intelligence (AI) and deep learning, have significantly enhanced the accuracy and efficiency of object detection [27].

Deep learning techniques have seen significant advancements in their application to environmental monitoring and object detection. For instance, Temitope Yekeen and Balogun [13] reviewed machine learning and deep learning advancements in marine oil spill detection, highlighting their role in improving prediction accuracy and vulnerability assessments. Zhou et al. [28] proposed enhancements to Faster R-CNN for better recognition of occlusions and small objects, demonstrating its potential applicability to complex scenarios such as oil spill detection. Pirinen and Sminchisescu [29] explored deep reinforcement learning for region proposal networks, offering insights into improving object detection in dynamic environments. Similarly, Guo et al. [30] showcased the adaptability of Mask R-CNN for specific tasks like citrus picking, underlining its versatility across different domains.

Several studies have demonstrated the significant potential of deep learning models in oil spill detection. For instance, Ghorbani and Behzadan [31] employed deep neural networks to achieve instance segmentation of oil spills, highlighting the adaptability of these models to diverse marine conditions. Salau and Krieter [32] applied Mask R-CNN for segmentation tasks, demonstrating its effectiveness in handling high-resolution datasets for environmental monitoring. Furthermore, Dehghani-Dehcheshmeh et al. [6] utilized hybrid CNN-transformer networks integrated with Sentinel-1 SAR data, achieving notable accuracy in oil spill detection under complex scenarios. Such advancements underscore the transformative role of deep learning and AI-driven techniques in enhancing the precision and reliability of oil spill monitoring. The development of powerful object detection algorithms has revolutionized how environmental data is processed and interpreted, enabling the rapid identification of spills and other anomalies [3, 18, 33].

This study contributes to the literature by introducing a novel approach that integrates Sentinel-1 SAR data with the Mask R-CNN deep learning model. Unlike traditional methods that rely heavily on optical imagery or lower-resolution radar data, this approach provides a robust framework for detecting and monitoring oil spills with high accuracy. By addressing limitations such as low-resolution datasets and environmental constraints, the proposed method significantly enhances the precision and reliability of oil spill detection. Furthermore, this research provides a transferable methodology that can be applied to other environmental monitoring challenges, thereby broadening its scientific impact.

This research also highlights the significance of employing high-resolution temporal and spatial data, such as that provided by Sentinel-1, in conjunction with sophisticated AI tools to guarantee prompt detection and response to oil spills. The integration of these technologies not only exemplifies the advancements in environmental monitoring but also provides a framework for addressing future challenges in oil spill management through more accurate, real-time tracking and decision-making processes. Such advancements offer the potential to significantly mitigate the environmental and economic impacts of oil spills, ensuring more sustainable and responsible management of this vital energy resource. Moreover, this study seeks to address these challenges by employing Sentinel-1 SAR satellite data and sophisticated deep learning algorithms for more efficient and precise oil spill detection, thereby contributing to enhanced environmental protection and resource management strategies.

In the context of this study, deep learning algorithms integrated with ArcGIS software are employed for the purpose of oil spill detection. This approach leverages Sentinel-1 radar data in order to ensure the highest possible degree of accuracy in both spill detection and area estimation [3]. The deployment of pre-trained deep learning models within ArcGIS reduces the workload for researchers by streamlining the detection process, which is particularly advantageous when working with large datasets [34]. The application of deep learning methods not only accelerates the speed of detection but also enhances the precision of spill tracking, thereby facilitating more effective response strategies in the event of an environmental disaster [35]. The use of ArcGIS, which is widely recognized for its robust geospatial analysis capabilities, further supports this by allowing for seamless integration of data, efficient workflow management, and enhanced visualization of oil spill extents.

2. Material and Method

2.1. Study area

The study focuses on the MV Wakashio and MT Princess Empress oil spills aresignificant environmental disasters in recent history. The MV Wakashio incident occurred off the southeastern coast of Mauritius in the Indian Ocean when the Japanese-owned bulk carrier MV Wakashio ran aground on a coral reef near Pointe d'Esny on July 25, 2020 (Figure 1a). Pointe d'Esny is a crucial sanctuary for rare wildlife and a UNESCO-recognized area of ecological significance. The accident resulted in the release of over 1,000 tonnes of fuel oil into the pristine waters, severely affecting the marine ecosystem, coastal habitats, and local communities dependent on these resources for their livelihoods. The affected area encompasses the Mahebourg lagoon, extending from the lagoon of Pointe d'Esny to the surrounding mangroves, seagrass beds, and coral reefs. This region is renowned for its rich biodiversity, which includes numerous endemic species and serves as a breeding ground for a variety of marine life. Additionally, the area is a significant contributor to the local economy, primarily through eco-tourism, which attracts visitors to its pristine marine habitats and protected environments. The impact of the oil spill posed a direct threat not only to the ecological balance of the region but also to the economic well-being of the local communities. Hence, the severity of the spill’s effects on both environmental and socio-economic aspects underscores the importance of efficient oil spill monitoring and cleanup.

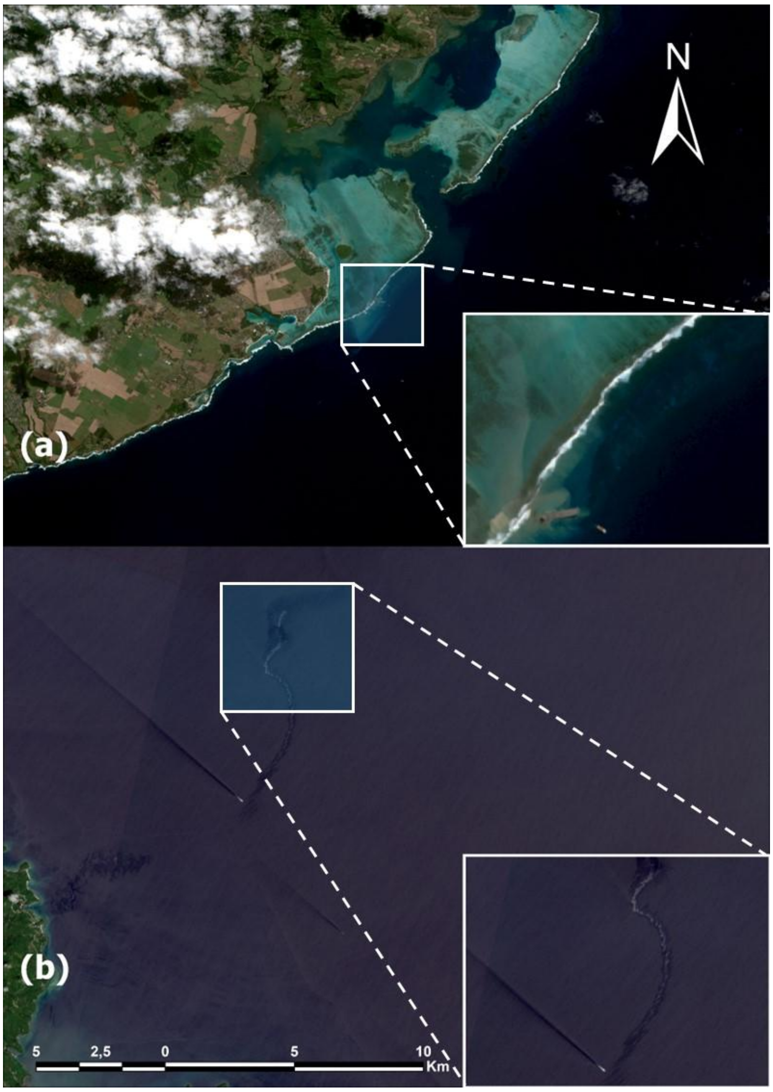

Figure 1. (a) MV Wakashio and (b) MT Princess Empress Oil Spill Zones

The MT Princess Empress incident occurred on February 28, 2023, when the tanker, carrying 800,000 liters of industrial oil, sank off the coast of Naujan, Oriental Mindoro, Philippines (Figure 1b). The spill caused extensive environmental damage, affecting marine ecosystems, local fisheries, and coastal communities, and required a large-scale cleanup effort. The area affected by the MT Princess Empress oil spill, particularly the waters off Oriental Mindoro in the Philippines, holds significant environmental importance due to its rich marine biodiversity and ecological value. These waters are part of the Verde Island Passage, which is often referred to as the "center of the center of marine biodiversity" in the world. The region is home to a vast array of coral reefs, seagrass beds, and mangrove forests that provide critical habitats for countless marine species, including those that are vital to local fisheries. The region's economic activities, including fishing and eco-tourism, play a crucial role in sustaining livelihoods. Additionally, it serves as a vital component in preserving ecological balance and safeguarding coastal regions from erosion. The repercussions of the spill on a highly sensitive and globally significant ecosystem underscore the imperative for prompt and effective environmental protection and restoration initiatives.

Given the ecological richness of these areas, this research emphasizes the need for rapid and accurate detection of oil spills to minimize the environmental and economic damage. The unique characteristics of these regions, particularly its vulnerable coastal habitats, provide a critical context for testing the effectiveness of advanced remote sensing technologies, such as the Sentinel-1 SAR satellite, and deep learning techniques in detecting and tracking oil spills. These areas serves as an ideal location for demonstrating the application of innovative solutions to mitigate environmental disasters and enhance response strategies.

2.1. Data

In this study, satellite data from the Sentinel-1 mission is utilized for the detection of oil spills. The Sentinel-1 satellite, operated by the European Space Agency (ESA), provides high-resolution Synthetic Aperture Radar (SAR) data. The satellite operates in multiple modes, including the Interferometric Wide Swath (IW) mode, which was used in this study. The IW mode offers a ground resolution of 5 m × 20 m, with a coverage width of 250 km. This mode is particularly suitable for monitoring large-scale environmental phenomena, such as oil spills, due to its ability to balance high resolution with extensive spatial coverage. Sentinel-1 also offers dual polarization (VV and VH), which enhances its capacity to distinguish between oil spills and other surface features. The satellite's temporal resolution of six days ensures consistent monitoring, enabling rapid detection and timely responses to environmental disasters. Additionally, the Ground Range Detected (GRD) products used in this study are preprocessed to reduce speckle and improve feature interpretability, further increasing the utility of Sentinel-1 data for oil spill detection.

While optical satellite systems such as Landsat and MODIS have been widely used for environmental monitoring, their dependency on clear weather conditions and daylight limits their applicability in dynamic and cloudy environments. In contrast, Sentinel-1's radar-based technology enables consistent data acquisition regardless of weather or lighting conditions. Additionally, compared to other SAR systems like Radarsat-2, Sentinel-1's open-access policy and high temporal resolution (six days) provide significant advantages for large-scale and rapid monitoring efforts.

S-1 represents the inaugural space mission of the European Space Agency (ESA), comprising two satellite constellations, S-1(A) and S-1(B). S-1(A) was launched on April 3, 2014, while S-1(B) was launched on April 25, 2016. The central frequency of S-1 is 5.40 GHz, which corresponds to a wavelength of 5.55 cm. It is equipped with C-band technology. The C-band frequency range extends from 4 to 8 GHz. The temporal resolution of S-1 is six days, and it offers both single (HH or VV) and dual polarizations (HH + HV or VH + VV). S-1 is capable of functioning in four distinct acquisition modes. The Stripmap (SM), Interferometric Wide Swath (IW), Extra-Wide Swath (EW), and Wave (WV) modes are available. The IW mode is conducive to the monitoring of terrestrial and coastal regions with a ground resolution of 5 m × 20 m. The ground range coverage of IW is 251.8 km, with resolution ranges of 20 × 22 for high resolution and 88 × 89 for medium resolution. Each mode is capable of generating Single Look Complex (SLC) and Ground Range Detected (GRD) products at Level-1 (L1), as well as Ocean (OCN) products at Level-2 (L2). The standard GRD products are multi-looked, which serves to diminish speckle in the image and enhance the interpretability of features. Multi-looking is implemented on all bursts of the IW and EW modes of S-1, with the GRD products produced independently. Subsequently, all bursts within sub-swaths are amalgamated to provide a continuous GRD image in each polarization channel. The detection of oil spills is facilitated by the utilisation of SAR sensors operating in the C-band (Sentinel 1). The S-1 IW and EW modes remain the preferred and dependable methods for marine oil spill detection due to their rapid and near real-time data delivery within 24 hours and their conflict-free operations.

For the training of the deep learning model was facilitated by the utilization of 381 Sentinel-1 scenes, which encompassed a diverse array of oil spill stages under varying environmental conditions (e.g., calm seas, rough weather, cloud cover). The data included images from both VV and VH polarizations to ensure comprehensive feature representation. This diversity in temporal and spatial conditions enhances the model's ability to generalize across real-world scenarios. Additionally, the dataset was augmented using rotation and flipping techniques to increase variability and robustness. The data utilized for the detection of oil spills is presented in Table 1.

Tablo 1. Specifications of satellite data used for the study.

Sensing Date	Platform	Processing Level	Polarization
29-07-2020	Sentinel 1B	Level-1C	VV
06-03-2023	Sentinel 1A	Level-1C	VV

These characteristics of Sentinel-1 directly contributed to the effectiveness of oil spill detection in this study. The fine resolution enabled precise segmentation of oil spill boundaries, while the polarization data improved the discrimination between oil slicks and natural water patterns. In addition, the six-day temporal resolution enabled timely data collection, critical for tracking the dynamic progression of the oil spill incidents.

2.1. Method

Subsequent to the collection of data, a series of image preprocessing techniques were employed, including picture subsetting, calibration, speckle filtering, multi-looking, ellipsoid correction, and land/sea masking. At the outset, the images were subsetted with the objective of reducing their overall size while focusing exclusively on the region of interest. The SAR images are calibrated to ensure that the pixel values accurately represent the radar backscatter of the reflecting area. Calibration enables the comparison of SAR images obtained at different times and from different modes. Speckle noise is an inherent property of SAR imaging that impairs image quality and complicates the differentiation of image features. Consequently, speckle filtering is a crucial step in the process of precise oil spill detection and image categorization. The Lee Sigma filter is employed with a 7 x 7 kernel size for the purpose of eliminating speckle. The Lee sigma filter is capable of preserving cellular resolution while simultaneously retaining edge sharpness, thereby making it an effective tool for identifying oil spill features. The Lee sigma filter is based on two sigma Gaussian distribution probabilities and incorporates the speckle multiplicative noise model, as outlined in Eq. (1).

$$z(k,l) = x(k,l) * v(k,l) \tag{1}$$

Where z(k,l) is the (k,l)th pixel in intensity or amplitude of a SAR imagery, x(k,l) is the reflectance, v(k,l) represents speckle noise and characterized by a distribution with E[v(k,l)] = 1.

Multi-looking is a processing technique that is employed to address the challenges posed by intricate image geometry, inherent speckle, and the need to enhance image interpretability. The range look was set to 1, the azimuth looks to 2, and the mean ground range square pixel was established at 5.39. Ellipsoid correction serves to mitigate distance distortions, thereby rendering the image's geometric representation to be closely aligned with the real world. This work employs the Geolocation Grid (GG) to perform the ellipsoid correction. To prevent the processing of terrestrial regions, the "mask out land" operation is implemented. This operation converts all land pixels into null values and diminishes the image size.

This research focuses on the impacted zone within a marine and coastal ecosystem, aiming to evaluate the extent of the oil spill and its effects using Sentinel-1 SAR imagery and Mask R-CNN for detailed analysis and segmentation. The chosen areas, due to its ecological significance and the magnitude of the environmental threat posed by the oil spill, provides a critical context for applying innovative technology solutions to address and mitigate such maritime disasters.

To analyze and segment the Sentinel-1 data, Mask R-CNN was selected due to its superior performance in pixel-level segmentation tasks. Unlike traditional object detection models, such as Faster R-CNN or U-Net, Mask R-CNN generates precise segmentation masks, which are critical for delineating oil spill boundaries accurately. This capability is particularly advantageous in complex marine environments, where small spills or occluded features pose significant challenges. Additionally, its modular architecture, which integrates Region Proposal Networks (RPN) and segmentation mask generation, enables efficient processing and detection, reducing manual intervention compared to traditional machine learning approaches.

The innovative aspects of this study lie in its seamless integration of advanced preprocessing techniques, such as speckle filtering and multi-looking, with the Mask R-CNN model. Additionally, the use of transfer learning to fine-tune the model with Sentinel-1 data ensures its adaptability to real-world conditions. By leveraging ArcGIS for data processing and visualization, this approach also streamlines workflow management and enhances the practical applicability of the method. These advancements collectively demonstrate the potential of combining satellite imagery with deep learning to address complex environmental challenges.

Mask R-CNN extends Faster R-CNN by adding a branch for predicting segmentation masks on each Region of Interest (RoI), in parallel with the existing branch for classification and bounding box regression [25]. This model is particularly suited for tasks requiring precise localization of objects within an image, making it ideal for our application. For the task of object instance segmentation, our study employed the widely recognized Mask R-CNN model due to its straightforward design and prevalent use in scholarly research [26]. This method effectively identifies objects of distinct shapes within high-resolution images and generates precise segmentation masks for each instance.

The architecture of Mask R-CNN incorporates multiple convolutional and pooling layers, culminating in several fully connected layers [27]. Each convolutional layer undergoes a three-step process: convolution, application of a nonlinear activation function, and pooling. Subsequent to each convolutional operation, a feature map is generated, which is then relayed to the subsequent layer for further processing. Mask R-CNN builds upon the architecture of Faster R-CNN by introducing an additional branch that operates concurrently with the existing bounding box recognition branch to predict segmentation masks for objects [24]. Following this, Fast R-CNN takes over, utilizing RoIPool to extract features from each proposed box, subsequently classifying the objects and refining their bounding boxes.

Mask R-CNN enhances this structure by adding a third pathway specifically designed for generating precise object masks, distinguishing it from its predecessors [28]. Not only is Mask R-CNN straightforward to train, but it also boasts versatility, adapting effortlessly to various applications, ranging from human pose estimation to the identification of distinct entities like vehicles or buildings [29]. Mask R-CNN operates through a two-stage process. Initially, the model employs a Region Proposal Network (RPN) to scrutinize the feature maps, creating regions of interest (RoIs) [36]. It leverages the ResNet architecture as its foundational backbone, integrating both high-level and low-level features from various layers through a residual convolution network combined with a feature pyramid network.

This integration effectively captures both the precise location details and deep semantic information from images. Subsequently, for each RoI, a process known as RoI pooling is utilized to scale down the feature map using a nearest neighbor technique, selectively extracting pivotal features [31]. However, this pooling method can lead to a misalignment of the extracted features with the RoIs. To rectify this and achieve finer RoI accuracy, RoI Align employs bilinear interpolation for each region. Finally, Mask R-CNN concludes by generating masks for each RoI, alongside classifying and bounding each detected object, enhancing the precision of object detection and segmentation tasks [29,37]. The mask R-CNN model was pre-trained using a predefined set of Sentinel-1 images labelled with the presence of oil spills. The data training process was performed by the Oil Spill Detection Deep Learning package available in ArcGIS Deep Learning Pre-Trained Packages [38]. The training process involved tuning the hyperparameters of the model such as learning rate, chunk size and number of epochs to optimise the detection accuracy. Transfer learning techniques were applied using a pre-trained model on the COCO dataset and further fine-tuned with our custom dataset of satellite imagery to improve the model's ability to recognise oil spills.

The performance of the trained Mask R-CNN model was assessed using standard metrics for object detection and segmentation, including precision, recall, and the Intersection over Union (IoU) for both bounding boxes and segmentation masks. The validation dataset was used to test the model's effectiveness in accurately detecting and segmenting oil spills. Additionally, qualitative assessments were performed by visually inspecting the model's predictions against ground truth annotations to ensure the accuracy of the segmentation results.

The parameter choices for the Mask R-CNN model were guided by prior studies and iterative testing during model training. For instance, the learning rate was set to 0.001, following the recommendations of Ghorbani and Behzadan [31], who demonstrated its suitability for segmentation tasks involving Sentinel-1 data. Similarly, the number of epochs (50) and chunk size (16) were optimized through cross-validation to balance model accuracy and training efficiency. These parameter settings were selected to achieve the highest IoU and recall values on the validation dataset.

The model was implemented using the PyTorch framework, due to its flexibility and extensive support for deep learning models. All computations were performed on a high-performance computing cluster equipped with NVIDIA GPUs to expedite the training and inference processes.

3. Results

The integration of Sentinel-1 SAR satellite data with the Mask R-CNN deep learning model yielded effective and precise detection of oil spills. The findings of the study are centered on the detection and delineation of the MV Wakashio and MT Princess Empress oil spill, exemplifying the capacity of Sentinel-1 SAR for monitoring maritime disasters. The radar imagery processed from Sentinel-1 was instrumental in detecting the extent of the oil spill, which was estimated to cover an area of approximately 1.17 km^2 and 1.07 km^2 for MK Wakashio and MT Princess Empress incidents respectively. The spill area was calculated through the processing of high-resolution satellite data by the Mask R-CNN model, which successfully segmented the regions of oil contamination from the surrounding water.

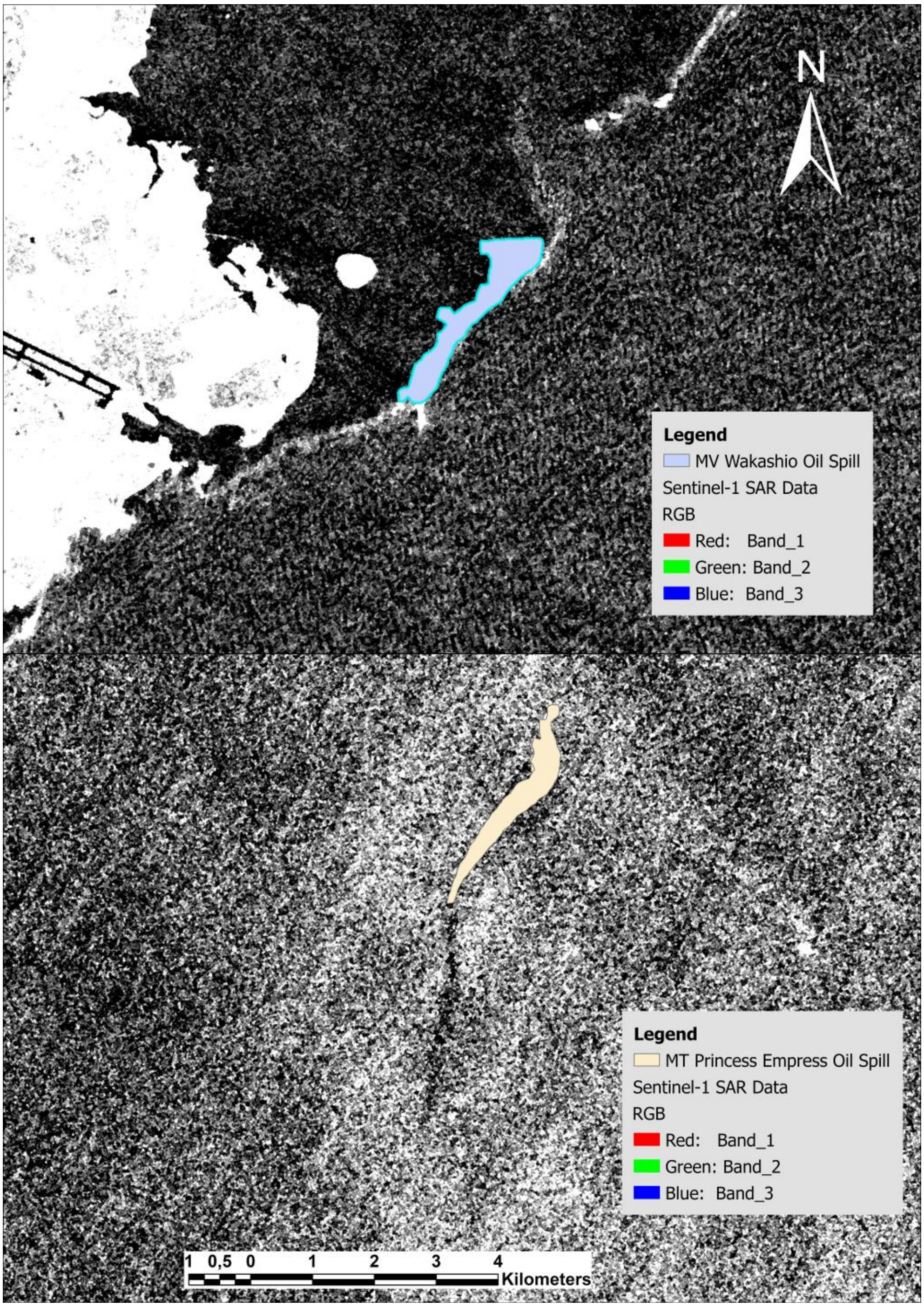

Figure 2. Oil Spill Extraction Results

The overall accuracy of the detection was found to be 80% for MV Wakashio and 81% for MK Princess Empress, demonstrating the reliability of using SAR data combined with deep learning techniques. The model's performance for MV Wakashio incident was evaluated using precision (82%), recall (78%), and IoU (76%) and for MT Princess

Empress incident was evaluated using precision (83.8%), recall (80.2%) and IoU (74.8%). These metrics indicate the model's ability to accurately detect and delineate oil spills while minimizing false positives and negatives. For comparison, similar studies by de Ahmed et al. [5], de Moura et al. [39], Zhang et al. [40] and Yang et al. [41] reported IoU values of 0.96, 0.62, 0.78 and 0.69, respectively, demonstrating the relative effectiveness of our approach. Furthermore, the qualitative assessment showed that the segmentation masks aligned closely with ground truth annotations, confirming the model's reliability in real-world scenarios.

The use of Sentinel-1 SAR images allowed the model to bypass the limitations faced by optical sensors, particularly in distinguishing oil spills from natural water patterns and overcoming challenges posed by weather conditions, such as cloud cover. Figure 2 illustrates the detected oil spill areas, highlighting the effectiveness of this method in visualizing the spread and extent of contamination.

Further analysis of the detection process revealed that the Mask R-CNN model was able to identify the boundaries of the oil spill with a high degree of precision, which is crucial for determining the necessary area for remediation. The segmentation masks generated by the deep learning model facilitated the estimation of the oil-covered surface, which is essential for the optimal allocation of resources during the cleanup operations. Moreover, the model's capacity to process extensive datasets expeditiously rendered it especially advantageous in disaster scenarios, where prompt detection is crucial for minimizing environmental impact. The integration of these technologies offers a notable enhancement in both speed and accuracy compared to traditional methods, rendering them a valuable asset for future applications in oil spill monitoring and management.

Rapid detection of oil spills is paramount in preventing ecological disasters and mitigating their impact on marine ecosystems and coastal communities. The urgency to address oil spills as they occur necessitates innovative approaches that can swiftly and accurately assess the situation, enabling timely response measures. The significance of this research lies in its ability to offer such a solution, harnessing the power of Sentinel-1 satellite data and advanced deep learning techniques. By providing a method for fast and precise identification of oil spills, this study contributes a valuable tool for environmental protection efforts. Moreover, the ability to quickly determine the spread and extent of oil contamination aids in the efficient allocation of cleanup resources, thereby minimizing the ecological damage and facilitating quicker restoration of affected areas. Through enhancing the speed and accuracy of oil spill detection, this research plays a crucial role in the broader endeavor to safeguard marine biodiversity and preserve the health of our oceans.

4. Discussion

The findings of this study emphasize the efficacy of integrating Sentinel-1 SAR data with the Mask R-CNN deep learning model for precise oil spill detection. The model demonstrated an overall accuracy of 80% for MV Wakashio and 81% for MK Princess Empress, with a precision of 82%, recall of 78%, and IoU of 76% for MV Wakashio incident and for MT Princess Empress incident was evaluated with a precision of 83.8%, recall of 80.2% and IoU of 74.8%. These results highlight the capability of the proposed methodology to achieve high segmentation accuracy, even under challenging conditions such as mixed environmental signals or cloud cover. Compared to optical satellite-based methods, which often face limitations in adverse weather conditions, the use of radar-based Sentinel-1 data provides consistent and reliable monitoring capabilities.

The achieved IoU value of 76% is comparable to values reported in similar studies, such as Ahmed et al. [5], Moura et al. [39], Zhang et al. [40], and Yang et al. [41], which reported IoU values of 0.96, 0.62, 0.78, and 0.69, respectively. These comparisons demonstrate that the methodology presented in this study performs competitively with existing approaches while offering advantages in terms of automation and adaptability. The high spatial resolution of 5 m × 20 m and the dual-polarization (VV and VH) capabilities of Sentinel-1 were critical in differentiating oil spills from natural water patterns. These findings align with studies such as Dehghani-Dehcheshmeh et al. [6], where Sentinel-1's radar data significantly enhanced the accuracy of oil spill detection.

The model's capability to distinguish between oil spills and false positives, such as algal blooms, was enhanced by leveraging Sentinel-1's dual-polarization (VV and VH) capabilities. These features allowed for more accurate discrimination of surface features by examining the backscatter properties of different materials. However, occasional false positives were observed in regions with high environmental variability. To address these challenges, future research could explore the integration of auxiliary datasets, such as optical imagery or additional radar parameters, to further reduce false detections.

The integration of the Mask R-CNN model provides an added advantage by enabling precise delineation of oil spill boundaries, which is essential for effective resource allocation during cleanup operations. Compared to traditional segmentation methods discussed in Ghorbani and Behzadan [31], which required extensive preprocessing and manual input, the automated nature of the Mask R-CNN significantly streamlined the detection process. Additionally, the transfer learning approach, which utilized pre-trained weights fine-tuned with Sentinel-1 data, further enhanced the model's adaptability to real-world scenarios.

Despite these advancements, challenges remain in improving the model's performance in highly dynamic marine environments, where wave patterns or other environmental factors may introduce noise into the detection process. Future research could focus on incorporating additional datasets, such as multi-temporal SAR imagery or optical data, to improve the robustness and generalizability of the model.

The findings of this study contribute not only to academic literature but also to practical applications in environmental protection and disaster management. The integration of Sentinel-1 SAR data with advanced deep learning models presents a scalable solution for real-time monitoring of marine oil spills. This methodology has the potential to inform policy development, guide resource allocation during cleanup operations, and contribute to global efforts in mitigating environmental disasters.

5. Limitations

This study, while demonstrating promising results, is subject to several limitations that warrant consideration. Firstly, the temporal resolution of Sentinel-1 SAR data, while relatively high at six days, may not always align with the immediate timing of oil spill incidents. This can delay the rapid detection required for critical environmental response measures. Additionally, the spatial resolution, although sufficient for large-scale spills, may pose challenges in detecting smaller spills, particularly in complex coastal regions with high environmental variability.

Secondly, the effectiveness of the Mask R-CNN model is influenced by the quality and diversity of the training dataset. In this study, the dataset was limited to pre-labeled Sentinel-1 images, which may not fully capture the variability of real-world oil spill scenarios, such as those occurring under extreme weather conditions or in regions with unique marine characteristics. The model's ability to distinguish oil spills from similar phenomena, such as algal blooms or sediment patterns, could also be improved.

Lastly, the reliance on computational resources, including high-performance GPUs for model training and inference, may limit the accessibility of this approach for organizations with constrained resources. Future work should focus on optimizing computational efficiency to ensure broader applicability.

Addressing these limitations through the incorporation of supplementary datasets, hybrid modeling approaches, and enhanced algorithmic refinement could significantly improve the robustness and applicability of oil spill detection methodologies.

6. Conclusion and Recommendations for Future Studies

The integration of Sentinel-1 SAR satellite data with advanced deep learning techniques for the detection and monitoring of oil spills, as evidenced in the case of the MV Wakashio and MT Princess Empress incidents, represents a significant leap forward in environmental disaster management. This research highlights the importance of timely and accurate detection mechanisms in mitigating ecological catastrophes, safeguarding marine biodiversity, and protecting coastal communities. By enabling rapid identification of spills, the study demonstrates how satellite imagery can be utilized for effective environmental monitoring, leading to efficient response strategies and conservation of resources, including energy savings during clean-up operations. The ecological significance of areas affected by spills like MV Wakashio and MT Princess Empress underscores the urgent need for innovative surveillance technologies.

The findings of this study demonstrate the efficacy of integrating Sentinel-1 SAR data with sophisticated deep learning methodologies, particularly the Mask R-CNN model, for the identification of oil spills. The detection technique benefits considerably from the elevated spatial and temporal resolution of Sentinel-1 SAR, thereby facilitating a comprehensive investigation of the affected regions. The MV Wakashio and MT Princess Empress incidents exemplifies the utility of satellite data in facilitating more effective environmental disaster management through the rapid detection of oil spills, thereby enabling more timely reaction and resource distribution initiatives. The employment of Mask R-CNN enhances the precision of detection, enabling the delineation of oil spills and the estimation of their extent, which is crucial for the effective implementation of remediation strategies. The combination of these technologies represents a significant advancement in the reduction of environmental consequences associated with oil spills.

However, certain limitations were also identified in the investigation. While Sentinel-1 SAR provides substantial data, its temporal resolution may impede the expedient identification of oil spills, particularly in rapidly evolving scenarios. Furthermore, despite the elevated accuracy of the deep learning algorithm, it encounters difficulties in differentiating oil spills from other analogous occurrences, such as algae blooms, which can impact detection precision. Further research may be enhanced by the integration of supplementary datasets and the optimization of deep learning algorithms, with the aim of improving detection reliability across a range of marine settings. Further investigation of these areas may facilitate the development of more effective oil spill detection methodologies, thereby enhancing environmental protection strategies.

Future improvements to this methodology could focus on increasing data diversity by incorporating multi-temporal and multi-sensor datasets. This approach would enhance the model's generalization capabilities and improve performance in diverse marine environments. Additionally, further optimization of the Mask R-CNN architecture, such as the incorporation of lightweight models or hybrid approaches, could reduce computational costs while maintaining high accuracy.

While this study demonstrated the potential of integrating Sentinel-1 SAR data with the Mask R-CNN model for accurate oil spill detection, there remain opportunities for further research and development. Future work could focus on increasing data diversity by incorporating multi-temporal and multi-sensor datasets, enabling the model to generalize across different marine environments and conditions. Additionally, optimizing the Mask R-CNN architecture through lightweight models or hybrid approaches could reduce computational costs, making this methodology more accessible for real-time applications.

To address challenges such as false positives from algal blooms or sediment patterns, integrating auxiliary datasets, such as optical imagery or additional radar parameters, could further enhance detection accuracy. Moreover, the development of real-time monitoring systems, including cloud-based or mobile applications, would allow for faster and more efficient responses to oil spills. Finally, this approach could contribute to global efforts in environmental protection by informing policy development and supporting disaster management initiatives. These advancements would strengthen the applicability of the proposed methodology and extend its impact beyond academic research.

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