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VESSEL DETECTION USING YOLO AND SATELLITE IMAGERY TO ENHANCE CUSTOMS PATROL EFFICIENCY

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ABSTRACT

Penyelundupan melanggar peraturan Bea Cukai melalui pergerakan barang secara ilegal melintasi perbatasan nasional. Meskipun patroli laut Bea Cukai digunakan untuk mencegah penyelundupan, luasnya perairan Indonesia dan kondisi yang tidak terduga membuat patroli yang terus-menerus tidak efisien dan berisiko. Pendekatan yang lebih tepat diperlukan. Penelitian ini mengeksplorasi bagaimana integrasi citra satelit dengan pembelajaran mendalam dapat meningkatkan kemampuan pengawasan dan pemantauan Bea Cukai. Menggunakan metodologi CRISP-DM, penelitian ini memeriksa potensi penggunaan YOLOv8 dan YOLONAS dengan citra satelit yang dikumpulkan dari Sentinel-2. YOLOv8 mencapai mAP50 sebesar 0.465 dan mAP50-95 sebesar 0.269, sementara YOLONAS mencetak 0.409 dan 0.235. Evaluasi menggunakan 16 citra satelit mengungkapkan bahwa YOLONAS sering salah mengidentifikasi objek bukan kapal, seperti awan dan pulau, sebagai kapal, sementara YOLOv8 mempertahankan akurasi yang lebih tinggi tanpa kesalahan ini. Selain itu, kinerja YOLOv8 meningkat dengan skala peta yang lebih kecil, seperti yang dibuktikan oleh nilai kepercayaan yang meningkat untuk objek yang terdeteksi. Hasil penelitian ini dapat digunakan untuk meningkatkan kemampuan Bea Cukai dalam mendeteksi kapal di daerah yang rawan penyelundupan dan mengidentifikasi rute penyelundupan baru yang potensial, memungkinkan patroli laut yang lebih terarah dan efisien, sehingga mencegah aktivitas ilegal di sepanjang garis pantai Indonesia.

Smuggling violates Customs regulations through the illegal movement of goods across national borders. While Customs sea patrols are used to prevent smuggling, Indonesia's vast waters and unpredictable conditions make constant patrolling inefficient and risky. A more precise approach is necessary. This research explores how integrating satellite imagery with deep learning can improve Customs surveillance and monitoring capabilities. Using the CRISP-DM methodology, this research examines the potential of using YOLOv8 and YOLONAS with satellite imagery collected from Sentinel-2. YOLOv8 achieved a mAP50 of 0.465 and mAP50-95 of 0.269, while YOLONAS scored 0.409 and 0.235, respectively. Evaluation using 16 satellite images reveals that YOLONAS often misidentifies non-vessel objects, such as clouds and islands, as vessels, while YOLOv8 maintains higher accuracy without these errors. Additionally, YOLOv8's performance improves with smaller map scales, as evidenced by the increased confidence values for detected objects. The results of this study can be used to enhance Customs' ability to detect vessels in smuggling-prone areas and identify potential new smuggling routes, enabling more targeted and efficient sea patrols and thus preventing illegal activities along the Indonesian coastline.

1. INTRODUCTION

Indonesia occupies a strategic position along major global trade routes, allowing 40% of international commerce, which is 90% transported by sea, to transit through Indonesian water (Morris and Paoli, 2018; Ministry of Transportation, 2023). Its vast maritime area, spanning over 6 million square kilometres, presents significant challenges for effectively monitoring and enforcing maritime regulations, including detecting potential smuggling activities. (Marzuki et al., 2021; Wirawan, 2022; Morris and Paoli, 2018). Smuggling is the illegal transportation of goods or persons across borders, violating applicable laws and regulations. For example, narcotics smuggling cases in Indonesia have risen throughout the years. It rose from 26.614 cases in 2010 to 32.470 cases in 2013 and 44.321 cases in 2015. BNN also reported that Indonesia has the highest ranking in narcotics distribution among Southeast Asian regions (Prayuda et al., 2019). Rahmawati, 2022 stated in her research that based on the Directorate General of Customs and Excise report, Indonesia has occurred a loss with value of up to Rp4.772 trillion in 2019 due to illegal smuggling. While in 2020, the value gone up to Rp6.367 trillion.

Smuggling is considered one of the violations in the customs and excise fields, where illegal goods are transported in or to the nation's territory. Customs is widely known to have duties and responsibilities in supervising and servicing the traffic of goods entering and leaving the customs area (Johantri et al., 2020 in Misbach et al., 2022). In Indonesia, Customs has three main functions: as a Community Protector, Trade Facilitator, and Industrial Assistance, safeguarding Indonesian citizens from illegal goods that could cause harm to Indonesian citizens and economy, preventing illegal trading and giving industrial assistance in the nation (Direktorat Jenderal Bea dan Cukai, 2023). Their business process aims to safeguard international trade logistics and supply chains from threats posed by smugglers, commercial fraudsters, terrorists, and potentially hazardous goods that could endanger lives. At the same time, they focus on streamlining trade operations by ensuring efficient processing for low-risk activities across all business areas (Vorotyntseva et al., 2020).

To enforce the eradication of illegal goods and smuggling, customs have strategies involving information gathering and sea patrols (Ningsih et al., 2024). Information gathering is carried out in the context of early detection of violations in the customs and excise field (Tanjung et al., 2023). It complies with Customs Regulation Number 04/BC/2021 which mandates supervision to be carried out in order to ensure the fulfilment of state rights and compliance with provisions in the field of customs and/or excise. Following the information gathering, Customs Sea Patrols are conducted to do surveillance or take enforcement actions. (Direktorat Jenderal Bea dan Cukai, 2021; Misbach et al., 2022). Media has reported how customs sea patrols thwarted smuggling attempts by vessels via sea routes. The latest news in June 2024 reported that the Aceh Customs patrol fleet succeeded in thwarting the smuggling of 15.9 million cigarettes worth nearly IDR 37.8 billion, with potential state revenue loss reaching more than IDR 50 billion (Agus, 2024). Another smuggling thwart was also reported by Bengkalis customs, preventing a total of 28 tons of illegal mangos and shallots from Malaysia from entering Indonesia. Smuggling attempts usually don't employ large vessels. In 2019, Aceh Customs thwarted an attempt to smuggle crystal methamphetamine and shallots using a motorboat. The estimated import value of the shallots was about IDR 1,56 billion, with an estimated state revenue loss of IDR 545,9 million (Direktorat Jenderal Bea dan Cukai, 2019). In 2022, Riau Customs intercepted a speedboat attempting to smuggle IDR 14 billion worth of lobster seeds (Direktorat Jenderal Bea dan Cukai, 2022). Customs patrols are typically scheduled as independent, integrated, or coordinated operations. (Direktorat Jenderal Bea dan Cukai, 2020). Frequent sea patrols are conducted in areas bordering countries like Malaysia, Singapore, Philippines, Timor Leste, Australia, and Papua New Guinea, as these regions are common entry and exit points for smuggling illegal goods, including used clothing, agricultural products, electronics, narcotics, and other dangerous or other economically harmful goods (Direktorat Jenderal Bea dan Cukai, 2020).

Continuous sea patrols for monitoring and surveillance are both expensive and time-consuming (Khairi and Sa'ari, 2021). Additionally, unpredictable weather and unsafe conditions pose a high risk of accidents. To address this, customs require a well-structured management system for sea patrols. They rely on analysed data regarding transport movements entering customs territory, including the number and types of detected vessels, as well as external transport entering the area, to aid in the planning, execution, and evaluation of maritime patrols (Direktorat Jenderal Bea dan Cukai, 2021). The data and information itself are gathered from many resources, such as the Automatic Identification System (AIS), for targeting, profiling, and document research (Tanjung et al., 2023). AIS is widely regarded as the most significant advancement in maritime navigation since the introduction of radar (Prasat et al., 2017). It helps to identify vessels and assists in target tracking and search operations (NATO Shipping Centre, 2021) as it embodies many records on vessel locations, speed over ground (SOG), course over ground (COG) and various fixed data, such as vessel types, dimensions, and identifiers. However, it has limitations in detecting small vessels that are often used in smuggling (Zheng et al., 2023). Unlike large vessels, small vessels and yachts are not obligated to employ AIS. This results in the inability to detect illegal activities by small vessels using AIS (Dogancay et al., 2021). Furthermore, AIS does not always provide comprehensive and seamless coverage of the entire maritime domain (Soldi et al., 2021). With the emergence of advanced technology, many argue that customs authorities should adopt modern artificial intelligence capabilities. Such a system would serve as an ally for international trade participants and enhance government efficiency, allowing for better anticipation and mitigation of smuggling threats. (Vorotyntseva et al., 2020).

To enhance customs' surveillance and monitoring capabilities, integrating satellite imagery with advanced AI-based object detection models like YOLOv8 and YOLO-NAS offers a cost-effective and efficient solution. Satellite imagery can cover vast areas, providing crucial data on maritime traffic and potential smuggling activities, enabling more precise and timely interventions. Additionally, it allows real-time monitoring of complex, wide-ranging areas, significantly improving the effectiveness of sea patrols. AI algorithms can be trained to detect irregular vessel movements in restricted or high-risk zones, automatically alerting customs authorities to potential smuggling activities or unauthorised maritime traffic. In recent years, You Only Look Once (YOLO) has emerged as an alternative approach to the widely adopted Convolutional Neural Networks (Adegun et al., 2023), which is said to have better performance (Hussain, 2023).

These characteristics align well with the vast, high-quality, and real-time satellite imagery, enabling YOLOv8 to meet the demands of automatic surface-level inspection, such as fast detection with high accuracy within constrained computational resources (Hussain, 2023). Therefore, this paper aims to explore the potential of integrating satellite imagery with artificial intelligence models, YOLOv8 and YOLONAS, for vessel detection to enhance the precision of Indonesian Customs authorities in combating smuggling and optimising sea patrols.

2. LITERATURE REVIEW

Disruptive Technology

The theory of using artificial intelligence in customs activities adheres to the continuous improvement principles, which is one of the main values of Indonesian Customs. Artificial intelligence falls under “disruptive technologies” that can radically transform existing economic domains, facilitate novel modalities of work, production, and consumption, and catalyse broader societal shifts (Burri, 2017). Disruptive technologies have so many potential benefits for any aspect of life. It could introduce new opportunities driven by new technologies (Christensen & Raynor, 2013) and improve workflow procedures and increase efficiency, which can result in cost advantages (Bengtsson & Wang, 2016). The idea of using artificial intelligence to help customs in their tasks and functions has been widely studied around the world. It could assist the customs authorities' operations, the filing and issuing of customs declarations, and the detection of things under customs control that pose a higher risk of breaking customs laws (Vovchenko et al., 2022). A more practical statement was released by Vovchenko et al., 2022 that Artificial intelligence technology could open new opportunities for the customs regulation framework within the Eurasian Economic Union (EAEU).

One of the topics frequently studied in artificial intelligence is object detection (Srivastava et al., 2021), which is closely related to video analysis and image understanding (Zhao et al., 2019). The history began with the development of deep learning and its representative tool, namely, the Convolutional Neural Network (Zhao et al., 2019) to You Only Look One (YOLO). In recent years, the development of object detection algorithms has significantly advanced, giving broader opportunities for individuals or organisations to customise and utilise to suit their specific needs. Data sources are also evolving. For example, the use of satellite imagery covering the Earth's surface provides extensive data for image analysis. The combination of satellite imagery and artificial intelligence to detect images has become a prominent area of research. Recent developments in computer vision, particularly deep learning, have enabled the successful automation of imagery intelligence tasks on aerial images (Xia et al., 2018; Mundhenk et al., 2016; Alganci et al., 2020) and could help customs in surveillance and monitoring (Deepthi et al., 2021; Gajalaksmi et al., 2020; Ophoff et al., 2020).

SATELLITE IMAGERY

Data has been growing rapidly in recent years, and its format also varies from structured to unstructured, including images or video. One example of unstructured big data is satellite imagery, collected from sources such as remote sensing imagery, social media, and sensors (Nguyen & Le, 2020). Satellite imagery has been expanding quickly and has been utilised in many analyses to help solve and monitor problems (Burke et al., 2021). It has been used frequently in many applications, such as surveillance, military, geospatial surveys, environmental impacts, and change monitoring. As Burke et al. (2021) show the potential uses of satellite imagery usage for understanding and promoting sustainable development, Nguyen et al. (2020) have also successfully used satellite images to monitor land use in paddy areas. Shifting costly, slow, and sparse traditional land monitoring to autonomous and more intelligent systems by using remote sensing on satellite data for cheap and timely paddy mapping. In maritime security management, ship detection using remote sensing has a crucial role in enhancing maritime security (Stofa et al., 2020) and maritime surveillance (Wang et al., 2021).

Recognising its potential, the Indonesian government has made satellite imagery available for ministries and agencies to use and established a legal framework for its utilisation. Satellite Imagery Law Number 21 year 2013 on Space mandates Pustekdata to provide Indonesian government-licensed remote sensing data for all ministries, agencies, military, police, and local governments. To meet the need for national remote sensing, Pustekdata provides an Inderaja catalogue that has been integrated with remote sensing data obtained from satellite imagery in various resolutions, namely low, medium, high, and very high resolution. Users can access and check the availability of remote sensing data at Pustekdata through the Inderaja catalogue.

Medium-resolution satellite imagery is often freely accessible, while high and very high-resolution imagery typically requires commercial fees. An example of medium-resolution imagery comes from Sentinel-2, which consists of two identical satellites, Sentinel-2A and Sentinel-2B. These satellites operate in a sun-synchronous orbit at an altitude of 786 km, positioned 180 degrees apart. This configuration provides imagery of the earth's land surface every 10 days with one satellite or 5 days with both satellites. These satellites can be used for operational observations such as land cover maps, land change detection maps and geophysical variables. Sentinel-2 L1C data consists of 13 spectral bands with the following details: 10 m spatial resolution of 4 bands (B2, B3, B4, B8); 20 m spatial resolution of 6 bands (B5, B6, B7, B8A, B11, B12); 60 m spatial resolution of 3 bands (B1, B9, B10) (Pustekdata-Lapan, 2018; Suhet, 2015). For Sentinel-2 imagery, a 10 m spatial resolution means that each pixel represents a square area on the ground that is 10 metres by 10 metres. The same principle applies to the 20 m and 60 m spatial resolutions. Thus, the smaller the spatial resolution, the more detailed the objects it can capture.

YOLO

YOLO is a deep learning algorithm that was introduced in the computer vision community by Joseph Redmon et al. in a paper titled 'You Only Look Once: Unified, Real-Time Object Detection' (Redmon et al., 2016). It has gained popularity due to its high degree of accuracy with a compact model architecture (Hussain, 2023; Talaat & ZainEldin, 2023; Terven et al., 2023) and has become central real-time object detection systems for video monitoring applications (Terven et al., 2023).

Image 1. Two Stage and Signel Stage Detector in Object Detection

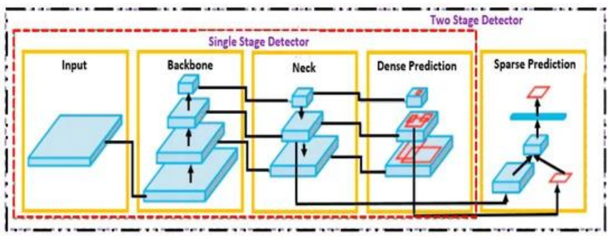

Image source: Hussain, 2023

YOLO is a single-step detector in object detection architecture classification. Instead of splitting the detection process into two stages, feature extraction and regression or classification, for yielding the result, YOLO merges the processes into one, enabling classification and regression via a single pass. This resulted in lighter computational demand. A prominent example of a two-stage detector is the R-CNN, showcasing high accuracy but low computational efficiency (Hussein, 2023). YOLO has also been acknowledged to meet industrial requirements, such as accuracy, lightweight, and edge-friendly deployment conditions. The difference between single-step and second-step detectors is shown in image 1.

YOLO has been proposed to help in real-world applications, such as surveillance systems and public safety, autonomous vehicles and traffic management, industrial automation and quality control, healthcare imaging and diagnosis, environmental monitoring and wildlife conservation, and retail & customer experience (Hussain, 2024). A recent search provides YOLO model usage with a satellite-sensing remote image for landslide detection (Cheng et al., 2021). Research conducted by Li et al., 2020 comparing Faster R-CNN, YOLO, and Single Shot Multi-Box Detector (SSD) on agricultural greenhouse detection in high-resolution satellite images shows that YOLO has superiorities in accuracy and computational efficiency. Another implementation of YOLO is to detect ships from low-resolution optical satellite imagery (Xu et al., 2022). The real-time video feed monitoring and analysis from YOLO also have helped in the rapid detection of suspicious activities (Kumar P. et al., 2021). It also has been used in license plate detection (Chen, 2019) and traffic sign recognition (Dewi et al., 2022).

Since its introduction in 2016, the YOLO family has continuously evolved, progressing through versions YOLOv1, YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv6, YOLOv7, and most recently, YOLOv8 and YOLONAS in 2023 (Hussain, 2023; Terven et al., 2023), as shown in Image 2.

YOLOv8

YOLOv8 is built upon the success of the previous YOLO version. It incorporates novel features to further enhance performance and flexibility (Jocher et al., 2023). YOLOv8 can be used for various applications, including object identification, image categorisation, and segmentation (Talaat & ZainEldin, 2023). It was introduced by Ultralitycs with 5 scaled versions tailored to different application needs: YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large), and YOLOv8x (extra large). YOLOv8 uses a modified CSPDarknet53 backbone and C2f module for its architecture. The C2F module mixes high level features with contextual information to improve detection accuracy. To accelerate the computation, a spatial pyramid pooling fast (SPPF) layer is used.

YOLONAS

YOLONAS, released by Deci in May 2023, is a YOLO model enhanced with Neural Architecture Search (NAS) to automatically develop specialised network architectures tailored to specific use cases (Aharon et al., 2021; Manhas & Poonam, 2024) and is suitable for real-time applications to detect small objects, improve localisation accuracy, and deploy deep learning models (Terven et al., 2023). YOLONAS has been prominently used to detect vehicle plates in vast urban settings (Sonavane et al., 2021). YOLONAS originality includes quantization-aware modules called QSP and QCI, automatic architecture design using AutoNAC, hybrid quantisation method, and a pre-training regimen with automatically labelled data, self-distillation, and large datasets. These components were used to develop three model sizes: YOLO-NASS (small), YOLO-NASM (medium), and YOLO-NASL (large), altering the depth and positions of the QSP and QCI blocks (Terven et al., 2023).

3. RESEARCH METHODOLOGY

This research adopts the CRISP-DM Methodology. It is considered one of the de facto standards for data mining projects (Schröer, 2021) and is still relevant for data science projects (Martínez-Plumed, 2019). It has six iterative phases, as shown in Image 3. The phases consist of Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment. However, due to the nature of this study as a research paper, the deployment phase was not included, as no implementation was required.

Image 3. CRISP DM Stages

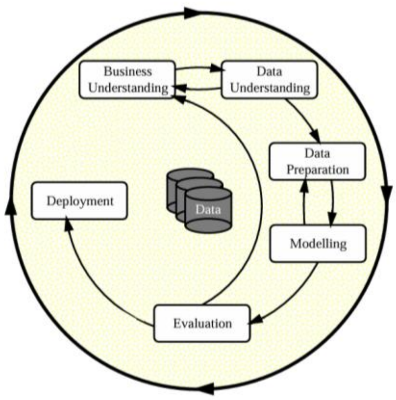

Image source: Wirth and Hipp, 2000

Business Understanding

The first step in the CRISP DM method is business understanding, which is evaluating and observing the company's circumstances to have a comprehensive understanding of the resources that are needed (Schröer, 2021). Since this research aims to enhance Customs' ability to prevent smuggling at sea more efficiently and cost-effectively, it is crucial to acquire in-depth knowledge of Customs operations, particularly sea patrols, as well as the state-of-the-art technologies that could support this effort.

Data Understanding and Data Preparation

The next step after business understanding is data understanding which focuses on gathering the necessary data for analysis. For this case, data related to satellites and vessels are needed to develop an artificial intelligence model for vessel detection. The data preparation process involves cleaning and organising the raw data to ensure it is ready to use in the modelling phase.

The dataset used is a publicly available dataset on Kaggle named "Ships/Vessels in Aerial Images" provided by Siddharth Sah, 2023. It consists of 9.697 train data, 2.165 validation data, and 1.573 test data, including its label. Additionally, the satellite imagery from Sentinel-2 was used. The satellite imagery contains four different scales (100, 200, 300, and 500 metres) for each coordinate. Random two coordinates containing vessels in Jakarta Bay were selected (Latitude: -6.0086, Longitude: 106.90682 and Latitude: -5.78099, Longitude: 106.93697) dated August 11, 2024. To further ensure that the models could accurately detect other common objects that might occur in the ocean, another location with small cloud coverage and containing vessels in the Malacca Strait was selected (Latitude: 1.64937, Longitude: 102.73092) dated August 12, 2024. Additionally, to evaluate the models on an area with no vessels but containing a group of small islands, east Halmahera Regency was selected (Latitude: 0.69224, Longitude: 128.4997) dated May 14, 2024. Each coordinate produces four satellite imagery with four different scales, so there are sixteen additional images from the satellite for testing in a real scenario.

In this research, since the "*ship/vessel in aerial images*" dataset is already splitted to data train, data validation and data test and it is ready to use as it comes in YOLO formatted data, no data preparation is needed. The satellite imagery data also did not require data preparation as it can be directly used in YOLO.

Modelling

To create a model, pre-trained models from both YOLO versions were used, namely YOLOv8m.pt from YOLOv8 and yolo_nas_m.pt from YOLONAS, and the training parameters were inherited from that model. The "m" or medium model was chosen considering the authors' limitations of time and computational power. Additionally, the author manually changes the parameters for the optimiser by changing from auto to AdamW and batch size reduced from default 16 to 4 and num_workers set to 8, so the YOLOv8 and YOLONAS have the same optimiser, training batch and worker threads. Finally, the model was trained for 50 epochs each, running on pytorch version 2.3.1 using NVIDIA GeForce RTX 3070 8 GB GPU with CUDA 11.8 and cuDNN 8.7.0 environment.

Evaluation

The evaluation metrics considered include mean Average Precision at 50% Intersection over Union (mAP50) and mean Average Precision at Intersection over Union from 50% to 95% (mAP50-95) across 50 epochs of training. mAP50-95 was selected due to its rigorous characteristics that evaluate detection accuracy among a range of Intersection Over Union (IoU) thresholds (Zanevych, 2024). mAP is one of the common evaluation metrics used in object detection. mAP is considered the main parameter used to compare how well various object identification models perform. mAP50-95 is considered a prominent and widely used metric for the YOLO algorithm. Zanevych, 2024, in his research about traffic light detection using YOLO models, implies that mAP50-95 thorough evaluation guarantees that the chosen models exhibit reliable performance in accurately identifying and categorising traffic signals in various scenarios. In terms of reliably detecting objects across various classes and confidence levels, models with greater mean average precision (mAP) values are thought to perform better overall.

4. RESULTS AND FINDINGS

Findings

The performance of YOLOv8 showed a consistent improvement throughout the training process. Starting with a mAP50 of 0.091 at the first epoch, the model steadily improved, reaching a peak mAP50 of 0.480 by the 46th epoch and slightly decreasing to a final mAP50 of 0.476 at epoch 50. The mAP50-95 metric followed a similar trend, rising from 0.043 in the first epoch to 0.292 at epoch 47 before a minor drop to 0.289 in the final epoch (Appendix I). The highest mAP50-95 value of 0.292 at epoch

47 was identified as the best model. When tested on test data, this model achieved a mAP50 of 0.465 and a mAP50-95 of 0.269, indicating a slight performance decline, likely due to differences between the training and test datasets.

In comparison, YOLONAS started with a higher initial mAP50 of 0.153 and improved to a final mAP50 of 0.399 by epoch 50. The mAP50-95 began at 0.064 and increased to 0.237 by the last epoch (Appendix I). The model's best performance occurred at epoch 48, with a mAP50-95 of 0.238. When tested on test data, YOLONAS achieved a mAP50 of 0.409 and a mAP50-95 of 0.235. The graphs of both models are shown in Image 4 and Image 5.

Both models were further evaluated using 16 satellite imagery from Sentinel-2, gathered from Jakarta Bay, the Malacca Strait, and East Halmahera Regency. The images were tested using the best-trained models with a 25% confidence threshold, as shown in Image 6.

Overall, at a 500-meter scale, YOLOv8 mostly failed to detect vessels, while YOLONAS detected most vessels and also mistakenly identified islands and clouds as vessels. As the scale decreased to 300 and 200 meters, YOLONAS detected all vessels but introduced errors with double bounding boxes and misclassified objects, whereas YOLOv8's detection improved at the smallest scale, YOLOv8 successfully detected all vessels, while YOLONAS always overestimated the number of vessels.

Discussion

This study addresses the limitations of previous vessel detection research by integrating satellite imagery with AI-based object detection models, YOLOv8 and YOLONAS. While prior studies have explored various AI models and satellite data for maritime surveillance, few have focused on the challenges of detecting small vessels in smuggling-prone areas like Indonesia's vast and remote waters. This research tested the performance of these models across different geographic areas and image scales in Indonesia, providing valuable insights into their practical applications.

The primary objective was to assess the effectiveness of YOLOv8 and YOLONAS in detecting vessels in Indonesian waters using Sentinel-2 imagery. The findings show that YOLOv8 consistently outperforms YOLONAS in accuracy and reliability, especially at smaller map scales. When tested on test data, YOLOv8 achieved 0.465 for the mAP50 score and 0.269 for the mAP50-95 score, while YOLONAS scored 0.409 and 0.235, respectively. When tested with Sentinel-2 satellite imagery, YOLOv8 and YOLONAS showed different results.

In the region of Jakarta Bay, in the image with the map scale of 500m, YOLOv8 failed to detect a vessel. In contrast, YOLONAS can detect almost all visible vessels in the area, but YOLONAS also mistakenly detects an island as a vessel. For the map scale of 300m, YOLONAS can detect all the vessels, where some of the detections have two different bounding box sizes and confidence levels, while YOLOv8 only detects one vessel. On a map scale of 200 metres, YOLONAS can detect all the vessels, with some vessels having two different bounding boxes, while YOLOv8 can only detect 4 out of 6 vessels in that area. For the final image scale in Jakarta Bay, YOLOv8 shows its capabilities to detect 3 out of 3 available vessels in the area with an increasing confidence level of detection of the same object from the previous map scale, as the vessel that previously couldn't be detected in map scale 200m, now YOLOv8 can detect it. Meanwhile, the YOLONAS model detects 5 out of 3 vessels.

A small cloud cover in the Malacca strait is suitable for testing the model's capabilities for detecting vessels with some unknown objects in the image. In the image with a map scale of 500 metres, YOLOv8 successfully detected some vessels without mistakenly identifying the clouds as vessels, whereas YOLONAS misclassified all objects, including clouds, as vessels. At the 300-metre scale, YOLOv8 failed to detect anything, despite the presence of three visible vessels and clouds, while YOLONAS detected all objects in the image where some of them detected twice. For the image with a scale of 200m, YOLOv8 and YOLONAS correctly detected the only vessel, but the YOLONAS detected the vessel twice. In the last image in the Malacca Strait, with the same coordinate but at a scale of 100m, the YOLOv8 maintains the performance by correctly detecting the vessel and ignoring the clouds, while YOLONAS detects a vessel twice and clouds as a vessel.

The final test area was in East Halmahera, where the coordinates contained only an island and no vessels. YOLOv8 performed correctly by not detecting any objects. However, YOLONAS mistakenly identified the island as a vessel at the 500, 300, and 100-metre scales.

YOLOv8 consistently outperforms YOLONAS in accuracy and reliability, especially at smaller map scales. YOLOv8's ability to distinguish between vessels and non-vessel objects like clouds and islands makes it more effective and reliable to be adopted by customs. For instance, in the Malacca Strait, YOLOv8 avoided misclassifying clouds as vessels, a problem that YOLONAS frequently encountered. YOLONAS often detected the same vessel twice, which could be addressed by adjusting detection thresholds. However, YOLONAS's tendency to misidentify objects and produce false positives limits its usefulness in customs operations, where precision is critical to avoid unnecessary patrols. In contrast, YOLOv8's improved accuracy with smaller map scales highlights its robustness in handling more detailed imagery, which is essential for detecting smaller vessels often used in smuggling operations.

5. CONCLUSIONS

YOLOv8 outperforms YOLONAS's capabilities in detecting vessels. The mAP50 and MAP50-90 evaluation metrics from training and testing show that YOLOv8 has a better result than YOLONAS. When tested on Sentinel-2 imagery in several scenarios, YOLOv8 successfully detects vessels without misclassifying other objects, a problem that occurred in YOLONAS. Additionally, YOLOv8's performance improves with smaller map scales, as evidenced by the increased confidence values for detected objects.

This research demonstrates that combining satellite imagery with YOLOv8 could be implemented to support customs in identifying vessels involved in illegal activities along sea routes and help in planning targeted sea patrols to prevent smuggling or enforce laws, creating precise and data-driven customs operations. While YOLONAS may be helpful for broader initial ocean scanning with lower accuracy, YOLOv8, especially with 100-metre scale imagery, is a more reliable option for precise vessel detection in real-world smuggling scenarios.

The findings from this research can be implemented to enhance Indonesian customs's ability to automatically detect vessels in areas prone to smuggling or uncover new smuggling routes. However, this study also highlights areas of improvement for future research. This study used medium YOLOv8 and YOLONAS base object detection models and medium-resolution satellite imagery with a spatial resolution of up to 10 metres limits the ability to detect smaller vessels. Moreover, the model was not tested in known smuggling hotspots. Future research could use an extra large YOLOv8 model (YOLOv8x) and higher-resolution satellite imagery, in collaboration with *Pustekdata*, to detect smaller vessels and train the model with real-world customs violation data for more targeted applications.

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APPENDIX

Evaluation metrics from YOLOv8 and YOLONAS training

epoch	YOLOv8		YOLONAS	
	mAP50	mAP50-95	mAP50	mAP50-95
1	0.0910	0.0434	0.1527	0.0640
2	0.1861	0.0828	0.1881	0.0867
3	0.2071	0.1036	0.2158	0.1036
4	0.2304	0.1101	0.2318	0.1149
5	0.2715	0.1385	0.2518	0.1273
6	0.2705	0.1364	0.2742	0.1381
7	0.3166	0.1668	0.2793	0.1440
8	0.3259	0.1709	0.2879	0.1525
9	0.3221	0.1662	0.3050	0.1596
10	0.3493	0.1919	0.3093	0.1641
11	0.3579	0.1966	0.3144	0.1669
12	0.3652	0.1857	0.3239	0.1721
13	0.3870	0.2116	0.3277	0.1762
14	0.3889	0.2131	0.3261	0.1741
15	0.3874	0.2113	0.3275	0.1766
16	0.3849	0.2080	0.3314	0.1780
17	0.4012	0.2223	0.3377	0.1811
18	0.4021	0.2297	0.3407	0.1852
19	0.4073	0.2313	0.3490	0.1939
20	0.4094	0.2325	0.3570	0.1987
21	0.3990	0.2304	0.3587	0.2054
22	0.4103	0.2424	0.3628	0.2070
23	0.4083	0.2331	0.3671	0.2109
24	0.4198	0.2361	0.3664	0.2130
25	0.4402	0.2525	0.3733	0.2165
26	0.4290	0.2519	0.3772	0.2195
27	0.4440	0.2590	0.3772	0.2208

28	0.4344	0.2552	0.3780	0.2234
29	0.4380	0.2550	0.3819	0.2275
30	0.4466	0.2642	0.3825	0.2283
31	0.4456	0.2644	0.3851	0.2294
32	0.4504	0.2689	0.3849	0.2285
33	0.4494	0.2679	0.3805	0.2269
34	0.4551	0.2731	0.3812	0.2273
35	0.4550	0.2694	0.3833	0.2281
36	0.4671	0.2797	0.3869	0.2307
37	0.4665	0.2779	0.3872	0.2320
38	0.4614	0.2783	0.3870	0.2323
39	0.4704	0.2803	0.3910	0.2331
40	0.4679	0.2807	0.3930	0.2345
41	0.4699	0.2837	0.3886	0.2328
42	0.4724	0.2851	0.3920	0.2343
43	0.4754	0.2849	0.3939	0.2343
44	0.4746	0.2862	0.3937	0.2359
45	0.4766	0.2880	0.3935	0.2361
46	0.4798	0.2900	0.3957	0.2374
47	0.4783	0.2918	0.3980	0.2377
48	0.4754	0.2889	0.3968	0.2382
49	0.4766	0.2889	0.3971	0.2367
50	0.4757	0.2886	0.3990	0.2370

Source: Training Result

Image 2. YOLO Evolution

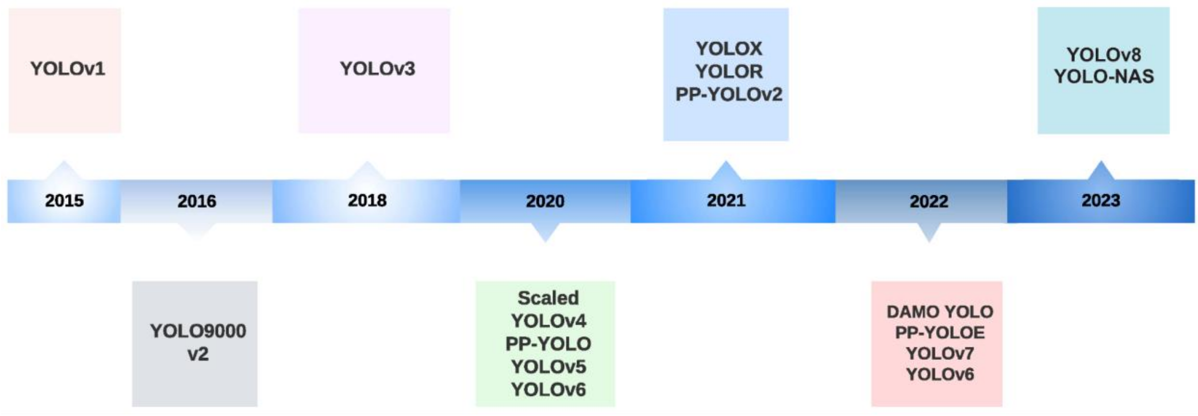

Image source: Terven et al., 2023

Image 4. mAP50 Graph

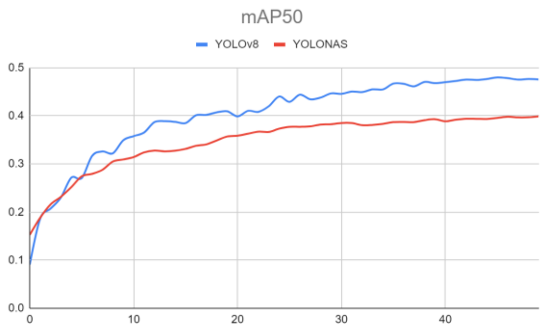

Image source: Training Result

Image 5. mAP50-95 Graph

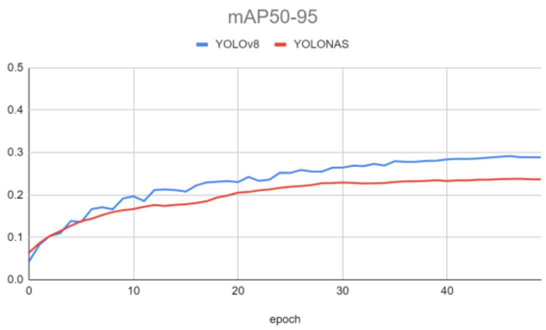

Image source: Training Result

Image 6. Test result on Sentinel-2 Imagery

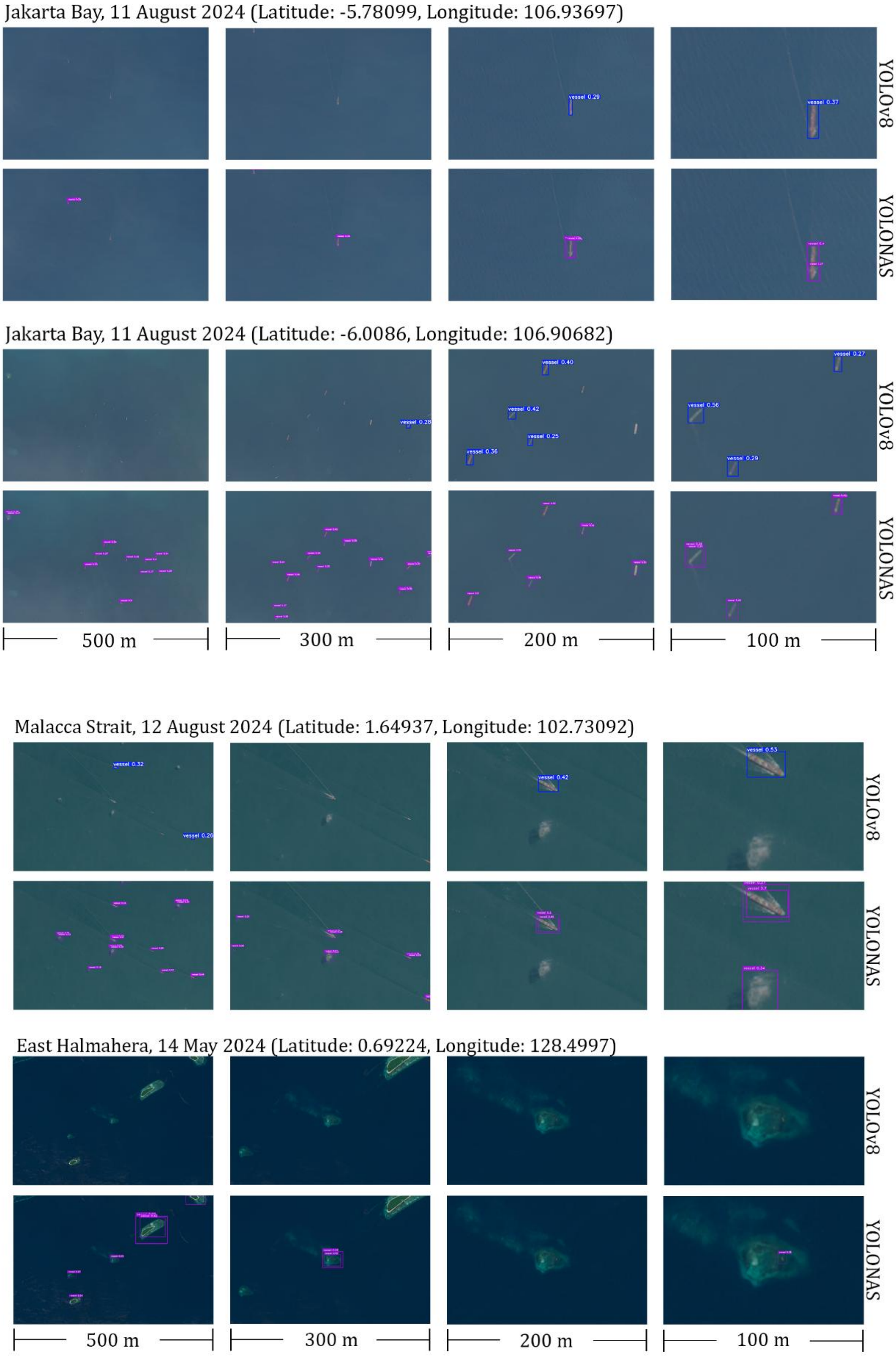

Image source: Test Result