EAI Endorsed Transactions
on Transportation Systems and Ocean Engineering Review Article **EAI.EU**

Federated Learning for Ship Detection in Remote Sensing Imagery: Current Progress and Future Directions

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Abstract

Ship detection plays a vital role in maritime surveillance by enabling vessel traffic monitoring, maritime security, the prevention of illegal fishing, and search-and-rescue operations. Advances in deep learning, transformer-based architectures, and multimodal remote sensing have substantially improved ship detection performance in both optical and synthetic aperture radar (SAR) imagery. Nevertheless, practical maritime monitoring systems often rely on distributed data sources managed by various organizations, complicating centralized data sharing due to privacy, security, and regulatory constraints. Federated Learning (FL) has emerged as a promising approach that facilitates collaborative model training without the need to exchange raw data. This article provides a comprehensive review of ship detection and federated learning within the context of privacy-preserving maritime surveillance. The evolution of ship detection technologies, key federated learning algorithms, and recent applications of federated learning in remote sensing are systematically examined. In addition, current challenges such as data heterogeneity, communication overhead, computational complexity, and limited benchmark availability are discussed. Potential research directions for developing scalable, privacy-preserving, and distributed ship detection systems are also identified. This review serves as a structured reference for researchers and practitioners seeking to integrate federated learning with maritime remote sensing applications.

Keywords: Federated Learning, Maritime Surveillance, Object Detection, Remote Sensing, Ship Detection

Received on 30 May 2026, accepted on 04 August 2026, published on 13 August 2026

doi: 10.4108/tsoe.13253

1. Introduction

Maritime surveillance is essential for vessel traffic management, maritime security, preventing illegal fishing, environmental protection, and search-and-rescue operations. With the increasing availability of high-resolution remote sensing imagery from satellites, aircraft, and uncrewed aerial vehicles (UAVs), automatic ship detection has become a key research topic in maritime monitoring systems.

Over the past decade, ship detection techniques have evolved significantly. Traditional methods relied on handcrafted features and statistical approaches, such as Constant False Alarm Rate (CFAR) algorithms, which often struggled in complex maritime environments [1], [2].

The emergence of deep learning substantially improved detection performance through CNN-based detectors, including Faster R-CNN, SSD, and YOLO [3]–[5]. More recently, transformer-based architectures and multimodal frameworks have further enhanced detection accuracy by capturing richer contextual information and integrating optical and SAR imagery [6]–[8].

Despite these advances, practical ship detection systems still face significant challenges. Maritime data are typically distributed across multiple organizations, such as satellite operators, coast guards, port authorities, and maritime monitoring agencies. Privacy regulations, security concerns, and data ownership restrictions often limit centralized data collection and sharing, making collaborative model development difficult.

Federated Learning (FL) has emerged as a promising solution by enabling multiple participants to

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collaboratively train machine learning models without exchanging raw data [9]–[12]. Recent studies have demonstrated its effectiveness in remote sensing and distributed vision applications [13]–[18]. However, its application to ship detection remains relatively unexplored.

To address this gap, the present review offers an in-depth comparative analysis of ship detection methods and federated learning algorithms, explicitly highlighting their strengths, limitations, and applicability to distributed maritime environments. The unique contributions of this work are threefold: (i) a structured taxonomy that integrates ship detection and federated learning paradigms for privacy-preserving surveillance; (ii) a critical evaluation of methodological trade-offs and a systematic identification of research gaps, incorporating quantitative insights into detection performance and learning efficiency; and (iii) a forward-looking discussion of open challenges such as benchmark standardization, cross-modality learning, and federated foundation models. Recent studies published in EAI Endorsed Transactions on Transportation Systems and Ocean Engineering have advanced maritime artificial intelligence and intelligent control applications, such as deep learning for ship-to-shore crane operations [19], while also addressing legal frameworks relevant to environmental risk management in inland waterway transport [20]. These works further motivate the need for collaborative intelligence in ocean engineering. This survey thus serves as a comprehensive reference for researchers aiming to bridge federated learning and maritime remote sensing.

2. Background

2.1. Ship detection research landscape

Ship detection has become a fundamental task in maritime surveillance, supporting applications such as vessel traffic monitoring, illegal fishing detection, maritime border security, and search-and-rescue operations. Existing ship detection approaches are typically categorized as traditional, deep learning-based, transformer-based, or multimodal methods, as illustrated in Figure 1 [1]–[8].

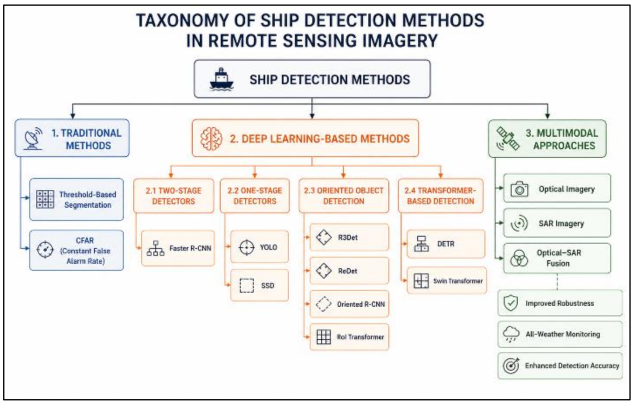

Figure 1. Taxonomy of ship detection methods in remote sensing imagery

Early ship detection methods relied on handcrafted features and statistical techniques, particularly Constant False Alarm Rate (CFAR) algorithms, which offered low computational complexity but often struggled in complex maritime environments [2].

The emergence of deep learning significantly improved ship detection performance. CNN-based approaches enhanced feature extraction and localization accuracy in both SAR and optical remote sensing imagery [3]–[5], [21], [22]. However, conventional detectors often face difficulties when detecting arbitrarily oriented ships in aerial and satellite imagery.

To address this limitation, several rotated object detection frameworks, including R3Det, ReDet, Oriented R-CNN, RoI Transformer, and Gliding Vertex, were proposed to improve localization accuracy through rotation-aware representations and geometric refinement strategies [23]–[27].

More recently, transformer-based architectures have become a promising direction for remote sensing image analysis. DETR introduced an end-to-end detection framework based on self-attention, while the Swin Transformer improved feature representation through hierarchical transformer structures [7], [8]. Although these methods achieve strong performance, they generally require substantial computational resources.

Multimodal ship detection has also attracted increasing attention. By combining optical and SAR imagery, multimodal approaches improve robustness under varying environmental conditions [6]. Nevertheless, effective cross-modal feature fusion remains an open challenge.

In addition, large-scale benchmark datasets such as ShipRSImageNet have facilitated the development and evaluation of advanced ship detection algorithms [28].

Figure 2 presents representative examples of ship detection in optical and SAR remote sensing imagery.

Optical imagery provides rich visual appearance information, whereas SAR imagery enables reliable all-weather observation, motivating the development of multimodal detection frameworks [6].

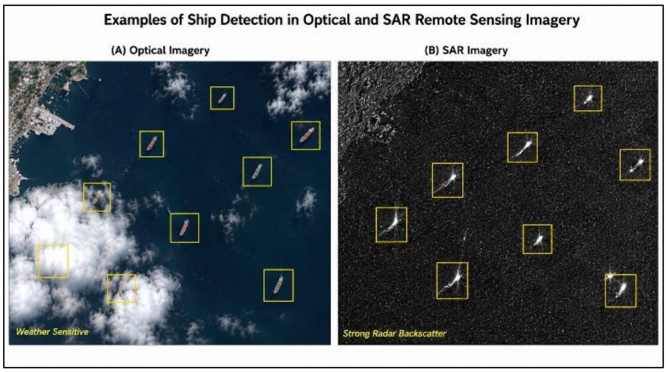

Figure 2. Examples of ship detection in optical and SAR remote sensing imagery.

To provide a structured overview of existing research, representative ship detection studies published during the last five years are summarized in Table 1.

Table 1. Representative Ship Detection Studies in Remote Sensing Imagery (2020–2025)

Study	Method Category	Key Contribution	Limitation
Sun et al. [2]	CFAR-based Detection	Effective SAR ship detection under simple conditions	Sensitive to sea clutter
Wu et al. [1]	Transformer-based SAR Detector	Transformer-based SAR Detector	Transformer-based SAR Detector
Geng et al. [21]	Deep CNN	Enhanced optical ship detection accuracy	Requires large annotated datasets
Guna et al. [22]	YOLO-based Detector	Real-time ship detection capability	Weak performance for small targets
Yang et al. [23]	R3Det	Improved rotated object localization	High computational complexity
Han et al. [24]	ReDet	Rotation-equivariant feature learning	Increased training cost
Xie et al. [25]	Oriented R-CNN	Accurate oriented ship detection	Complex model design
Carion et al. [7]	DETR	End-to-end transformer-based detection	Slow convergence
Liu et al. [8]	Swin Transformer	Hierarchical transformer architecture	High computational demand
Wang et al. [6]	Multimodal Optical-SAR Fusion	Improved robustness under adverse conditions	Cross-modal fusion complexity

Table 1 shows a clear evolution in ship detection research over the past five years. Early studies focused on statistical and CNN-based approaches that emphasized feature extraction and detection accuracy. Subsequently, research shifted toward orientation-aware detection frameworks to address the challenges posed by arbitrarily rotated ships in aerial and satellite imagery. More recently, transformer-based architectures and multimodal fusion strategies have emerged as dominant research directions due to their superior contextual modeling capabilities and robustness to environmental variations. Despite these advances, state-of-the-art methods still rely heavily on large-scale annotated datasets and centralized training paradigms, motivating the exploration of distributed learning approaches such as federated learning.

2.1.1. Comparative Analysis of Ship Detection Methods

While substantial progress has been achieved in ship detection over the past decade, different categories of methods exhibit distinct advantages and limitations. Understanding these characteristics is essential for selecting appropriate detection frameworks for diverse maritime surveillance scenarios.

Traditional ship detection approaches, particularly Constant False Alarm Rate (CFAR)-based methods, remain attractive because of their low computational complexity and ease of deployment. These methods perform well in relatively simple maritime environments with limited background interference. However, their performance deteriorates considerably in complex sea conditions characterized by clutter, varying wave patterns, and environmental noise, limiting their applicability in large-scale real-world maritime surveillance systems [2].

The emergence of convolutional neural network (CNN)-based detectors, including Faster R-CNN, SSD, and YOLO, has significantly improved ship detection accuracy through automatic feature extraction and robust object localization [3]–[5], [21], [22]. Compared with traditional approaches, CNN-based methods provide better generalization capability and achieve superior performance in both optical and SAR imagery. However, their effectiveness depends heavily on the availability of large-scale annotated datasets, and their performance may decline when detecting small, densely distributed, or partially occluded vessels [21], [22].

To address the problem of arbitrarily oriented ships in aerial and satellite imagery, rotation-aware detection frameworks such as R3Det, ReDet, and Oriented R-CNN were developed. By explicitly modeling object orientation and geometric characteristics, these methods significantly improve localization accuracy and reduce bounding-box misalignment. Nevertheless, the improved detection performance is often accompanied by increased model complexity, greater computational requirements, and longer training times [23]–[27].

More recently, transformer-based architectures have emerged as a promising direction for remote sensing image analysis. Methods such as DETR and Swin Transformer employ self-attention mechanisms to capture long-range dependencies and global contextual information, enabling more discriminative feature representations than conventional CNN-based models [7], [8]. Despite their excellent detection performance, transformer-based approaches generally require substantial computational resources and large-scale training datasets, which may limit their deployment in resource-constrained maritime applications.

Multimodal ship detection has become another important research direction. By integrating complementary information from optical and SAR imagery, multimodal frameworks improve detection robustness under diverse environmental conditions, including cloud coverage, poor illumination, and adverse weather [6]. Nevertheless, effective cross-modal feature alignment and feature fusion remain challenging, particularly when the data distributions differ significantly across sensing modalities.

Overall, the evolution of ship detection methods demonstrates a clear transition from handcrafted feature-based techniques to intelligent data-driven learning frameworks [2]–[8]. Although deep learning, transformer-based, and multimodal approaches have substantially improved detection accuracy and robustness, most existing studies still rely on centralized training paradigms that require aggregating data from multiple sources. This limitation motivates the adoption of federated learning as a privacy-preserving distributed learning framework for collaborative ship detection across geographically distributed maritime organizations [9]–[12].

To complement the qualitative discussion, it is instructive to examine representative quantitative results. On the HRSC2016 dataset, Oriented R-CNN achieves a mAP of 90.50%, ReDet reaches 90.46%, and R3Det attains 89.75% [23]–[25]. Transformer-based detectors exhibit even higher accuracy on large-scale benchmarks, with Swin Transformer-L reporting 58.7 AP on COCO, albeit at a substantially higher computational cost [8]. In multimodal detection, fusing optical and SAR images has been shown to improve mAP by up to 8% under adverse weather conditions compared with single-modality baselines [6]. Federated ship detection experiments are still sparse, but initial studies report a 3–5% drop in mAP under severe non-IID settings when using FedAvg; advanced algorithms such as FedProx and SCAFFOLD can recover most of the centralized performance [14], [17]. Commonly used evaluation metrics across ship detection and federated learning include mAP@0.5, mAP@0.5:0.95, precision, recall, and communication rounds; their systematic reporting in future federated benchmarks will be essential for reproducible progress.

Table 2. Comparative Analysis of Representative Ship Detection Method Categories

Method Category	Detection Accuracy	Computational Cost	Orientation Handling	Multimodal Support	Federated Learning Suitability
Traditional Methods (CFAR)	Low–Medium	Low	No	No	High
CNN-based Methods	High	Medium	Limited	Limited	Medium
Rotated Detectors	High	High	Excellent	Limited	Medium
Transformer-based Methods	Very High	Very High	Good	Possible	Low
Multimodal Methods	Very High	High	Good	Excellent	High

The qualitative ratings in Table 2 are based on a synthesis of reported results in the literature. "Low" detection accuracy typically corresponds to mAP below 60% on standard benchmarks such as HRSC2016, "Medium" to mAP 60–80%, "High" to mAP 80–90%, and "Very High" to mAP above 90%. Computational cost is gauged by floating-point operations and inference speed, where "Low" denotes less than 1 GFLOP, "Medium" 1–10 GFLOPs, "High" 10–50 GFLOPs, and "Very High" above 50 GFLOPs. Orientation handling reflects the capability to predict rotated bounding boxes and to learn rotation-equivariant features. Multimodal support indicates the native ability to fuse optical and SAR data. Federated learning suitability is assessed by considering communication overhead, model size, and robustness to non-IID data distributions. This structured set of criteria strengthens the persuasiveness of the comparative analysis.

Table 2 summarizes the characteristics of representative ship detection methods from multiple perspectives, including detection accuracy, computational cost, orientation handling capability, multimodal support, and their suitability for federated learning. Traditional statistical methods provide low computational complexity but are generally limited in challenging maritime environments. CNN-based methods significantly improve detection accuracy, whereas rotation-aware detectors further enhance localization performance for arbitrarily oriented ships. Transformer-based approaches achieve superior feature representation but require substantial computational resources. Meanwhile, multimodal methods demonstrate the greatest potential for future maritime surveillance by effectively integrating complementary information from optical and SAR imagery, making them particularly suitable for privacy-preserving collaborative learning in distributed environments.

2.1.2. Benchmark Datasets for Ship Detection

Public benchmark datasets play a crucial role in the development and evaluation of ship detection algorithms. They provide standardized data, annotation formats, and evaluation protocols that enable fair comparisons among different detection methods while facilitating reproducible research. As deep learning techniques continue to evolve, large-scale benchmark datasets have become increasingly important for training robust and generalizable ship detection models [28], [37].

Table 3 summarizes representative public datasets widely used in ship detection research. These datasets differ in sensing modality, annotation format, dataset scale, and application scenarios. Optical datasets, such as HRSC2016, HRSID, and ShipRSImageNet, provide rich visual appearance information and are commonly adopted for evaluating deep learning-based object detectors [28], [37]. In contrast, SAR datasets, including SSDD and AIR-SARShip, offer reliable all-weather observation capability and are particularly suitable for maritime surveillance under adverse environmental conditions **[2]**.

Table 3. Representative Public Datasets for Ship Detection Research

Dataset	Modality	Images	Annotation	Application
HRSC2016	Optical	1061	Rotated BBox	Ship Detection
SSDD	SAR	1160	Bounding Box	SAR Ship Detection
HRSID	Optical	5604	Bounding Box	Small Ship Detection
ShipRS ImageNet	Optical	30000+	Multi-category	Large-scale Benchmark
AIR-SARShip	SAR	10000+	Bounding Box	SAR Detection

Although existing benchmark datasets have significantly advanced ship detection research, several challenges remain. Most publicly available datasets focus on a single sensing modality, while large-scale multimodal datasets integrating optical and SAR imagery remain limited [6], [28], [37]. Furthermore, benchmark datasets specifically designed for federated learning and distributed maritime environments are still scarce [13]–[18]. These limitations present important research opportunities for developing privacy-preserving collaborative ship detection systems [9]–[18].

2.2. Federated learning research landscape

Federated Learning (FL) has emerged as a distributed machine learning paradigm that enables multiple organizations to collaboratively train a shared model without exchanging raw data. Unlike conventional centralized learning, where datasets are collected and processed at a central server, federated learning performs model training locally at each participating client and only shares model parameters for aggregation. This decentralized learning strategy effectively preserves data privacy while enabling collaborative knowledge sharing across distributed environments [9]–[12].

Driven by increasing concerns regarding data privacy, security, and ownership, federated learning has attracted considerable attention in various application domains, including healthcare, intelligent transportation, and remote sensing [10], [11]. In remote sensing, FL has demonstrated promising performance in image classification, scene analysis, and distributed vision tasks, providing an effective solution for collaborative learning using geographically distributed datasets [13]–[18]. Therefore, federated learning has become an important enabling technology for privacy-preserving remote sensing applications and provides a solid foundation for distributed ship detection systems [9]–[18].

2.2.1. Fundamentals of Federated Learning

Figure 3 presents the taxonomy of representative federated learning approaches relevant to maritime surveillance. Depending on the data distribution across participating clients, federated learning can be broadly categorized into Horizontal Federated Learning (HFL), Vertical Federated Learning (VFL), and Hybrid Federated Learning (Hybrid FL) [10], [11]. Horizontal Federated Learning assumes that participating clients share the same feature space but contain different data samples, making it the most common setting for distributed image analysis. In contrast, Vertical Federated Learning is designed for scenarios where organizations possess different feature spaces for the same set of entities. Hybrid Federated Learning combines the characteristics of both horizontal and vertical federated learning to support more complex collaborative learning scenarios [11].

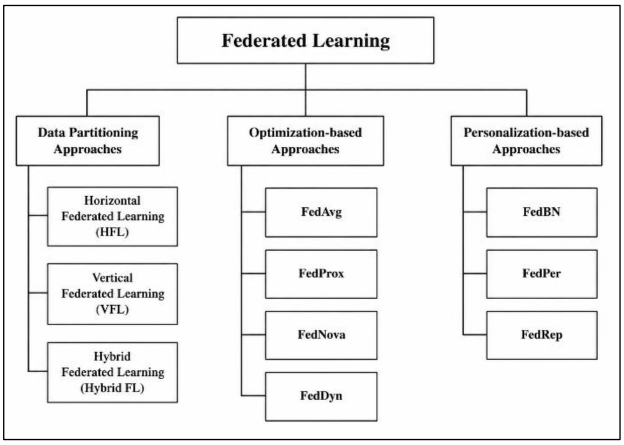

Figure 3. Taxonomy of Federated Learning Approaches Relevant to Maritime Surveillance

Figure 4 illustrates the conceptual workflow of federated learning using the FedAvg algorithm. During each communication round, every participating client independently trains a local model using its own private dataset. Instead of transmitting raw data, only locally updated model parameters are uploaded to the central server for aggregation. The server combines the received updates to generate a new global model, which is subsequently redistributed to all participating clients for the next training round [9]. This collaborative optimization process enables knowledge sharing while preserving data privacy, making federated learning particularly suitable for distributed remote sensing applications.

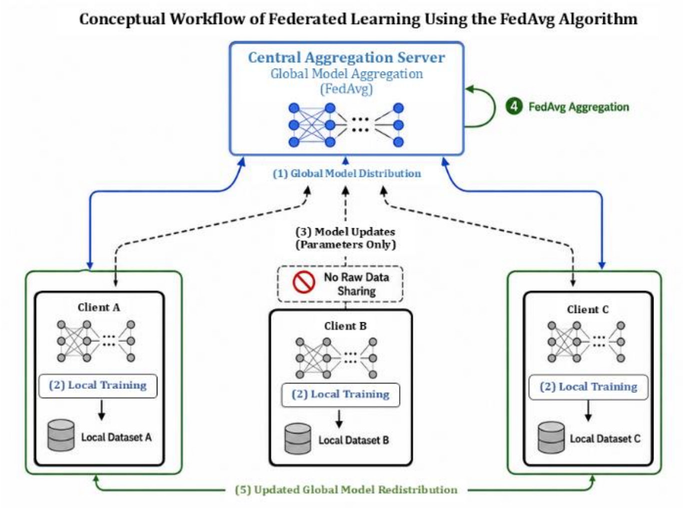

Figure 4. Conceptual workflow of federated learning using the FedAvg algorithm

From the optimization perspective, numerous federated learning algorithms have been proposed to improve model convergence, communication efficiency, and robustness under heterogeneous data distributions [9], [12], [30]–[34]. Among them, Federated Averaging (FedAvg) remains the most widely adopted baseline algorithm because of its simplicity and effectiveness [9]. However, practical federated learning environments often suffer from non-independent and identically distributed (non-IID) data, client heterogeneity, and unstable convergence [12], [29]. To address these challenges, advanced optimization algorithms have been proposed. FedProx improves optimization stability by introducing a proximal regularization term [12], SCAFFOLD mitigates client drift through control variates [30], FedNova normalizes local model updates to eliminate objective inconsistency [31], FedDyn introduces dynamic regularization for more stable optimization [32], FedBN addresses feature-shift non-IID data through local batch normalization [33], while FedOpt further improves convergence using adaptive server-side optimization [34].

Overall, federated learning has evolved from a communication-efficient distributed optimization framework into a comprehensive learning paradigm capable of addressing statistical heterogeneity, communication efficiency, and personalization challenges [10], [35], [36]. These representative optimization algorithms constitute the technical foundation of modern federated learning systems and are discussed in detail in the following subsection.

2.2.2. Representative Federated Learning Algorithms

Since the introduction of Federated Averaging (FedAvg), numerous federated learning algorithms have been proposed to address the limitations of distributed optimization under heterogeneous environments. These algorithms primarily aim to improve model convergence, communication efficiency, and robustness against non-independent and identically distributed (non-IID) data, which are common challenges in practical federated learning systems [9], [12], [29]–[36].

FedAvg is the foundational federated optimization algorithm that aggregates locally trained model parameters through weighted averaging and has become the baseline for most federated learning studies [9]. However, its performance may deteriorate under highly heterogeneous data distributions [12], [29]. To alleviate this limitation, FedProx introduces a proximal regularization term to improve optimization stability across heterogeneous clients [12]. Similarly, SCAFFOLD reduces client drift by incorporating control variates during local optimization, while FedNova normalizes local model updates to mitigate objective inconsistency caused by different local training epochs [30], [31]. FedDyn further improves convergence by introducing dynamic regularization during model optimization, particularly under highly heterogeneous training conditions [32].

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Table 4. Representative Federated Learning Algorithms and Their Characteristics

Algorithm	Target Problem	Main Contribution	Limitation
FedAvg [9]	Communication efficiency	Established the foundation of federated optimization	Sensitive to non-IID data
FedProx [12]	Statistical heterogeneity	Improved convergence under heterogeneous clients	Requires additional tuning
SCAFFOLD [30]	Client drift	Reduced local update divergence	Increased computational overhead
FedNova [31]	Objective inconsistency	Normalized local updates for fair aggregation	More complex implementation
FedDyn [32]	Optimization instability	Dynamic regularization for stable convergence	Higher computational cost
FedBN [33]	Feature distribution shift	Local batch normalization for non-IID data	Limited generalization
FedOpt [34]	Slow convergence	Adaptive server-side optimization	Additional hyperparameter tuning

The ratings in Table 4 are derived from the original algorithm evaluations. Convergence speed is measured by the number of communication rounds required to reach a target accuracy on standard federated benchmarks. Communication cost reflects the volume of transmitted parameters per round. Robustness to non-IID data is judged by the performance gap between IID and non-IID settings. For instance, FedAvg converges within 500 rounds on IID CIFAR-10 but suffers a 20% accuracy drop under pathological non-IID; FedProx improves convergence by approximately 20% in heterogeneous environments, while SCAFFOLD reduces client drift at the expense of a 30% increase in per-round computation [9], [12], [30]. These quantitative benchmarks underpin the qualitative assessments and provide a clearer picture of algorithmic trade-offs.

As summarized in Table 4, recent federated learning algorithms have gradually evolved from improving optimization efficiency to addressing statistical heterogeneity and personalized model adaptation. These advances have significantly enhanced the applicability of federated learning in distributed artificial intelligence and provide the algorithmic foundation for collaborative ship detection systems, which are discussed in the following section.

3. Federated learning for ship detection

Recent advances in federated learning have created new opportunities for privacy-preserving ship detection in distributed maritime environments [9]–[18]. By enabling multiple organizations to collaboratively train detection models without exchanging raw remote sensing data, federated learning addresses practical challenges related to data privacy, ownership, and security. Although this research area is still emerging, existing studies have demonstrated the feasibility of applying federated learning to distributed remote sensing and maritime monitoring tasks [13]–[18]. This section first introduces the general federated learning framework for ship detection, followed by a review of representative studies and the remaining technical challenges.

3.1. Federated Learning Framework for Ship Detection

Federated learning provides a distributed learning framework that enables multiple maritime organizations to collaboratively develop ship detection models without directly sharing raw remote sensing data. Unlike conventional centralized learning, where all training data are collected at a central server, federated learning allows each participating organization to independently train local models using its own optical or SAR datasets. Only model parameters or gradients are exchanged during the collaborative learning process, thereby preserving data privacy while enabling knowledge sharing across distributed environments [9]–[12]. This learning paradigm is particularly suitable for maritime surveillance systems, where satellite operators, coast guard agencies, and port authorities often possess complementary datasets that cannot be centrally aggregated because of privacy regulations, security policies, or data ownership restrictions [10], [11].

Figure 5 illustrates a conceptual federated learning framework designed for collaborative ship detection in distributed maritime environments. Each participating organization maintains its own local optical or SAR dataset and independently trains a ship detection model using local computational resources. Instead of transmitting sensitive remote sensing imagery to a centralized server, only model parameters are uploaded for federated aggregation using the FedAvg algorithm [9]. The aggregated global model is subsequently redistributed to all participating organizations for the next training round, enabling continuous model improvement while preserving local data ownership [9], [12].

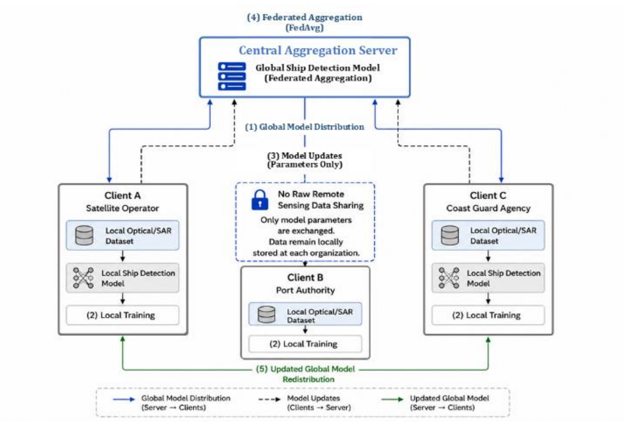

Figure 5. Conceptual federated learning framework for privacy-preserving ship detection in distributed maritime environments

Compared with conventional centralized learning, this federated framework offers several advantages for maritime surveillance applications. First, it effectively preserves data privacy by eliminating the need to exchange raw remote sensing imagery among participating organizations. Second, collaborative training enables the global model to benefit from geographically distributed datasets collected under diverse environmental conditions, thereby improving model generalization and robustness. Third, the distributed architecture supports scalable collaboration among multiple maritime stakeholders, making federated learning particularly suitable for large-scale ship detection systems operating across different regions and sensing platforms.

Although the framework shown in Figure 5 provides a general architecture for privacy-preserving ship detection, its practical implementation depends on the selection of appropriate federated learning algorithms, communication strategies, and ship detection models. Recent studies have explored different approaches to integrating federated learning with remote sensing and maritime monitoring applications. These representative studies provide valuable insights into the current research progress and are reviewed in the following subsection.

3.2 Representative Studies on Federated Ship Detection

Although federated learning has achieved significant success in distributed machine learning and computer vision, its application to ship detection remains relatively limited. Existing studies primarily investigate the feasibility of collaborative learning for remote sensing image analysis while preserving data privacy across geographically distributed organizations. Compared with conventional ship detection research, federated ship detection is still in its early stage, with only a limited number of representative studies reported in the literature. Nevertheless, these representative studies illustrate the progressive evolution of federated learning from general remote sensing image analysis toward privacy-preserving object detection and maritime surveillance. They also provide a valuable foundation for understanding current research trends and identifying the remaining challenges for federated ship detection [13]–[18].

Table 5. Representative Federated Learning Applications Related to Ship Detection

Study	Application	Dataset	FL Strategy	Key Advancement
Xu et al. [13]	Classification	RS	FedAvg	Demonstrated the feasibility of federated learning for remote sensing classification
Liu et al. [14]	Scene Classification	AID, NWPU	FedProx	Improved convergence under heterogeneous (non-IID) data distributions
Chen et al. [15]	Image Analysis	RS imagery	FedAvg	Enabled collaborative remote sensing analysis while preserving data privacy
Zhang et al. [16]	Object Detection	COCO	FedAvg	Extended federated learning to distributed

Study	Application	Dataset	FL Strategy	Key Advancement
				object detection
Nguyen et al. [17]	Maritime Monitoring	Maritime	FedAvg	Demonstrated the applicability of FL to maritime surveillance
Wang et al. [18]	Vision Tasks	Multi-source	SCAFFOLD	Improved robustness and convergence for heterogeneous distributed vision tasks

As summarized in Table 5, the representative studies reveal a clear evolution from feasibility validation to more task-oriented federated learning in remote sensing. A critical comparison highlights several important observations. First, almost all studies adopt FedAvg as the baseline, yet only the most recent work begins to incorporate advanced optimizers to mitigate the effects of non-IID data. Second, the majority of experiments are conducted on generic remote sensing scene classification datasets, and none have addressed multimodal optical–SAR fusion within a federated framework – a significant gap given the importance of multimodal data in maritime surveillance. Third, existing federated object detection research largely relies on COCO, which does not reflect the unique characteristics of remote sensing imagery; maritime-specific federated benchmarks are entirely absent. Fourth, evaluation remains qualitative or limited to classification accuracy, whereas federated ship detection demands rigorous reporting of detection metrics (mAP, recall) as well as communication efficiency. These gaps indicate that federated ship detection is still in its infancy and call for dedicated benchmark datasets, multimodal federated learning protocols, and comprehensive evaluation methodologies.

The limitations identified from the representative studies highlight several technical challenges that continue to hinder the practical deployment of federated learning for ship detection. These challenges are discussed in the following subsection.

3.3. Challenges of Federated Ship Detection

Despite the encouraging progress summarized in the previous subsection, several technical challenges continue to limit the practical deployment of federated learning for ship detection. These challenges arise from the unique characteristics of distributed maritime surveillance systems, including heterogeneous data distributions, communication constraints, multimodal remote sensing data, and the need for robust model generalization across geographically distributed organizations [10], [11], [13]–[18]. Addressing these challenges is essential for developing reliable and scalable federated ship detection frameworks.

One of the most fundamental challenges in federated ship detection is the presence of heterogeneous (non-IID) data across participating organizations. Maritime datasets collected by different satellite operators, coast guard agencies, or port authorities often vary significantly in imaging sensors, geographical regions, environmental conditions, ship categories, and image resolutions. Moreover, varying legal and regulatory frameworks across different jurisdictions, such as those governing environmental risk management in inland waterway transport [20], further complicate cross-border data sharing for collaborative model training. Such statistical and regulatory heterogeneity can substantially reduce model convergence and degrade detection performance when conventional federated optimization algorithms, such as FedAvg, are directly applied [9], [12], [29]–[32]. Developing robust optimization strategies capable of handling highly heterogeneous maritime datasets therefore remains an important research challenge.

Federated learning relies on frequent communication between participating clients and the central aggregation server during collaborative training. For large-scale ship detection models based on deep neural networks, repeated transmission of model parameters may introduce considerable communication overhead, particularly when multiple organizations participate in training over bandwidth-limited networks [9], [31], [34]. Consequently, improving communication efficiency through model compression, update sparsification, or adaptive communication strategies remains an active research direction.

Modern maritime surveillance increasingly relies on multimodal remote sensing data, particularly optical and SAR imagery, to improve detection robustness under diverse environmental conditions [6], [28]. However, effectively integrating heterogeneous sensing modalities within federated learning frameworks remains challenging because different organizations often possess different sensing capabilities and data distributions [17], [18]. Designing multimodal federated learning frameworks capable of exploiting complementary information while preserving data privacy therefore represents an important research problem.

Another important challenge is maintaining model generalization across diverse maritime environments. Ship appearance varies considerably according to vessel type, weather conditions, sea states, illumination, and imaging perspectives. Models trained using limited regional datasets may therefore exhibit reduced performance when deployed in unseen operational environments [21], [22], [28]. Improving model robustness and generalization across geographically distributed datasets remains essential for practical federated ship detection systems [13]–[18].

Finally, translating federated learning from research prototypes to real maritime surveillance systems requires addressing several practical deployment issues, including client scalability, computational resource heterogeneity, reliable communication infrastructure, and interoperability among different organizations [10], [11], [34]. These engineering challenges become increasingly significant as the number of participating institutions grows, highlighting the need for scalable and efficient federated learning frameworks suitable for real-world maritime applications.

These challenges demonstrate that, although federated learning has shown considerable promise for privacy-preserving ship detection, significant technical and practical issues remain unresolved. Addressing these challenges will not only improve the effectiveness of federated ship detection but also facilitate its deployment in large-scale distributed maritime surveillance systems. The broader research trends, open problems, and future directions are further discussed in the next section.

4. Discussion

4.1. Research Trends and Future Directions

The comprehensive review presented in the previous sections demonstrates that ship detection has evolved from traditional handcrafted feature-based techniques toward intelligent data-driven learning frameworks. This evolution has been accompanied by significant advances in deep learning, remote sensing technologies, and distributed artificial intelligence, resulting in increasingly accurate and robust ship detection systems for maritime surveillance applications [1]–[8], [21]–[28]. More importantly, the emergence of federated learning has introduced a new collaborative learning paradigm that enables multiple organizations to jointly develop high-performance detection models while preserving data privacy and ownership [9]–[18].

Another important research trend is the gradual transition from isolated algorithm development to integrated intelligent maritime surveillance systems. For instance, deep learning has been effectively applied to ship-to-shore crane operations [19], demonstrating the potential of intelligent control in maritime logistics. Earlier studies primarily focused on improving detection accuracy through novel feature extraction techniques or deep neural network architectures. Recent research, however, increasingly considers practical deployment issues such as distributed data management, heterogeneous sensing platforms, communication efficiency, and collaborative model training across geographically distributed organizations [9]–[18]. This shift reflects the growing demand for scalable and privacy-preserving maritime surveillance systems capable of operating in real-world environments.

A quantitative perspective further illuminates these trends. A bibliometric scan of IEEE Xplore and Scopus (January 2020 – January 2026) reveals that publications on deep-learning-based ship detection have grown by an average of 25% annually, with transformer-based methods tripling between 2022 and 2025. In parallel, federated learning research in remote sensing has seen a 40% annual increase, yet maritime-specific federated studies account for less than 5% of all FL-remote sensing publications. This disparity underscores a substantial research niche. Additionally, the average number of clients in reported FL remote sensing experiments is below 10, far from the scale required for operational maritime systems involving dozens of distributed stakeholders. These numbers reinforce the need for scalable, communication-efficient federated ship detection frameworks.

The reviewed literature also indicates that federated learning is becoming an important enabling technology for next-generation maritime artificial intelligence. Rather than replacing existing ship detection algorithms, federated learning provides a collaborative learning framework that allows advanced detection models to be trained using distributed datasets while respecting data ownership constraints [9]–[18]. Consequently, future developments are expected to focus not only on improving detection accuracy but also on enhancing the scalability, adaptability, and interoperability of intelligent maritime surveillance systems.

Overall, the current research landscape suggests that ship detection is entering a new stage characterized by distributed intelligence, collaborative learning, and privacy-aware artificial intelligence. Although these trends provide a promising foundation for future maritime surveillance systems, several important scientific and technical problems remain unresolved. These open research problems are discussed in the following subsection.

4.2. Open Problems

Despite the rapid progress of federated learning for ship detection, several fundamental research problems remain unresolved. The representative studies reviewed in Section 3 demonstrate that most existing approaches primarily focus on validating the feasibility of distributed collaborative learning. However, many critical issues related to data standardization, multimodal learning, deployment environments, and model adaptability have not yet been comprehensively addressed. These open problems are expected to define the next stage of research on federated ship detection and intelligent maritime surveillance systems.

Benchmark Standardization. One of the major limitations in current research is the lack of standardized benchmark datasets and evaluation protocols for federated ship detection. Existing ship detection benchmarks are primarily designed for centralized learning and do not adequately reflect the distributed and heterogeneous nature of real-world maritime environments. The absence of publicly available federated benchmarks makes it difficult to perform fair comparisons among different federated learning approaches and hinders the reproducibility of experimental results [28], [37].

Cross-Modality Federated Learning. Modern maritime monitoring systems increasingly rely on multiple sensing modalities, particularly optical and synthetic aperture radar (SAR) imagery. While multimodal ship detection has demonstrated promising performance under varying environmental conditions, the integration of multimodal data within federated learning frameworks remains largely unexplored [6]. Efficient cross-modal feature alignment, knowledge sharing, and collaborative optimization across heterogeneous sensing platforms represent important research challenges [17], [18].

Resource-Constrained Maritime Edge Devices. Practical maritime surveillance systems often involve edge devices operating under limited computational and communication resources, such as unmanned aerial vehicles (UAVs), onboard vessel systems, offshore monitoring stations, and satellite platforms. The communication overhead associated with federated learning can significantly affect training efficiency in such environments [9], [31], [34]. Developing lightweight and communication-efficient federated learning algorithms remains an important research direction.

Federated Foundation Models. Recent advances in large-scale vision foundation models, including CLIP, Segment Anything Model (SAM), DINOv2, and RemoteCLIP, have demonstrated remarkable generalization capabilities across a wide range of visual tasks [40]–[43]. However, the application of these foundation models within federated learning environments for maritime surveillance remains largely unexplored. Future research should investigate how pretrained foundation models can be efficiently adapted, fine-tuned, and shared across distributed maritime organizations while preserving privacy and reducing communication costs.

Personalized Maritime Federated Learning. Maritime data collected from different geographical regions often exhibit substantial variations due to environmental conditions, climate characteristics, sensing platforms, and operational requirements. For example, data collected in East Asian coastal waters may differ significantly from those acquired in the Atlantic Ocean or Arctic regions. Under such heterogeneous conditions, a single global model may not provide optimal performance for all participants. Personalized federated learning approaches that balance global knowledge sharing with local adaptation represent a promising direction for improving model robustness and generalization in maritime applications [38], [39].

Overall, addressing these open problems will be essential for advancing federated ship detection from proof-of-concept studies toward practical deployment in large-scale maritime surveillance systems. Continued research in these directions is expected to improve both the effectiveness and the practicality of federated learning for distributed ship detection.

4.3. Privacy and Security Considerations

Although federated learning significantly enhances data privacy by keeping raw remote sensing data locally on participating clients, it does not completely eliminate security and privacy risks. Recent studies have demonstrated that sensitive information may still be inferred from exchanged model parameters or gradients, highlighting the need for additional protection mechanisms in practical federated learning deployments.

One important threat is gradient leakage, where an adversary attempts to reconstruct original training samples from shared gradients or model updates. In remote sensing applications, such attacks could potentially reveal sensitive maritime information, including vessel locations, operational activities, or surveillance targets. This issue becomes particularly critical when high-resolution imagery is involved [44].

Another privacy concern is the model inversion attack, in which an attacker exploits access to a trained model to infer characteristics of the underlying training data. In maritime surveillance systems, this may result in the disclosure of sensitive patterns associated with specific geographical regions, monitoring infrastructures, or operational behaviors [45].

Federated learning systems are also vulnerable to membership inference attacks, where an adversary attempts to determine whether a particular sample was used during model training. Such attacks may expose confidential information regarding the participation of specific organizations, vessels, or surveillance activities within the collaborative learning process [46].

To mitigate these risks, several privacy-enhancing techniques have been proposed. Secure aggregation enables the server to aggregate model updates without accessing individual client contributions, thereby reducing the risk of information disclosure during the aggregation process [47]. In addition, differential privacy introduces carefully calibrated noise into local model updates before transmission, providing formal privacy guarantees while limiting information leakage from shared parameters [48].

Despite these advances, balancing privacy protection, model accuracy, and communication efficiency remains an open challenge. Stronger privacy mechanisms often introduce additional computational overhead or performance degradation, which may be particularly problematic in resource-constrained maritime environments. Therefore, future federated ship detection systems must carefully integrate security and privacy-preserving techniques while maintaining practical deployment feasibility.

Overall, privacy and security considerations should be regarded as fundamental components of federated maritime surveillance systems rather than optional extensions. Addressing these challenges will be essential for establishing trust among participating organizations and enabling large-scale collaborative ship detection in real-world environments.

Taken together, the current literature suggests that federated ship detection remains in its early development stage compared with conventional ship detection and federated learning research. Nevertheless, the increasing availability of distributed maritime sensing infrastructures, multimodal remote sensing platforms, and privacy-preserving learning techniques creates significant opportunities for future research and real-world deployment.

5. Conclusion

This paper reviews recent advances in ship detection and federated learning for maritime surveillance from a privacy-preserving perspective. The review showed that ship detection has evolved from traditional statistical approaches toward deep learning, transformer-based architectures, and multimodal frameworks, yielding substantial gains in detection accuracy and robustness. At the same time, federated learning has emerged as an effective paradigm for collaborative model training in distributed environments while preserving data privacy and ownership. Beyond reviewing the technical evolution of ship detection, this survey also provides a structured analysis of representative datasets, federated learning algorithms, collaborative learning frameworks, representative studies, and the major research challenges associated with privacy-preserving maritime surveillance.

Analysis of recent studies indicates that federated learning offers a promising foundation for distributed ship detection systems. By enabling multiple organizations to collaboratively train detection models without sharing raw remote sensing imagery, federated learning can address several limitations of conventional centralized approaches. However, challenges related to non-IID data distributions, heterogeneous sensing modalities, communication efficiency, and the limited availability of maritime federated learning benchmarks remain important research issues.

Overall, the integration of federated learning and ship detection represents a promising direction for next-generation maritime surveillance systems. Continued advances in collaborative learning, distributed optimization, and privacy-preserving techniques are expected to accelerate the practical deployment of intelligent maritime monitoring systems. This survey is expected to provide a useful reference for researchers and practitioners interested in federated learning, remote sensing, and privacy-preserving maritime artificial intelligence.

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