Optimizing Computational Load and Energy Efficiency in UAV-Based Port Surveillance System

Hariharan Sureshkumar[1], Shardul Gharat[1], Dhumravarna Ambre[1],
Lavanya Shetty[1], Aniruddha Kadam[1], Danish Ansari[1], Gajanan Birajdar[2]
[1]Department of Computer Engineering, Ramrao Adik Institute of Technology, Navi Mumbai, India
[2]Department of Electrical Engineering, Ramrao Adik Institute of Technology, Navi Mumbai, India

2024 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC) | 979-8-3503-6655-6/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICSPCC62635.2024.10770489

***Abstract*—The unauthorized entry of vessels into restricted port areas poses significant security risks and regulatory challenges. Traditional surveillance methods often fall short of providing timely and comprehensive monitoring, leading to potential security breaches and operational inefficiencies. We propose a system that utilizes image stitching technology onboard the drones for enhanced mapping and object detection applications. This research addresses the issue of identifying unauthorized watercraft and vessels entering authorized port regions and notifying the appropriate authorities by transmitting real-time coordinates of the intruding vessel. Unauthorized vessel detection is carried out by using a Deep Learning Algorithm on the Microprocessor onboard each drone. Pub-Sub Model is used for fast and secure communication between the Drones and the MIS. Authorities use drones to scan the designated area simultaneously, processing images by image stitching and storing them in the drones. It will process on the drone's platform and verify the authorization of the vessel, if the unauthorized vessel is detected, then The Image along with the coordinates of the vessel is sent to the MIS via the Pub-Sub Model. Drones process this by balancing the workload over a certain period.**

***Index Terms*—Maritime surveillance, Image stitching, Unauthorized vessels**

I. Introduction

Advancements in technology have significantly enhanced UAV capabilities in sectors like security and surveillance [1], [2]. This paper presents a UAV-based system using image stitching to improve mapping and object detection, focusing on identifying unauthorized vessels in port regions. Unauthorized vessel access poses serious security threats [3]. Traditional surveillance methods often fail to provide timely monitoring, leading to potential security breaches and operational inefficiencies. Our approach employs the YOLO model on the Res5 Sipeed Maixduino K210 for real-time detection and identification of intruding vessels.

Image stitching technology seamlessly combines multiple images into detailed maps, enabling drones to survey maritime zones while processing images onboard. A Pub-Sub Model facilitates real-time communication between drones and the Maritime Information System (MIS), ensuring swift action by authorities. Additionally, distributing the workload among multiple drones optimizes resource efficiency and reduces processing time [4], enhancing the overall effectiveness of maritime surveillance operations.

II. Related Work

Recent research has extensively explored UAV networks for surveillance, focusing on object detection optimization, communication protocols, and overcoming inherent challenges. The Drone-based Multi-scope Object Detection (DroMOD) system [5] enhances object detection efficiency via drones but faces latency issues due to reliance on transmitting changed images. Projects like Vega [6] address tradeoffs between coverage area, detection latency, and quality in drone-based surveillance, proposing efficient deployment frameworks and algorithms.

The SEAGULL project [7] highlights the importance of integrated systems for maritime situation awareness, achieving high precision and recall in vessel detection. Other notable advancements include neural networks on embedded platforms [8], efficient deployment of region-based object detectors [9], and cost-effective aerial surveillance systems [10]. Collectively, the literature demonstrates significant progress in UAV-based surveillance, promising enhanced real-time public safety and situational awareness.

III. Proposed Methodology

A. System Design

1) System components:

- Drone: The unmanned aerial vehicle, equipped with RGB and IR cameras or imaging sensors, serves as the primary data acquisition unit in the system. It maneuvers through the airspace, sending and receiving images of targeted areas or objects in real time. The drone also has onboard processing capabilities.
- Receiver: The receiver processes data streamed from onboard drones, undertaking initial raw data preprocessing. Its function is pivotal in ensuring data conformity for subsequent tasks such as image stitching and object detection essential for seamless progression in data processing workflows.
- Controller: Upon detecting objects in the fused and stitched image, the controller possesses the capability to transmit both images and coordinates of the identified objects. This functionality enhances situational awareness and facilitates targeted response strategies in various applications.

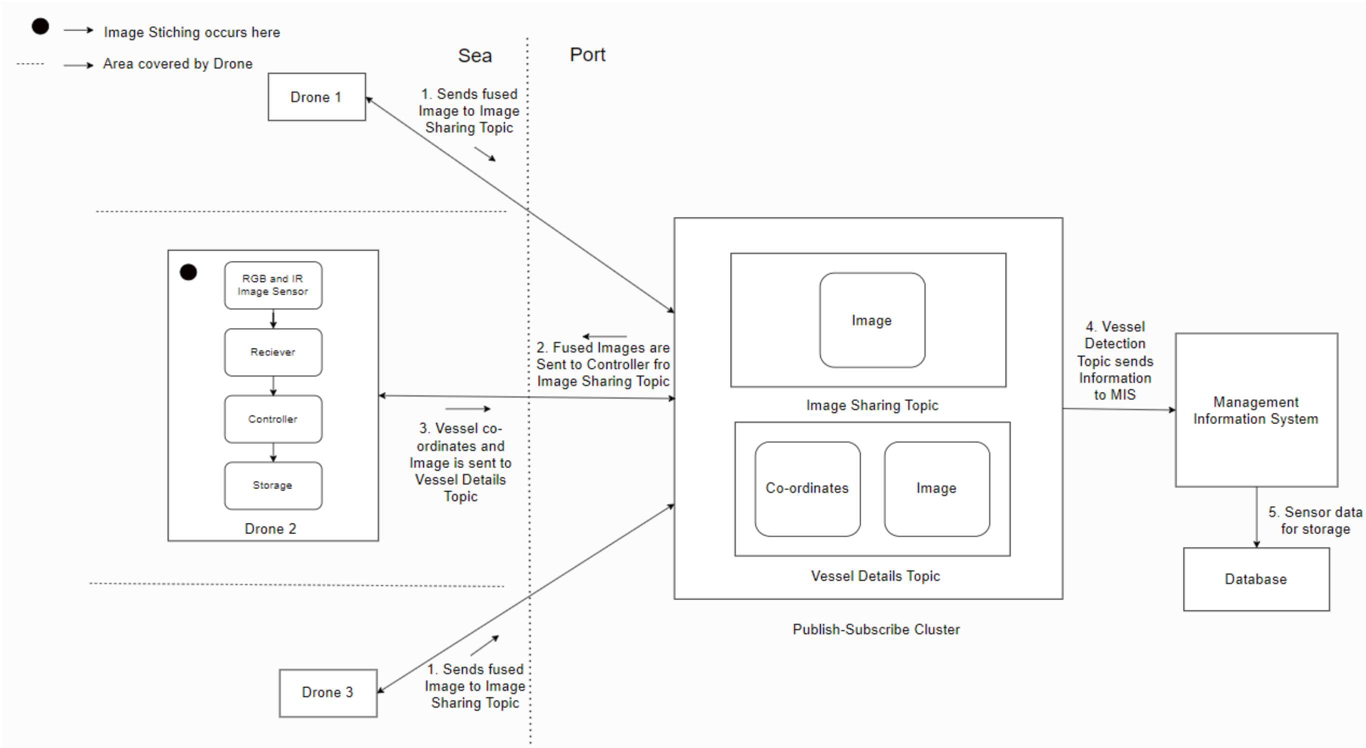

Fig. 1. System diagram illustrating the integration of drones equipped with image sensors, receivers, controllers, and storage units, connected to a publish-subscribe cluster. The publish-subscribe cluster hosts two topics: ”Image Sharing” for inter-drone image sharing and ”Vessel Details” for conveying vessel coordinates and images to the MIS. The MIS, a subscriber to the ”Vessel Details” topic, displays information on-screen and archives it in the database for storage.

- Drone Storage: The drone’s onboard storage device temporarily stores images received from other drones. These images are then used for tasks like image stitching and object detection. This setup enables quick access to data, facilitating efficient processing and real-time decision-making.
- Pub-Sub Model: The system employs the Pub-Sub model to securely transfer images and coordinates between drones and the Management Information System (MIS). This ensures that the drone responsible for image stitching and object detection receives the necessary data without direct coupling to other components.
- Management Information System: The MIS receives the Image and coordinates of the unauthorised vessel through the Pub-Sub Model. The MIS displays the coordinates of the Unauthorized vessel on a Map along with the image for identification. The above information is also sent to the Database for storage.
- Database: The system makes use of a distributed NoSQL database with a column-oriented layout for data storage. This database uses cutting-edge technologies to effectively organise and store data on top of a distributed file system. A connector makes it easier for data to move across components, promoting smooth system integration and communication. With the help of this method, data can be automatically moved from its source to its intended storage place.

2) System Overview: After the drones are launched to pre-established locations within the port area, the system divides [11] the area into separate segments. With onboard RGB and IR sensors for data collection, every drone takes high-resolution photos of its assigned area on its own. The gathered data is then subjected to sensor fusion, which combines data from RGB and IR images to create a complete and precise depiction of the surroundings. The drone system’s situational awareness is improved by this fused data, allowing it to recognise and react to any potential threats or anomalies in the port area.

Once Sensor Fusion is finished, the drones start sending the fused images to a specific network node so that they can be processed further. The DroneBalance algorithm, which optimally divides computational tasks among available drones to maximise system efficiency and resource utilisation, is the basis for the dynamic selection of this node. The chosen node uses computer vision algorithms and techniques to carry out image stitching and object detection tasks. [12]

A publish-subscribe communication model is used, with Apache Kafka acting as the message broker, to enable smooth communication and data exchange between drones and processing nodes. Kafka is used for managing real-time data streams produced by the drone system because of its high throughput and low latency. ”Image Sharing” and ”Vessel

Details" are two topics that are defined within the Kafka ecosystem. The "Image Sharing" topic makes it easier for drones to share their captured images, allowing for cooperative image processing and analysis. Upon object detection, the coordinates of the vessel and the image will be sent to the Management Information System through "Vessel Details".

Relevant data, including vessel coordinates and image data, is extracted and sent to the Management Information System (MIS) for additional analysis and decision-making after objects or anomalies within the captured images are successfully detected. By acting as a central location for the storage, analysis, and visualisation of the gathered data, the MIS gives authorities situational awareness about port operations and security.

The system architecture makes use of Apache HBase, a distributed NoSQL database system, for dependable and effective data management. Large volumes of heterogeneous data produced by the drone system can be easily handled by HBase thanks to its scalability, fault tolerance, and column-oriented data storage. This allows for seamless integration with the MIS and supports the analysis and retrieval of historical data.

The DroneBalance Algorithm optimizes coverage in a certain area. It estimates the total distance D based on the area width W and determines the number of drones needed n. Each drone travels an equal fraction D' of the total distance. In our optimized algorithm, we have introduced a new parameter, the threshold distance D_{thresh}, which is calculated as 70% of D', as an example, to ensure efficient use of battery power [13]. We chose 70% as the threshold value to provide a buffer for the drones to return safely to their base after completing their tasks. However, this value can be adjusted or modified according to specific requirements and constraints. For instance, setting the threshold to 30% may be appropriate in scenarios where the area to be covered is relatively small or the battery capacity of the drones is higher. Adjusting this threshold value allows for flexibility in adapting the algorithm to different situations while ensuring that the drones can return safely to their base.

B. Image processing model

1) Sensor Fusion: In our research, we propose a sensor fusion technique using the VGG19 neural network to integrate RGB and infrared (IR) images. This fusion process enhances object detection accuracy [14], particularly in low-light conditions like nighttime surveillance. We apply low-pass filtering and feature extraction to both image types, generating saliency maps that highlight crucial regions. The final fused output [15], [16] combines low-frequency elements with high-frequency components, resulting in improved detection capabilities. Additionally, to address motion blur caused by drone movement, we incorporate an image restoration method. Overall, our approach enhances maritime security by enabling better detection of unauthorized vessels during nighttime surveillance operations.

2) Image Stitching: In our research paper, we utilize image stitching [17], [18] to create a composite image from multiple images captured by drones. [19] These images, which have undergone sensor fusion, are received from various drones through a Pub-Sub cluster. We employ OpenCV for image stitching, seamlessly combining these images into a larger, unified image [20]. Object detection is then performed on the stitched image.

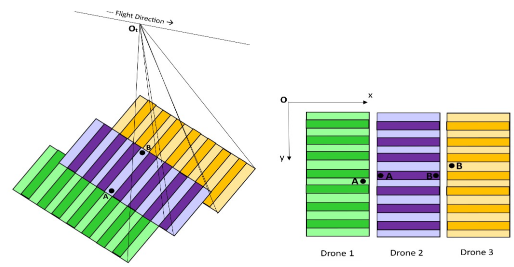

Fig. 2. Image Acquisition Trajectory

3) Object Detection: The image processing model proposed for marine port [21] surveillance leverages the YOLO (You Only Look Once) architecture, with MobileNet_0.75 serving as the backbone neural network. YOLO is a state-of-the-art real-time object detection system known for its speed and accuracy, making it well-suited for deployment on drones with limited computational resources. MobileNet_0.75, a lightweight convolutional neural network (CNN), is chosen as the backbone architecture to balance model efficiency and performance.

4) Feature Extraction Backbone: The backbone architecture, MobileNet_0.75, is responsible for extracting features from input images. MobileNet_0.75 consists of depthwise separable convolutions and pointwise convolutions, which reduce the computational complexity while preserving representation quality. This enables efficient feature extraction from aerial images captured by drones.

5) Loss Function: YOLO uses a custom loss function that combines localization loss, confidence loss, and classification loss. The localization loss penalizes errors in bounding box predictions, while the confidence loss penalizes incorrect confidence scores for object presence. The classification loss penalizes the misclassification of object classes. This multi-task loss function ensures that the model optimizes across all aspects of object detection.

6) Transfer Learning with MobileNet_0.75: Transfer learning is employed to adapt the pre-trained MobileNet_0.75 model to the specific task of marine port surveillance. The pre-trained MobileNet_0.75 model, trained on a large-scale dataset such as ImageNet, serves as the initialization for the feature extraction backbone of YOLO. By leveraging the learned representations from ImageNet, the model can effectively

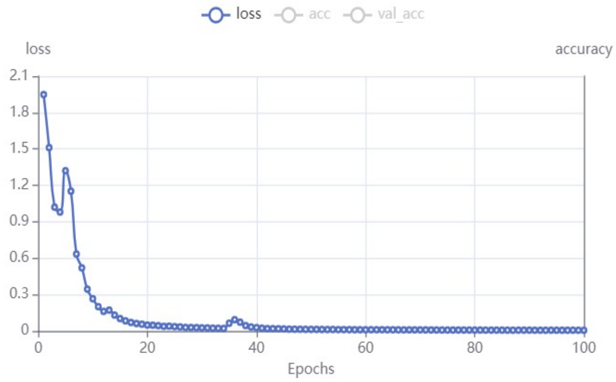

Fig. 3. Loss Function Graph of Model

capture high-level features relevant to object detection tasks, even with limited labeled data in the target domain. During transfer learning, only the parameters of the feature extraction layers in MobileNet_0.75 are fine-tuned on the marine port surveillance dataset, while the parameters of the detection head are initialized randomly and trained from scratch. This allows the model to adapt to the specific visual characteristics and object classes present in marine port images captured by drones.

7) Computational Efficiency Considerations: One of the primary motivations for choosing YOLO with MobileNet_0.75 is its computational efficiency, which is crucial for real-time object detection on drones equipped with Maixduino K210 boards. MobileNet_0.75 strikes a balance between model size, inference speed, and accuracy, making it well-suited for deployment on resource-constrained devices. Furthermore, the unified architecture of YOLO enables end-to-end inference in a single pass, minimizing computational overhead and memory footprint during deployment.

In summary, the proposed model architecture combines the speed and efficiency of YOLO with the lightweight design of MobileNet_0.75 to achieve real-time object detection for marine port surveillance using drones [22]. Transfer learning with MobileNet_0.75 allows the model to leverage pre-trained representations and adapt to the specific surveillance task, while computational efficiency considerations ensure optimal performance on edge devices. [23], [24]

IV. Experiments and Performance Analysis

In our research, we utilized a dataset comprising 3000 images, split into a training set of 2700 images and a validation set of 300 images. Each image was annotated to categorize vessels as Authorized or Unauthorized. Employing Transfer Learning with the YOLO model, we trained our system, achieving a peak accuracy of 78% on the validation set after 90 epochs of training.

Through dataset curation and strategic partitioning, we ensured representative training and validation subsets. Leveraging Transfer Learning with the YOLO model enabled us to capitalize on pre-existing knowledge, resulting in precise

Algorithm 1 Optimized DroneBalance Algorithm

Require:
Total area width (W)
Number of drones available (n)
Weight, battery capacity, and weather conditions.
Threshold battery percentage (T) = 70%
Ensure:
Distance covered by each drone (D')
Distribution of surveillance tasks among drones

```
Calculate the total distance to be covered (D) based on the width of the area:
D = Function(W)
Determine the number of drones (n) needed based on the width of the area:
n = Function(W)
Calculate the distance covered by each drone (D') by dividing the total distance (D) by the number of drones (n):
D' = D/n
Determine the threshold distance (D_thresh) for each drone to cover such that they use 70% of their battery capacity:
D_thresh = 0.7 × D'
Initialize variables:
CurrentDroneIndex = 1
CurrentBatteryPercentage = 100
Initialize array to track remaining distance for each drone: RemainingDistance[1...n]
while CurrentDroneIndex ≤ n do
    RemainingDistance[CurrentDroneIndex] = D'
    while RemainingDistance[CurrentDroneIndex] > D_thresh do
        Perform surveillance with the current drone covering distance D_thresh.
        RemainingDistance[CurrentDroneIndex] −= D_thresh
        if RemainingDistance[CurrentDroneIndex] > 0 then
            Stop onboard processing.
            Assign the next drone in line (increment CurrentDroneIndex) for image stitching and object detection tasks.
        end if
    end while
end while
Output the results:
Distance covered by each drone (D')
Distribution of surveillance tasks among drones.
```

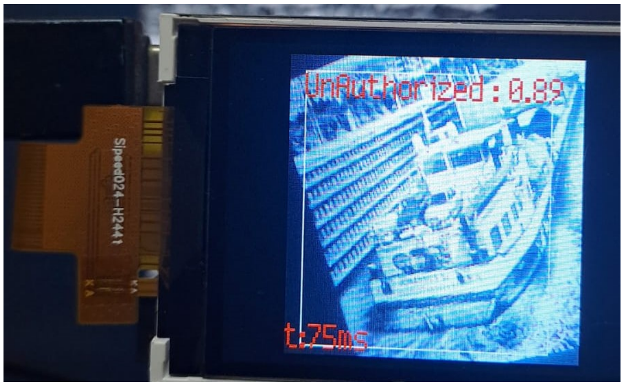

Fig. 4. Visualizing unauthorized vessel detection on Res5 Microprocessor screen with YOLO model.

Fig. 5. Performance Evaluation of YOLO Model on Ships Images Dataset, Analyzing Loss and Accuracy Dynamics.

vessel classification.

Learning curves are essential tools for comprehending the training dynamics and efficacy of the YOLO model throughout 100 epochs. These curves encompass the loss curve, training accuracy curve, and validation accuracy curve, each shedding light on the model's convergence and its ability to generalize.

A. Loss Curve

The behavior of the loss curve is notable during training. Initially, over the first 5 epochs, the loss fluctuates, indicative of the model's exploration of parameter space. Subsequently, there's a sharp decline in loss until the 13th epoch, suggesting rapid learning and enhanced fitting to the training data. Following this initial drop, the loss steadily decreases, reaching a minimal value of 0.006 by the 100th epoch. This sustained reduction in loss underscores the model's capacity to refine predictions and minimize errors progressively.

B. Training Accuracy Curve

The training accuracy curve offers insights into the model's performance on the training dataset. Initially, the accuracy fluctuates for the initial 8 epochs as the model adapts to the training data. However, beyond this phase, the curve stabilizes, maintaining a relatively constant value around 0.16 for each epoch. While the training accuracy remains consistent, it indicates the model's stable performance on the training set throughout the training duration.

C. Validation Accuracy Curve

The validation accuracy curve assesses the model's generalization to unseen data across 100 epochs, with validation conducted every 10 epochs. From the 10th epoch onwards, the validation accuracy curve displays a promising upward trajectory. Initially, at the 10th epoch, the validation accuracy stands at 0.2, indicating moderate performance on the validation set. Subsequently, the validation accuracy steadily increases, reaching 0.7 by the 20th epoch and continues to gently rise in increments of approximately 0.015 every 10 epochs thereafter. The peak validation accuracy of 0.785 is attained at the 90th epoch, highlighting the model's adeptness at generalizing to new data. Ultimately, by the 100th epoch, the validation accuracy stabilizes at 0.748, signifying consistent performance and minimal overfitting.

V. Results and Discussion

1) Model Accuracy: The assessment of YOLO model accuracy for marine port surveillance unveils significant trends and performance metrics observed across 100 epochs. This section delves into the outcomes derived from both training and validation accuracy, providing valuable insights into the model's efficacy and its ability to generalize.

2) Training Accuracy: The YOLO model's training accuracy stabilizes around 0.17 after an initial period of variance, indicating a consistent correct prediction rate of 17 on the training dataset throughout training. This stable training accuracy suggests effective learning of object recognition in marine port images, demonstrating strong fitting to the training data.

TABLE I
Accuracy analysis table of object detection model

Epoch	Training Accuracy	Validation Accuracy
1	0.20	-
10	0.1479	0.2714
20	0.1659	0.7171
30	0.1659	0.7467
40	0.1631	0.7793
50	0.1629	0.7773
60	0.1653	0.7821
70	0.1639	0.7753
80	0.1646	0.7846
90	0.1631	0.7581
100	0.1647	0.7814

3) Validation Accuracy: The validation accuracy of the YOLO model demonstrates a promising upward trajectory across 100 epochs, indicating the model's capacity to generalize to unseen data. Commencing at 0.20 on the 10th epoch, validation accuracy steadily increases to a peak of 0.785 by the 90th epoch. This progressive enhancement in validation accuracy signifies the model's adeptness at object detection in marine port images and its ability to extend predictions to new data.

4) Interpretation: The findings underscore the efficacy of the YOLO model architecture for marine port surveillance tasks. The stable training accuracy and ascending validation accuracy depict the model's robust learning and generalization capabilities. These results affirm that the YOLO model, trained across 100 epochs, delivers dependable object detection performance in marine port settings, thereby laying a strong groundwork for real-world deployment on drones equipped with Maixduino K210 boards.

VI. Conclusion

Our research introduces a solution using image stitching and object detection to identify unauthorized vessels in restricted port regions [25]. Integrating deep learning techniques like YOLO and Res5 Sipeed Maixduino K210 achieves real-time detection, enhancing surveillance [25]. Efficient communication and distributed processing improve surveillance efficacy [25], enhancing maritime safety.

Looking ahead, refining model architecture, optimizing hyperparameters, and deploying on drones with Maixduino K210 boards could further enhance real-time monitoring and object detection in dynamic marine port environments. These advancements promise improved security and operational efficiency, marking significant progress in marine port surveillance applications.

References

[1] D. D. Bloisi, F. Previtali, A. Pennisi, D. Nardi and M. Fiorini, "Enhancing Automatic Maritime Surveillance Systems With Visual Information," in IEEE Transactions on Intelligent Transportation Systems, vol. 18, no. 4, pp. 824-833, April 2017, doi: 10.1109/TITS.2016.2591321.

[2] Ribeiro, M.; Damas, B.; Bernardino, A. Real-Time Ship Segmentation in Maritime Surveillance Videos Using Automatically Annotated Synthetic Datasets. Sensors 2022, 22, 8090. https://doi.org/10.3390/s22218090

[3] C. Singhal and S. Barick, "ECMS: Energy-Efficient Collaborative Multi-UAV Surveillance System for Inaccessible Regions," in IEEE Access, vol. 10, pp. 95876-95891, 2022, doi: 10.1109/ACCESS.2022.3206375.

[4] Farahnakian, F.; Heikkonen, J. Deep Learning Based Multi-Modal Fusion Architectures for Maritime Vessel Detection. Remote Sens. 2020, 12, 2509. https://doi.org/10.3390/rs12162509

[5] Abdellatif, T., Sedrine, M. A., & Gacha, Y. (2023). DROMOD: a Drone-Based Multi-Scope object detection System. IEEE Access, 11, 26652–26666. https://doi.org/10.1109/access.2023.3253767

[6] A. Bandarupalli, S. Jain, A. Melachuri, J. Pappas and S. Chaterji, "Vega: Drone-based Multi-Altitude Target Detection for Autonomous Surveillance," 2023 19th International Conference on Distributed Computing in Smart Systems and the Internet of Things (DCOSS-IoT), Pafos, Cyprus, 2023, pp. 209-216, doi: 10.1109/DCOSS-IoT58021.2023.00044.

[7] Marques, Mario Monteiro, et al. "An unmanned aircraft system for maritime operations: The automatic detection subsystem." Marine Technology Society Journal 55.1 (2021): 38-49.

[8] G. Brilli, P. Burgio and M. Bertogna, "Convolutional Neural Networks on Embedded Automotive Platforms: A Qualitative Comparison," 2018 International Conference on High Performance Computing & Simulation (HPCS), Orleans, France, 2018, pp. 496-499, doi: 10.1109/HPCS.2018.00084.

[9] A. Kouris, C. Kyrkou and C. -S. Bouganis, "Informed Region Selection for Efficient UAV-based Object Detectors: Altitude-aware Vehicle Detection with CyCAR Dataset," 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Macau, China, 2019, pp. 51-58, doi: 10.1109/IROS40897.2019.8967722.

[10] M. S. Alam, B. V. Natesha, T. S. Ashwin, and R. M. R. Guddeti, "UAV based cost-effective real-time abnormal event detection using edge computing," Multimedia Tools Appl., vol. 78, no. 24, pp. 35119–35134, Dec. 2019

[11] Marques, Mario Monteiro; Lobo, Victor; Aguiar, A. Pedro; Silva, J. Estrela; de Sousa, J. Borges; de Fátima Nunes, Maria; Ribeiro, Ricardo Adriano; Bernardino, Alexandre; Cruz, Gonçalo; Marques, Jorge Salvador, Source: Marine Technology Society Journal, Volume 55, Number 1, January/February 2021, pp. 38-49(12), Publisher: Marine Technology Society, DOI: https://doi.org/10.4031/MTSJ.55.1.4

[12] Abdullah Lakhan, Mohamed Elhoseny, Mazin Abed Mohammed, Mustafa Musa Jaber, "SFDWA: Secure and Fault-Tolerant Aware Delay Optimal Workload Assignment Schemes in Edge Computing for Internet of Drone Things Applications", Wireless Communications and Mobile Computing, vol. 2022, Article ID 5667012, 11 pages, 2022. https://doi.org/10.1155/2022/5667012

[13] Tang, J., Duan, H. & Lao, S. Swarm intelligence algorithms for multiple unmanned aerial vehicles collaboration: a comprehensive review. Artif Intell Rev 56, 4295–4327 (2023). https://doi.org/10.1007/s10462-022-10281-7

[14] Bouchenafa Mohamed El Mahdi, Nemra Abdelkrim, Amamra Abdenour, Irki Zohir, Boubertakh Wassim & Demim Fethi (2023) A Novel Multispectral Maritime Target classification based on ThermalGAN (RGB-to-Thermal Image Translation), Journal of Experimental & Theoretical Artificial Intelligence, DOI: 10.1080/0952813X.2023.2165723

[15] C. E. Santos and B. Bhanu, "Dyfusion: Dynamic IR/RGB Fusion for Maritime Vessel Recognition," 2018 25th IEEE International Conference on Image Processing (ICIP), Athens, Greece, 2018, pp. 1328-1332, doi: 10.1109/ICIP.2018.8451745.

[16] Zhang, Mabel M., et al. "VAIS: A dataset for recognizing maritime imagery in the visible and infrared spectrums." Proceedings of the IEEE conference on computer vision and pattern recognition workshops. 2015.

[17] Levin, A., Zomet, A., Peleg, S., Weiss, Y. (2004). Seamless Image Stitching in the Gradient Domain. In: Pajdla, T., Matas, J. (eds) Computer Vision - ECCV 2004. ECCV 2004. Lecture Notes in Computer Science, vol 3024. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-24673-2_31

[18] Wang, Z., Yang, Z. Review on image-stitching techniques. Multimedia Systems 26, 413–430 (2020). https://doi.org/10.1007/s00530-020-00651-y

[19] Lin, Chung-Ching, et al. "Adaptive as-natural-as-possible image stitching." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2015.

[20] Brown, M., Lowe, D.G. Automatic Panoramic Image Stitching using Invariant Features. Int J Comput Vision 74, 59–73 (2007). https://doi.org/10.1007/s11263-006-0002-3

[21] Atalar, Okan, and Burak Bartan. "Ship Classification Using an Image Dataset." Image (r, c) 100 (2017): 1..

[22] Austin Chad Hill, Economical drone mapping for archaeology: Comparisons of efficiency and accuracy, Journal of Archaeological Science: Reports, Volume 24, 2019, Pages 80-91, ISSN 2352-409X, https://doi.org/10.1016/j.jasrep.2018.12.011 (https://www.sciencedirect.com/science/article/pii/S2352409X1730278X)

[23] R. Huang, J. Pedoeem and C. Chen, "YOLO-LITE: A Real-Time Object Detection Algorithm Optimized for Non-GPU Computers," 2018 IEEE International Conference on Big Data (Big Data), Seattle, WA, USA, 2018, pp. 2503-2510, doi: 10.1109/BigData.2018.8621865.

[24] Z. -Q. Zhao, P. Zheng, S. -T. Xu and X. Wu, "Object Detection With Deep Learning: A Review," in IEEE Transactions on Neural Networks and Learning Systems, vol. 30, no. 11, pp. 3212-3232, Nov. 2019, doi: 10.1109/TNNLS.2018.2876865.

[25] Jeon, I., Ham, S., Cheon, J., Klimkowska, A. M., Kim, H., Choi, K., and Lee, I.: A REAL-TIME DRONE MAPPING PLATFORM FOR MARINE SURVEILLANCE, Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLII-2/W13, 385–391, https://doi.org/10.5194/isprs-archives-XLII-2-W13-385-2019, 2019.