UAV-Driven Maritime Object Detection and Classification: Literature Review of AI Models, Data, and Performance

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Abstract: This literature review explores the integration of UAVs and AI in maritime surveillance, analyzing 59 peer-reviewed studies from 2020–2025. It highlights trends in object detection and classification, common methodologies, model architecture (notably YOLO), and evaluation metrics like mAP. Detection targets include boats, ships, and swimmers, with varying research focus. The review identifies technological approaches, research gaps, and growing interest in UAV-based maritime monitoring.
Keywords: UAV. Maritime Environment. Object Detection. Model Architecture. Machine Learning.
Abbreviations: UAV, Unmanned Aerial Vehicle. mAP, mean Average Precision. CNN, Convolutional Neural Network. IoU, Intersection over Union. FPS, Frames Per Second. AI, Artificial Intelligence.

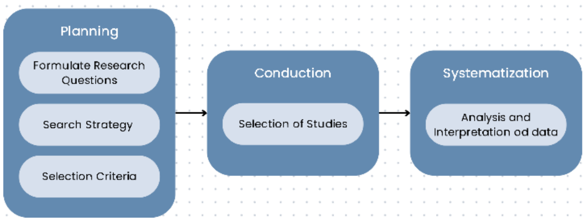
1. Introduction

Marine environments present challenges for object detection, these environments are typically more adverse and unstable than those encountered in autonomous driving applications, due to factors such as fog, rain, wave interference, shoreline complexity, and the absence of structured features like lane lines, all of which significantly reduce visibility [1]. Traditional monitoring systems also face limitations related to spatial coverage, temporal constraints, and operational costs. They often face limitations related to spatial coverage, temporal constraints, and operational costs [2].
Unmanned Aerial Vehicles (UAVs) integrated with Artificial Intelligence (AI) have emerged as an alternative approach for maritime object detection and classification, these can operate in coastal areas, harbors, and open ocean locations to collect imagery for monitoring. Their efficient deployment is particularly valuable when large regions need to be rapidly surveyed [3].
This literature review analyzes UAV-based maritime surveillance with AI integration by surveying methodological approaches, comparing performance across detection targets (vessels and swimmers), examining architectural preferences and evaluation metrics, and identifying research gaps.

2. Methodology

The study is characterized as exploratory, using literature review as method and bibliometric analysis as procedure, assisting in trends identification in knowledge expansion in UAV maritime object detection, as well as research gaps, and in the identification of journals most used for research dissemination in this specific area.
The study design was divided into three main stages: planning, conduction, and systematization, as can be seen in Figure 1. From the objective, a protocol was developed with research questions, keywords, inclusion and exclusion criteria.

Figure 1. Methodology diagram.



2.1. Planning

The exploratory approach required planning research questions to map methods, identify trends, and point out gaps in UAV maritime object detection studies.

2.1.1 Formulate Research Questions

The work is guided by seven research questions, addressing aspects of UAV-driven maritime object detection systems: RQ1: What are the primary research objectives in UAV-driven maritime object detection studies?; RQ2: What techniques enhance maritime imagery for automated analysis?; RQ3: Which deep learning architectures and computational techniques show optimal performance for maritime object detection tasks?; RQ4: What evaluation metrics and validation methodologies assess system performance?; RQ5: How extensively are UAV systems integrated into current research implementations?; RQ6: What environmental conditions and maritime contexts are primarily addressed in current research?; RQ7: How do the models perform on the defined dataset?
RQ1 aims to map the main technology domain applications. RQ2 and RQ3 analyze technical aspects, with emphasis on image processing and AI architecture. RQ4 seeks to understand performance evaluation and validation methods. RQ5 examines system integration. Finally, RQ6 and RQ7 synthesize the findings addressing application contexts.

2.1.2 Search Strategy and Selected Databases

The keywords used were: (learning model) AND ("classification" OR "detection" OR "segmentation") AND (aerial image) AND ("maritime" OR "boat" OR "ship" OR "swimmer").
The search was conducted in the following databases: IEEE Xplore Digital Library; ScienceDirect (Elsevier); MDPI Publications. These databases ensure peer-reviewed quality and academic credibility.
Related to time, we are looking for studies published between January 2020 and April 2025 to capture recent research developments, including both journal articles and conference proceedings in English.

2.1.3 Selection Criteria

Inclusion Criteria:

- Studies addressing classification, detection, or segmentation of vessels or swimmers in maritime environments.
- Research incorporating UAV applications or aerial imagery analysis.
- Publications providing methodological descriptions and quantitative results.
- Peer-reviewed studies published in reputable venues (2020-2025).
- Full-text accessibility for analysis.
- Primary research contributions (excluding reviews and meta-analyses).

Exclusion Criteria:

- Incomplete publications (expanded abstracts, conference posters, position papers).
- Studies lack keywords in title, abstract, or keyword sections.
- Research does not directly address maritime object detection tasks.
- Inaccessible full-text publications.
- Duplicated publications or multiple versions of same studies.
- Secondary research (reviews, surveys, opinion pieces).

2.2. Research Conduction

The initial search yielded 2,498 results, with 127 studies proceeding to full-text evaluation after title and abstract screening. As illustrated in Figure 2, publication volume increased from 8 studies in 2020 to 47 in 2024. In terms of publication venues, ScienceDirect accounted for the largest share, followed by IEEE and MDPI, as shown in Figure 3.

Figure 2. Articles Distribution by Year.

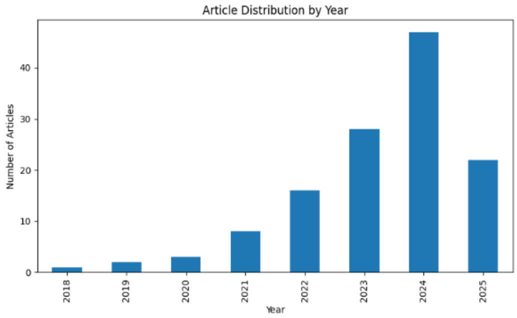
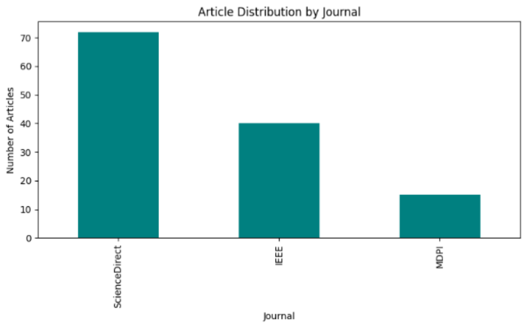


Figure 3. Articles Distribution by Journal.



After applying the established criteria, 59 studies were selected for final analysis. Data extraction employed was helpful to address model architectures, evaluation metrics and preprocessing techniques.

2.3. Research Systematization

In the systematization of results, quantitative analysis was performed including frequency analysis of methodological approaches, aggregation of performance metrics and statistical analysis, temporal trend analysis of publication patterns, and comparative analysis between detection targets and environmental conditions. Qualitative synthesis involves thematic analysis of research trends, identification of methodological patterns, assessment of technological maturity levels. Data visualization and tabulation were performed by the authors using extracted information from the selected studies. All figures and tables represent original analysis and synthesis of the reviewed literature.

3. Results

The following sections seeks to answer the research questions, relating the found papers and their contributions on these topics.

3.1. Research Objectives Analysis (RQ1)

The research objectives focus on five main application domains, as shown in Table 1. Categories are not mutually exclusive. Articles may address multiple objectives simultaneously, resulting in overlapping classifications.

Table 1. Objectives and References

Objective	References
Maritime Monitoring (89.8%)	[1–53]
Coastal Security and Surveillance (25.4%)	[3, 6, 11, 13, 15, 21–25, 44, 45, 48, 50, 54]
Beach Safety Management (23.7%)	[5, 11, 13, 18, 22, 26–29, 32, 36, 44, 46, 50]
Search and Rescue Operations (15.3%)	[3, 5, 18, 26, 27, 29, 32, 36, 46]
Environmental Protection (6.8%)	[13, 44, 50, 54]

3.2. Preprocessing Techniques Analysis (RQ2)

The data composition involved public datasets (SeaDronesSee [55], Ships Dataset [56, 57], MOBdrones [58]), custom-built collections, and synthetic images generated to training.

Preprocessing included resizing (640×640 or 480×480), data augmentation (flips, rotations, contrast/brightness adjustments, mosaic), color conversion, histogram equalization, noise reduction, patch extraction, anchor box optimization, and simulation of adverse weather conditions.

Annotations, whether manual or automated, followed COCO and PASCAL VOC formats, including rotated bounding boxes and segmentation masks for improved precision. Data splitting predominantly adopted the hold-out method (70/20/10 or 80/20). These steps aimed to improve training quality, reduce detection errors and increase generalization, directly impacting metrics such as mAP, Precision.

3.3. Model Architecture Analysis (RQ3)

Regarding deep learning architecture, the analysis reveals a significant dominance of the YOLO (You Only Look Once) versions, which constitutes 65.9% of the analyzed implementations. Preference is distributed among its various versions, such as YOLOv5 and YOLOv8 with most implementations, as shown in Figure 4.

Figure 4. Most Used Architecture.

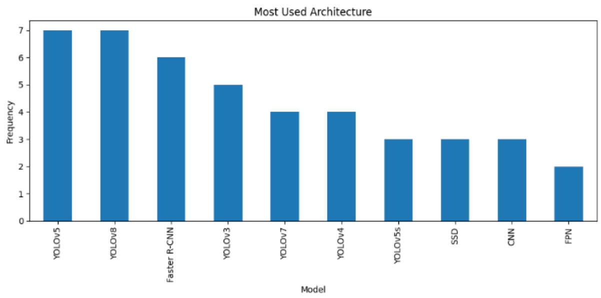


Table 2 presents Faster R-CNN as the most significant alternative. SSD and CNN are present, but seldom.

Table 2. Architecture and References

Architecture	References
YOLOv8	[4, 10, 18, 26, 34, 37, 62]
YOLOv5	[1, 4, 16, 43, 59–61]
Faster R-CNN	[1, 6, 24, 36, 61, 62]
SSD	[24, 47, 62]
CNN	[12, 27, 36]

3.4. Evaluation Metrics Analysis (RQ4)

The analyzed studies reveal the use of Mean Average Precision (mAP) as the main evaluation metric followed by Recall, Precision and FPS for processing speed, as shown in Figure 5. Other commonly used metrics include Average Precision (AP), F1-Score, Intersection over Union (IoU) and Accuracy, and computational efficiency indicators like Parameters and Gflops, as seen in Table 3.

Figure 5. Most Used Metrics.

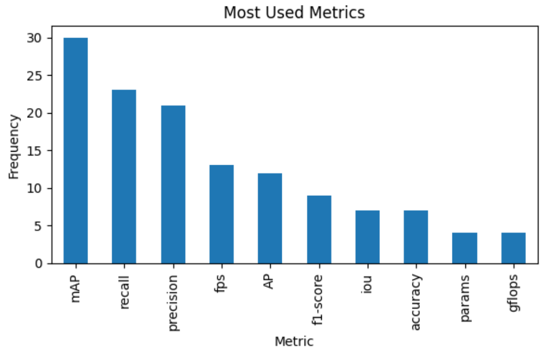


Table 3. Metric and References

Metric	References
mAP (50.8%)	[1, 2, 4, 5, 8–10, 13, 14, 17, 18, 21, 22, 24–26, 28, 29, 34, 35, 39–41, 43, 45, 54, 59–62]
Recall (38.9%)	[1, 4, 5, 10, 13–15, 20, 22, 23, 28, 30, 35, 38, 39, 41–43, 46, 50, 51, 54, 59]
Precision (35.5%)	[1, 5, 10, 14–16, 20, 23, 30, 34, 35, 38, 39, 41–43, 46, 50, 51, 54, 59]
FPS (22.0%)	[7, 9, 11, 16, 21, 24, 25, 28, 38, 41, 46, 49, 50]
AP (20.3%)	[5, 8, 10, 14, 31, 33, 36, 38, 40, 46, 47, 50],
F1-Score (15.2%)	[2, 5, 14, 20, 23, 34, 41, 42, 49]
IOU (11.8%)	[2, 6, 11, 15, 19, 24, 36],
Accuracy (11.8%)	[6, 12, 23, 34, 42, 44, 62]
Parameters (6.7%)	[7, 33, 46, 49]
Gflops (6.7%)	[7, 9, 38, 41]

3.5. UAV Integration Analysis (RQ5)

Although the focus of this review was on UAV-based applications, not all selected studies used images captured by UAVs. As presented in Figure **6**, the UAV integration analysis shows that 74.6% of studies explicitly reported UAV use, 18.6% studies did not specify the aerial platform, and 6.8% studies employed other aerial sources, as presented in Table 4.

Figure 6. Articles related to UAV.

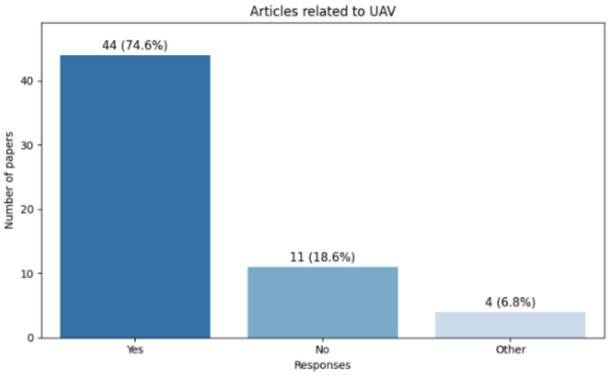


Table 4. UAV Related and References

UAV Related	References
Yes	[2–13, 15–32, 35, 36, 41, 46–50, 52, 54, 59–61]
No	[1, 33, 34, 37–40, 42, 44, 45, 62]
Others	[14, 43, 51, 53]

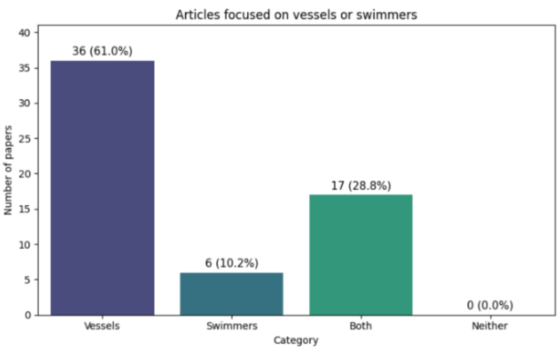
3.6. Environmental Context Analysis (RQ6)

The analysis of detection targets shows the distribution of research across maritime object categories. As seen in Table 5 and Figure 7, vessel detection takes the largest share, followed by combined approaches, and swimmer detection last.

Table 5. Object detection target and References

Object	References
Vessel	[1, 2, 5–8, 10–13, 15–17, 20–23, 25, 30, 31, 33, 34, 37–40, 42–46, 48, 52–54, 62]
Swimmer	[26, 27, 36, 41, 47, 61]
Both	[3, 4, 9, 14, 18, 19, 24, 28, 29, 32, 35, 36, 49–51, 59, 60]

Figure 7. Articles focused on vessels or swimmers.



3.7. Performance Analysis (RQ7)

Performance varies across datasets and detection targets, influenced by object type and environmental conditions. YOLO-based models generally provide stable results, achieving higher accuracy for vessel detection compared to swimmer detection.

In maritime-specific datasets, YOLOv8 variants have reached up to 97% accuracy in controlled environments [34]. However, detecting small objects remains a persistent challenge, with reduced accuracy observed for targets such as swimmers or distant vessels. Adverse weather conditions, including rain and haze, significantly degrade detection performance, with mean average precision dropping by 73% to 93% in synthetic datasets [1]. Nevertheless, approaches such as weather simulation and synthetic data augmentation have demonstrated improvements.

The use of multi-modal data, combining visible and near-infrared imagery, enhances generalization, achieving up to 99.5% AP@0.50 for larger vessels [39]. Similarly, transfer learning from general-purpose datasets like COCO, when fine-tuned for maritime applications, has produced mAP scores of up to 67.6% across detection classes [18]. Overall, vessel detection consistently outperforms swimmer detection across different models and environmental conditions.

4. Discussion

This review highlights UAV-driven maritime object detection trends. YOLO dominates implementations, reflecting efficiency needs for real-time UAV operations but limiting architectural diversity. Standardized metrics (mAP, Precision, Recall) enable cross-study comparison, and steady publication growth signals field maturation. However, performance gaps between vessel and swimmer detection expose persistent challenges in small-object identification under dynamic maritime conditions.

The analysis reveals that while maritime monitoring represents the dominant research objective, the field exhibits significant overlap in application domains. This multifaceted approach reflects the practical reality that UAV-based maritime surveillance systems must serve diverse stakeholder needs, from coastal security to search and rescue operations.

4.1. Research Gaps and Future Directions

Current research exhibits significant gaps in multi-modal sensor integration, with limited exploration of weather-robust fusion techniques despite maritime environments' demanding conditions. The absence of standardized benchmark datasets complicates method comparison and performance validation across studies.

Swimmer detection research is severely underrepresented, limiting search and rescue capabilities. Real-world validation studies are scarce. Adverse weather conditions cause dramatic performance drops, highlighting robustness limitations.

A few studies suggest improvement of small debris detection, exploration of architectures beyond YOLO, and development of frameworks for object identification, these directions lack implementation specificity. The call for multimodal systems for standardizing protocols and real-time operations requires more detailed technical frameworks.

4.2. Limitations

This review's scope limitations include English-language restriction and temporal boundaries (2020-2025), potentially excluding relevant international research and foundational studies. Database selection may miss specialized maritime publications, while evaluation metric heterogeneity limits direct performance comparisons and benchmark establishment.

5. Conclusions

The literature review indicates that YOLO architecture models are the predominant approach for object detection and classification in maritime environments, driven by their real-time efficiency, although their dominance in the field raises questions about the overall performance across different types of objects and environmental conditions. The work also revealed some gaps in the area, such as limited articles focused on swimmer detection and limited use of multimodal approaches, which could significantly improve system robustness under adverse conditions.

Furthermore, the growth of research in the area indicates field prosperity, with the following directions suggested for future studies: improvement of small debris detection; exploration of architectures beyond YOLO; a framework for object identification; and a multimodal system for standardizing protocols and real-time operations that considers the identified performance disparities.

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