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

***Abstract*—The unauthorized entry of vessels into restricted port areas poses significant security risks and regulatory challenges. Traditional surveillance methods often fall [1] short in providing timely and comprehensive monitoring, leading to potential security breaches and operational inefficiencies. We propose a system that utilizes [2] 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, notifies the appropriate authorities by transmitting real-time coordinates of the intruding vessel. Unauthorized vessel detection is carried out by using [3] Deep Learning Algorithm on the Micro-processor onboard each drone. Pub-Sub Model is used for fast and secure communication between the Drones and the MIS. Authorities use the drones to scan the designated area simultaneously, processing images by image stitching and storing them in the drones. It will process on the drones platform and verify the authorization of the vessel, if unauthorized vessel is detected, then The Image along with the co-ordinates of the vessel are sent to the MIS via the Pub-Sub Model. Drones process this by balancing the workload over a certain span of time.**

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

I. Introduction

Modern technology has been incorporated into unmanned aerial vehicles (UAVs) in recent years, revolutionizing a number of sectors, including security and surveillance. In order to significantly enhance mapping and object detection capabilities, this paper presents a system that makes utilization of image stitching technology within drone platforms. The main objective of this system is to address the critical challenge of identifying unauthorized watercraft and vessels entering authorized port regions. Unauthorized vessel [4] accessibility into restricted port regions involves serious regulatory and security threats. Conventional techniques for surveillance often struggle to provide complete and timely monitoring, which could result in operational inefficiencies as well as potential security breaches. Our research proposes a complex approach to get beyond these restrictions that makes use of deep learning techniques. Specifically, the YOLO model running on the Res5 Sipeed Maixduino K210 provides real-time detection and identification of intruding vessels.

The application of imagine stitching technology, which enables the smooth integration of several images taken from different areas into detailed maps of the monitored geographical area, is essential to our strategy. This enables drones to simultaneously examine designated maritime zones while advanced imagine stitching algorithms process images on board. A Pub-Sub Model is used to allow drones and the Maritime Information System (MIS) to communicate quickly and securely. This makes sure that the right authorities receive the real-time coordinates of any trespassing vessels efficiently, allowing for quick action and response. Furthermore, the workload is balanced among several drones over a certain amount of time in order to optimize resource efficiency and reduce processing time. The efficiency of maritime surveillance operations is improved overall because of this dispersed processing strategy, which guarantees prompt verification of vessel authorization.

II. Related Work

Over recent years, extensive research has delved into harnessing Unmanned Aerial Vehicle (UAV) networks for surveillance applications, driving advancements in object detection optimization, communication protocol refinement, and overcoming inherent challenges. The Drone-based Multi-scope Object Detection (DroMOD) system [5] represents a significant breakthrough, tailored to enhance object detection efficiency via drones. However, it grapples with ensuring seamless communication between the drone and server, reliant solely on transmitting changed images, potentially leading to latency issues . Additionally, projects like Vega [6] address the intricate tradeoffs between coverage area, detection latency, and quality in drone-based surveillance, proposing efficient drone deployment frameworks and algorithmic primitives.

Further, initiatives such as the SEAGULL project [7] underscore the pivotal role of integrated systems in supporting maritime situation awareness via UAVs, achieving high precision rates and recalls in vessel detection. Alongside advancements in neural networks on embedded platforms [8], strategies for efficient deployment of region-based object detectors [9], and proposals for cost-effective aerial surveillance systems [10], the literature reflects a thorough exploration of UAV networks for surveillance applications, promising heightened 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 airspace, sending and receiving images of targeted areas or objects in real-time. The drone also has onboard processing capabilities.

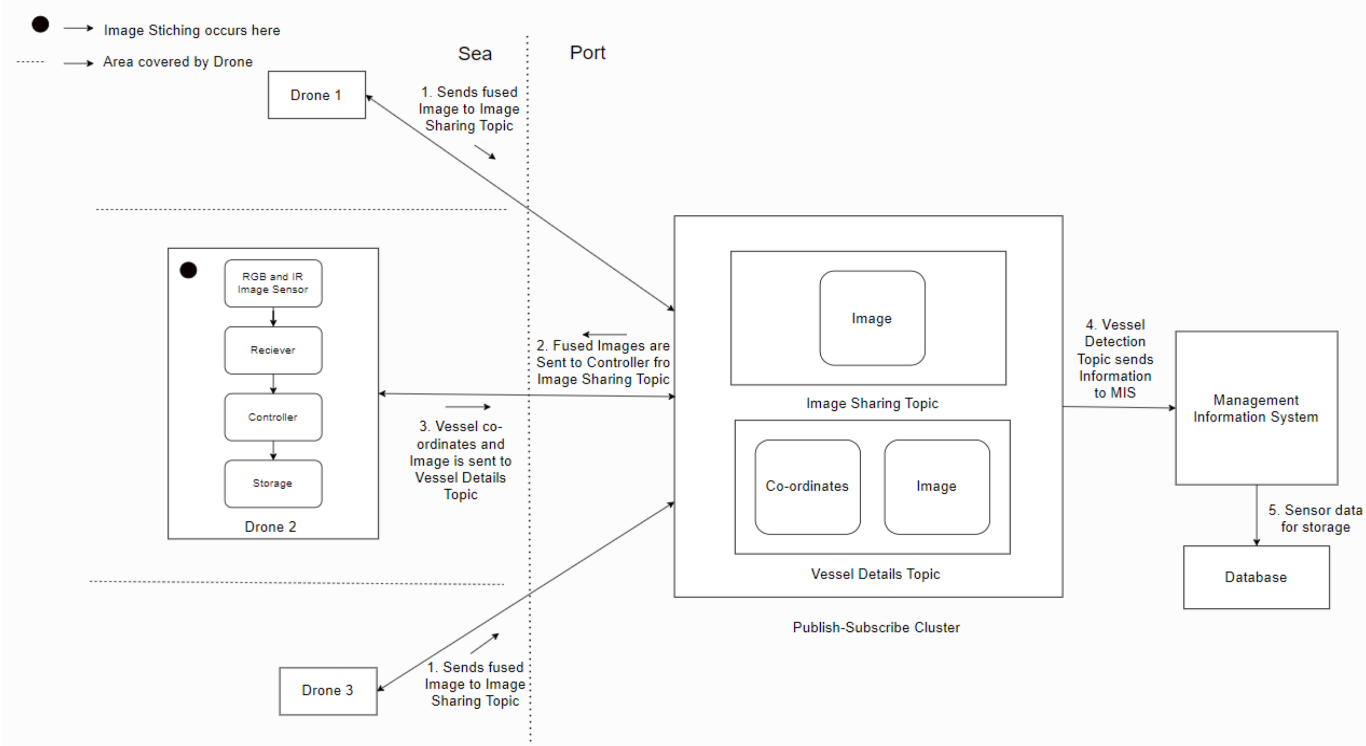

Fig. 1. System diagram illustrating the integration of drones equipped with image sensors, receivers, controllers, and storage units, connected to a publish-subscribe cluster. The publish-subscribe cluster hosts two topics: "Image Sharing" for inter-drone image sharing and "Vessel Details" for conveying 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.

- 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.
- 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 Image and co-ordinates of the unauthorised vessel through the Pub-Sub Model. The MIS displays the co-ordinates of the Unauthorized vessel on a Map along with the image for identification. The above information is also sent to 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.

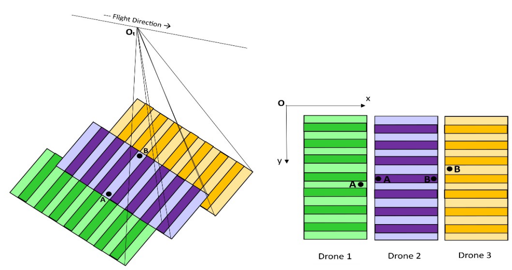

Fig. 2. Image Acquisition Trajectory

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 misclassification of object classes. This multi-task loss function ensures that the model optimizes across all aspects of object detection.

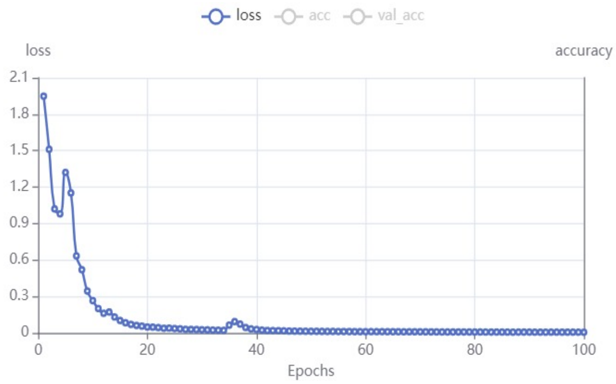

Fig. 3. Loss Function Graph

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 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]

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):
$D' = \frac{D}{n}$
Determine the threshold distance (D_{thresh}) for each drone to cover such that they use 70% of their battery capacity:
$D_{\text{thresh}} = 0.7 \times D'$
Initialize variables:
$CurrentDroneIndex = 1$
$CurrentBatteryPercentage = 100$
Initialize array to track remaining distance for each drone: $RemainingDistance[1...n]$
while $CurrentDroneIndex \leq n$ **do**
    $RemainingDistance[CurrentDroneIndex] = D'$
    while $RemainingDistance[CurrentDroneIndex] > D_{\text{thresh}}$ **do**
        Perform surveillance with the current drone covering distance D_{thresh}.
        $RemainingDistance[CurrentDroneIndex] -= D_{\text{thresh}}$
        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.

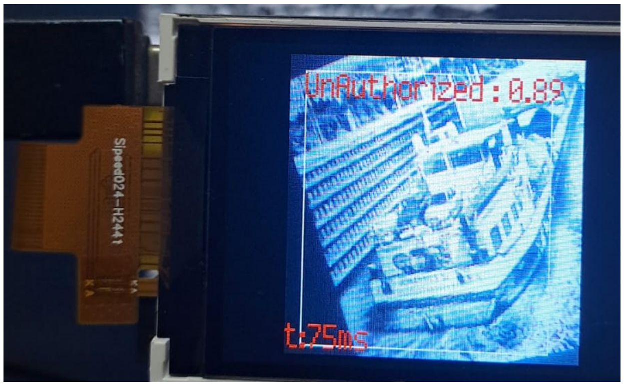

Fig. 4. Visualizing unauthorized vessel detection on Res5 Microprocessor screen with YOLO model.

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.

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

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 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.

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. Future Scope

The attainment of high validation accuracy by the YOLO model bodes well for marine port surveillance applications. Future endeavors could center on further refining the model architecture, optimizing hyperparameters, and integrating additional data augmentation techniques to augment model performance. Moreover, deploying the trained model on drones equipped with Maixduino K210 boards could facilitate real-time monitoring and object detection in dynamic marine port environments, fostering improved security and operational efficiency.

VII. Conclusion

In conclusion, our research introduces a solution that uses image stitching and object detection, to address the critical challenge of identifying unauthorized vessels in restricted port regions [25]. By integrating deep learning techniques like the YOLO model and the Res5 Sipeed Maixduino K210, we achieve real-time detection and identification of intruding vessels, enhancing surveillance effectiveness. The application of image stitching technology enables drones to generate detailed and high resolution maps of monitored geography, facilitating simultaneous examination of maritime zones. Efficient communication via a Pub-Sub paradigm ensures prompt transmission of vessel coordinates to the appropriate authorities, enabling swift response. Additionally, the distributed processing technique reduces processing time and enhances resource utilization, improving the efficacy of maritime surveillance operations.Through applying cutting edge technology and communication, our strategy improve situational awareness and reaction time, hence augmenting maritime safety.

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