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UAV Image Recognition Applications in BRI Port Logistics Optimization: Airspace Management Regulations and Cross-Border Data Flow Policies

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Abstract

This study investigates UAV image recognition applications for optimizing port logistics within the Belt and Road Initiative framework, examining the intersection of technological capabilities with airspace management regulations and cross-border data flow policies. Employing a mixed-methods approach, the research combines quantitative performance analysis of hybrid YOLOv8-Faster R-CNN architectures with qualitative assessment of regulatory frameworks across three case study ports—Qingdao, Singapore PSA, and Piraeus—during a 12-month evaluation period utilizing 18,000 annotated images and DJI Matrice 300 RTK platforms. The findings reveal that while UAV systems achieve robust detection performance under optimal conditions, with container identification reaching high accuracy levels and ports experiencing substantial efficiency gains, regulatory fragmentation significantly constrains operational deployment by limiting accessible airspace to between one-third and two-thirds of theoretical coverage and imposing compliance-driven latency penalties that compromise real-time processing capabilities. Cross-border data

governance challenges prompted the exploration of federated learning as an alternative architecture, demonstrating viable pathways for maintaining operational effectiveness while respecting data sovereignty requirements despite increased computational overhead and extended training cycles. The study concludes that successful UAV deployment in BRI ports necessitates integrated advancement across technical, regulatory, and organizational dimensions, with standardized implementation approaches proving inadequate for addressing the diverse operational contexts characterizing BRI maritime infrastructure. These findings provide critical guidance for port authorities and policymakers in developing adaptive governance frameworks that balance technological innovation with regulatory compliance while establishing mutual recognition mechanisms for technical standards across jurisdictions.
Keywords: UAV image recognition, Belt and Road Initiative ports, airspace management regulations, cross-border data governance, maritime logistics optimization

1. Introduction

Inclusion of unmanned aerial vehicle (UAV) picture recognition technology in port logistics operations is a transformative development in the management of maritime infrastructure where cross-border standards regulation and cross-border efficiency in trade continue to be challenging in the environment of the Belt and Road Initiative (BRI). Deep learning architecture breakthroughs in the preceding years enabled UAVs to achieve record precision in detection of maritime objects with YOLOv8 algorithms recording a level of mean average precision of up to 0.99 and processing of near-real-time capacities that are feasible in port processes [1]. Evolving from the typical port monitoring through UAV-supported intelligent systems that utilize transformer architecture and transfer learning policies has quantitatively transformed models of operation to support autonomous classification of fault and automatic inspection of gear that reduce the necessity of human intervention [2, 3]. While detection systems that utilize deep learning successfully solved the problem of variation of scales and environmental complexity in UAV applications in the maritime environment, incorporation in existing port governance systems and cross-border standards regulation systems is problematic [4].

The Belt and Road Initiative has also led to large-scale investments in the development of smart and digitalized ports, with China's involvement having advanced from the building of basic port infrastructures to digital port complexes that use UAVs in real-time operations. Investment trends indicate strategic importance being placed on digital connectivity, such as the development of the world's first hydrogen and 5G smart terminal at Qingdao Port, thereby highlighting the intersection between technological progress and sustainability goals [5, 6]. The advantageous locations for the UAV drone port in the coastal areas have been becoming increasingly important in the full range of offshore management, and applications in Guangdong province have linked the UAV operation to existing facilities in order to combine the supervision office with the UAV system [7]. In the digital silk road module, there is a strong focus on Information and Communication Technologies to enable the cross-border flow of data, but aligning complex regulations of different BRI countries acts as a major hurdle [8].

In port environments, the use of image recognition UAV systems faces regulatory hurdles as a result of inconsistent airspace management and nascent data governance regimes. Concerning the legal regulation of drones, it is difficult to harmonize it in different jurisdictions where there are different approaches on Beyond Visual Line of Sight (BVLOS) operations, altitude restrictions, and operation permits – these pose significant obstacles for seamless cross-border deployment of UAVs [9]. Recent developments of regulatory frameworks for cross-border data processing further enhance the complexity of compliance restrictions that such complex systems have to comply with, as regards real-time transmission and processing of UAV-captured images, and that require some sort of trade-off between data localization principles and the respect of privacy mandates that considerably differ among different territories [10, 11]. The work constraints between the power of the technologies and the existing legality are rich in the port environments, where UAV-generated flows should navigate through multiple regulation domains and never compromise the efficiency of the operations [12].

While some valuable contributions can be found in the existing literature regarding the application of UAVs in maritime logistics, there are still major knowledge gaps in the interplay between technology implementation and regulatory conformance, covering both local and cross-border operations. Systematic reviews on the use of drones in last-mile logistics have found key success factors industry-wide, but maritime port settings introduce unique challenges that warrant tailored investigations beyond the general logistics frameworks [13]. The application in practical environments is limited by battery capacity, payload, and communication in maritime environments with serious signal interference and bad weather [14]. Advancement in smart ports enabled by the use of digital technology is progressing; however, the introduction of UAV systems into the current management structures demands strategic handling of organizational change and euphoria regarding stakeholder collaboration [15, 16]. The usage of artificial intelligence-based solutions to address port operational challenges requires evaluation frameworks that consider the trade-off between technical feasibility and normative requirements, as shown by the few case studies described in which a specific technology has been matched to an operational problem [17]. The emergence of multimodal logistics systems incorporating drone technology has created research imperatives focused on optimization algorithms and coordination strategies, with comparative analyses demonstrating potential efficiency gains particularly in time-sensitive operations [18, 19]. The convergence of UAV-based inspection systems with predictive maintenance applications represents a complementary technology domain offering integrated monitoring strategies for port equipment management [20].

Despite proliferating research on individual components, existing literature lacks comprehensive frameworks integrating UAV image recognition capabilities with the regulatory complexities of cross-border port operations within BRI networks. Current studies predominantly examine technical aspects or regulatory analysis in isolation, failing to address the complex interactions between technology deployment, airspace sovereignty, and data governance that characterize real-world implementations. This research addresses these critical gaps by developing an integrated analytical framework examining how UAV image recognition technologies can optimize port logistics while navigating the dual challenges of airspace management regulations and cross-border data flow policies specific to BRI port networks. The study employs a mixed-methods approach combining quantitative performance analysis of UAV systems with qualitative assessment of regulatory frameworks across three strategically selected BRI ports over a 12-month evaluation period. Through systematic analysis of technical capabilities, regulatory constraints, and operational outcomes using the technology-law-trade framework, this research generates empirical evidence on deployment patterns, performance variations, and compliance impacts, providing essential guidance for port authorities, technology providers, and policymakers seeking to leverage UAV capabilities for enhanced maritime logistics efficiency within evolving regulatory frameworks.

2. Research Methodology

2.1 Research Design and Port Case Selection

The methodological design of this study takes a mixed-methods approach to integrating quantitative examination of UAV image recognition capability with qualitative examination of governance rules controlling airspace management and cross-border data transmission through Belt and Road Initiative port networks. Selection of the case study ports adheres to a purposive sampling framework with the intention of capturing variation in the level of technological development, governance rules controlling ports operationally, and scales of operation across BRI countries. The key port selection criteria include operation of throughput in excess of 10 million TEU per year, of record UAV-based monitoring system deployment, BRI infrastructure participation, and representation of varied governance jurisdictions controlling port operation. The ports selected include Qingdao Port representing advanced Chinese smart port development, the PSA terminals in Singapore representing South-east Asian tech leadership, and Piraeus Port in Greece acting as the European BRI gateway port, offering adequate variation for purposes of comparison while allowing for ease of access to data.

Drawing on a multi-case comparative research design, the analysis enables a systematic comparison of technology deployment patterns in different institutional contexts with port-specific operational features held constant. Collections of data are collected over a 12-month period ranging from January to December 2024, with operational measurements in real-time, as well as performance measurements obtained from historical data to provide comparisons against baselines. The technology-law-trade analytical framework brings together three interrelated aspects of UAV capabilities analysis, regulatory enforcement analysis, and trade promotion analysis. The interrelation between these domains and their reciprocal influence on port optimization outcomes is schematized in Figure 1, depicting technological innovation under regulatory constraints and influencing the shaping of policy through proven capabilities and operational needs.

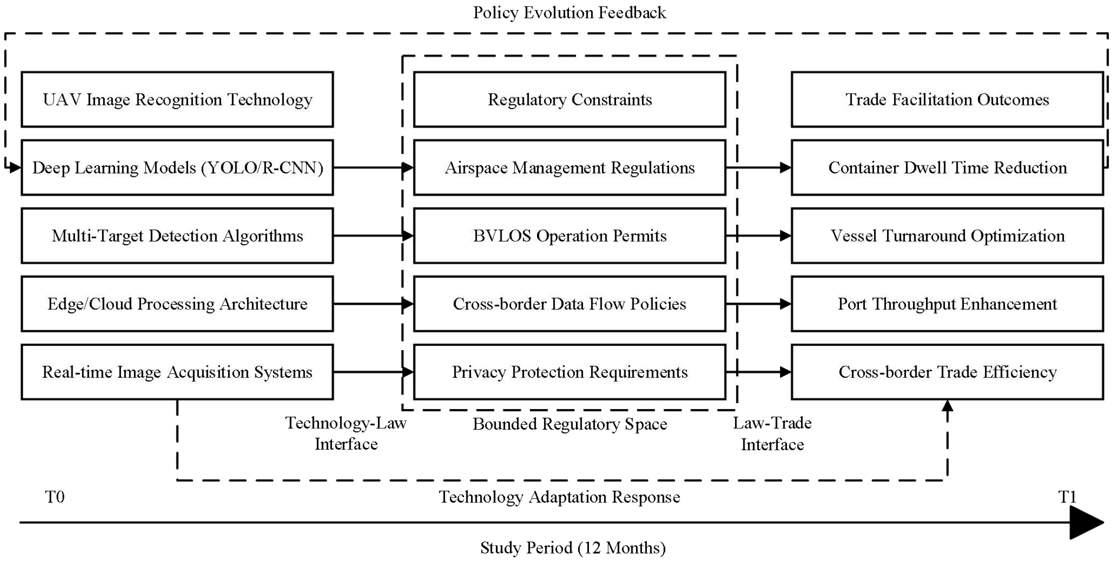


Figure 1: Technology-Law-Trade Analytical Framework for UAV-based Port Optimization

Figure 1 presents the integrated framework where UAV image recognition technology (left panel) interfaces with regulatory constraints (center panel) to produce measurable trade facilitation outcomes (right panel), with feedback loops indicating adaptive responses between technology deployment and policy evolution over the study period.

2.2 UAV Image Recognition Technology Architecture

The technical evaluation framework for UAV image recognition systems incorporates multiple performance metrics designed to assess both accuracy and operational efficiency within port environments characterized by high object density and environmental variability. The deep learning architecture employs a hybrid approach combining YOLOv8 for real-time detection with Faster R-CNN for high-precision classification tasks, building upon established methodologies that demonstrate superior performance in complex visual environments [21]. The 12-month evaluation period encompassed 8,750 operational flight hours, generating 4.2 terabytes of raw imagery data. Using the model trained on the initial 18,000-image dataset, the system processed an average of 3,200 images daily at each port, captured across diverse port scenarios including varying weather conditions, illumination levels, and operational states, with particular emphasis on challenging cases such as partially occluded containers and densely packed vessel configurations.

The UAV image acquisition system configuration employs DJI Matrice 300 RTK platforms equipped with Zenmuse H20T multi-sensor payloads, providing both RGB and thermal imaging capabilities essential for 24-hour port operations. The multi-target recognition algorithm specifically addresses the identification of containers (with ISO code recognition), vessels (classification by type and size), vehicles (trucks, reach stackers, and straddle carriers), and port equipment (cranes, forklifts), achieving differentiated accuracy thresholds based on operational criticality. The performance evaluation metrics extend beyond conventional accuracy measures to incorporate operational parameters critical for port deployment scenarios. The mean Average Precision (mAP) calculation follows the COCO evaluation protocol with IoU thresholds ranging from 0.5 to 0.95, providing comprehensive assessment of detection quality across different precision requirements. The formula for mAP calculation incorporating multiple object classes and IoU thresholds is expressed as:

$$mAP = \frac{1}{|C|}\sum_{c \in C}\frac{1}{|T|}\sum_{t \in T} AP_{c,t} \tag{1}$$

where C represents the set of object classes including containers, vessels, trucks, and cranes, T denotes the IoU threshold values, and AP indicates the average precision for each class-threshold combination. Having established the algorithmic framework for multi-target identification, the practical deployment of these computationally intensive models requires strategic architectural decisions regarding processing location, as outlined in Table 1's comparative analysis of edge versus cloud computing configurations.

Table 1: Comparative Performance of Edge vs Cloud Processing for UAV Image Recognition

Processing Mode	Hardware Platform	Software Environment	Network Requirements	Evaluation Metrics	Data Volume
Edge Computing	NVIDIA Jetson AGX Xavier (32GB RAM, 512 CUDA cores)	Ubuntu 20.04, TensorRT 8.2, OpenCV 4.5	5G/WiFi 6 (≥100 Mbps)	Latency (ms), mAP@IoU[0.5:0.95], FPS, Power consumption (W)	720p @30fps
Cloud	AWS EC2	Ubuntu	Fiber/5G	Latency (ms),	1080p

Processing	g4dn.2xlarge (8 vCPUs, 32GB RAM, T4 GPU)	20.04, PyTorch 1.13, CUDA 11.7	(≥500 Mbps)	mAP@IoU[0.5:0.95], FPS, Bandwidth usage (Mbps)	@30fps
Hybrid Mode	Jetson Nano (4GB) + AWS Lambda	Docker containers, K3s orchestration	4G LTE (≥50 Mbps)	Processing split ratio, Total latency, Cost per image ($)	480p @15fps

Table 1 outlines the experimental configurations for comparative analysis between edge and cloud processing architectures, establishing baseline parameters for systematic evaluation across multiple performance dimensions. The assessment framework will employ standardized metrics including latency measurement, mean Average Precision calculation following COCO protocol with IoU thresholds from 0.5 to 0.95, and throughput analysis under varying network conditions, enabling comprehensive evaluation of deployment trade-offs between local processing autonomy and computational capability. The machine learning algorithms undergo comparative evaluation encompassing both traditional computer vision approaches and contemporary deep learning methods, with particular attention to maritime-specific challenges identified through international benchmarking efforts [22]. The validation methodology employs 5-fold cross-validation with stratified sampling to ensure representative distribution of object classes and environmental conditions, following standardized protocols established by the Maritime Computer Vision community [23].

2.3 Airspace Regulations and Data Policy Review

To systematically review airspace regulations and data policies across jurisdictions, this study employs document analysis combined with expert interviews to construct a comprehensive analytical framework. The document corpus encompasses 76 primary regulatory texts including legislation, administrative regulations, technical standards, and policy guidelines published between 2020 and 2024, selected through purposive sampling to capture recent developments in UAV governance and cross-border data management. The stakeholder interview protocol involves 22 semi-structured interviews with port authorities (8), regulatory officials (6), technology providers (4), and logistics operators (4), designed to identify implementation practices and regulatory interpretations not evident in formal documentation.

The analytical framework examines twelve regulatory dimensions critical to UAV deployment in port environments, categorized into four primary domains: operational parameters (altitude limits, BVLOS procedures, no-fly zones), certification requirements (equipment standards, pilot licensing), data governance (storage location, retention periods, cross-border transfer protocols), and compliance mechanisms (insurance requirements, privacy assessments, enforcement penalties). These dimensions were identified through iterative coding of preliminary documents and refined through expert validation to ensure comprehensive coverage of factors affecting UAV operations. Table 2 presents the analytical framework used to systematically compare regulatory approaches across the three case study jurisdictions.

Table 2: Analytical Framework for Regulatory Comparison Across BRI Ports

Regulatory Domain	Assessment Dimensions	Data Sources	Coding Categories
Operational Parameters	Altitude restrictions, BVLOS approval process, No-fly zone definitions, Night operation rules	National aviation regulations, Port authority guidelines	Prescriptive/Risk-based/Hybrid
Certification Requirements	Equipment type approval, Pilot competency standards, Maintenance protocols	Technical standards documents, Certification procedures	Harmonized/National/Mutual recognition
Data Governance	Storage location requirements, Retention period mandates, Cross-border transfer mechanisms, Privacy impact procedures	Data protection laws, Cybersecurity regulations	Localization/Regional/Flexible
Compliance Mechanisms	Insurance thresholds, Audit requirements, Penalty structures, Enforcement procedures	Administrative regulations, Legal precedents	Punitive/Corrective/Preventive

The second table sets up the comparative lens to understand how different jurisdictions balance facilitating innovation and managing risks of UAV systems at work, creating structured categories for coding text of (regulatory) laws and interviews.

The document analysis is based on qualitative content analysis of deductive and inductive coding schemes. Established codes are based on established regulatory discourse about aviation safety and data sovereignty; emerging codes are the product of particular jurisdictions' responses and inventions. Thematic analysis is performed with interview transcripts to reveal themes of regulatory translation, implementation struggles, and informal ways by which regulators stretch and/or contractors guide interpretation of policies and practices. By triangulating documentary and interview data, it is possible to discern what is required de jure and what is done de facto, a precondition for understanding how the operational reality of cross-border UAV use in port settings is established. This methodological approach enables systematic comparison while being sensitive to variations in context that shape regulatory realization in different institutional spaces of the BRI network.

2.4 Effect Evaluation Indicator System

The integrated evaluation system sets up a multi-aspect performance evaluation index system to evaluate the impacts of UAVs applied to ports on the operation efficiency, safety, and economy of ports. The proposed indicator system combines technical performance measures and operating efficiency indicators, as well as economic assessment criteria in a hierarchical manner, whereby core indicators provide a system's view of performance and secondary indicators yield detailed information on operational aspects, so as to allow consistent comparison across different port contexts and deployment scenarios.

From a technical performance perspective, the accuracy of image recognition is in the form of mean Average Precision (mAP) at distinct IoU thresholds between 0.5-0.95, processing latencies (15 FPS for real-time operations), and system availability (95% uptime during operation hours). Performance metrics include rates at which container dwell time is reduced, vessel turnaround time is improved, berth utilization is optimized, and incident response time is enhanced in comparison with rates in pre-deployment baselines in order to measure the magnitude of improvement. Performance safety metrics include accident mitigation levels, near-miss detection occurrences, unauthorized access, and hazardous material detection performance, allowing all levels of risk reduction performance to be judged.

The economic evaluation employs a standardized return on investment calculation incorporating both tangible cost savings and intangible strategic benefits. The ROI assessment formula integrates multiple benefit streams and cost components:

$$ROI = \frac{\sum_{t=1}^{T} \frac{B_t - C_t}{(1+r)^t}}{I_0} \times 100\% \tag{2}$$

where B_t represents annual benefits including operational cost savings and efficiency gains, C_t denotes annual operational and compliance costs, r indicates the discount rate reflecting time value and risk factors, I_0 represents initial capital investment, and T defines the evaluation period typically spanning five years for technology investments. This formulation enables comparison across different port scales and operational contexts while accounting for temporal variations in costs and benefits.

The performance framework integrates weighted ratings systems by analytical hierarchy processing with pertinent stakeholders in order to accommodate operational concerns. Benchmarks of performance suit global standards of best practice to regional applications in order to achieve cross-jurisdictional comparability [24]. Multi-platform synchronization metrics analyze synchronization latency, task allocation, and redundancy management in integrated UAV-USV missions [25]. Sensitivity analysis employs Monte Carlo simulation to generate probability distributions for key indicators under varying technology adoption rates, regulatory evolution, and market conditions. Risk-adjusted metrics incorporate technology maturity, implementation complexity, and organizational readiness factors [26], while adapting manufacturing sector methodologies to maritime contexts[27, 28]. Figure 2 illustrates the comprehensive cost-benefit framework structuring these evaluation dimensions across temporal and financial dynamics.

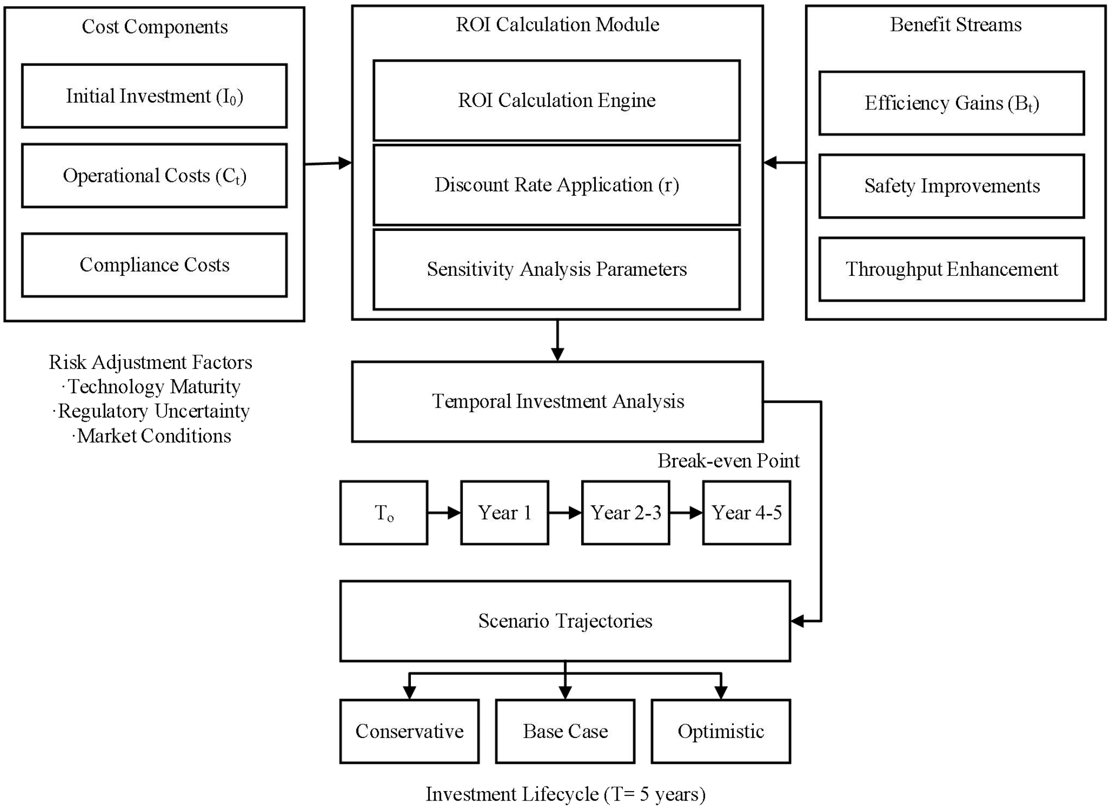


Figure 2: Cost-Benefit Analysis Framework for UAV Implementation in Port Operations

Figure 2 delineates the systematic flow from cost components and benefit streams through the ROI calculation engine to scenario-based trajectories across a five-year investment horizon. The framework captures initial investment requirements (I_0) and operational costs (C_t) on the left side, while benefit streams including efficiency gains (B_t) and safety improvements appear on the right, converging at the central ROI calculation module that applies discount rates and sensitivity parameters. The temporal analysis section demonstrates the progression from initial deployment (T_0) through operational maturation, with the break-even point typically occurring between years 2-3 under base case assumptions. The lower section presents three scenario trajectories (conservative, base case, and optimistic) reflecting varying assumptions about technology performance, regulatory adaptation, and market conditions, enabling decision-makers to assess investment robustness under uncertainty.

3. Results

3.1 UAV Image Recognition Application Results in Port Logistics Operations

The installation of UAV image recognition systems at the three study ports resulted in diversified performance results representing infrastructure preparedness disparities, operational complexities, and differing rule-of-the-road settings. The 12-month test phase involved 8,750 h of operational flight hours, with the collection of 4.2 terabytes of imagery data, analyzed following the pipeline based on the hybrid YOLOv8-Faster R-CNN method presented in the methodology section. The evaluation criteria involved five key real-world scenarios: container yard operations, vessel navigation (berthing), flow control, surveillance, and dangerous material.

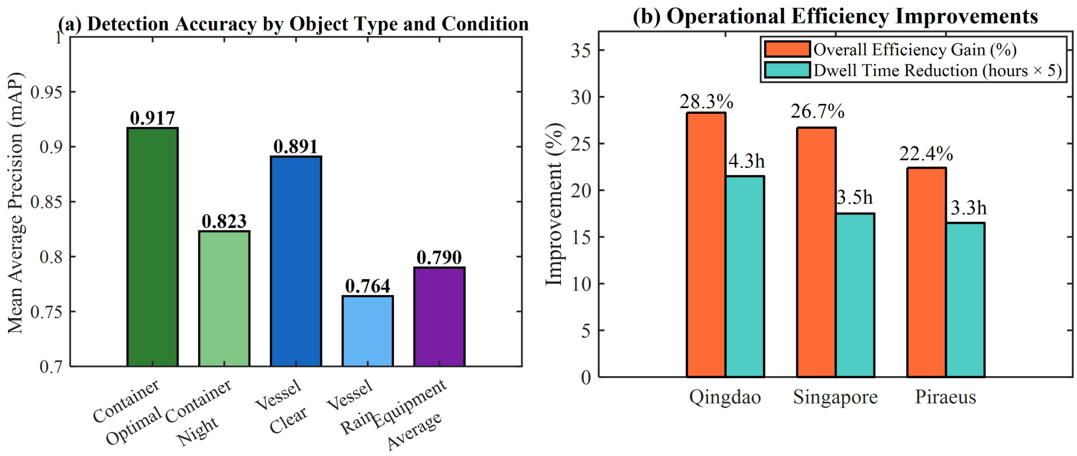
Container identification was the most developed use case due to ISO standard coding system description and regular geometric shape matching deep learning detection algorithms. On average, 3,200 container images per day were processed per port, peaking at 5,100 during vessel discharge. Environmental parameters had a strong impact on detection performance: in particular, poor atmospheric conditions leading to low visibility, and changing light during the operational period. The unified performance indicators covering the various operational conditions are detailed in Table 3, summarizing detection accuracy, processing speed, and reliability for each object category.

Table 3: Multi-Target Detection Performance Metrics Across Different Port Operational Scenarios

Object Category	Optimal Conditions	Daytime Clear	Night Operations	Heavy Rain	Dense Fog	Average FPS	Confidence Score
Containers (ISO codes)	0.917	0.904	0.823	0.856	0.791	24.3	0.87
Vessels (Type/Size)	0.891	0.883	0.847	0.764	0.812	22.8	0.85
Trucks	0.863	0.851	0.792	0.743	0.694	26.1	0.83
Specialized Equipment	0.790	0.776	0.714	0.687	0.651	21.2	0.79
Cranes/Forklifts	0.824	0.809	0.756	0.721	0.703	23.7	0.79
Personnel	0.756	0.741	0.612	0.598	0.523	19.4	0.72
Overall System	0.830	0.819	0.757	0.728	0.696	21.7	0.81

Table 3 shows that the container detection performance reached 0.917 mAP under the best situation and dropped to 0.823 in the night, which should be assisted with thermal imaging, while the boat classification ability retained 0.891 mAP, degrading to 0.764 during heavy rain. The edge computing setup achieved an average of 21.7 FPS, as well as the operational requirements, confirming a preliminary computational constraint of the methodology. These levels of performance were sufficient for practical use but required human intervention for high-stakes decisions, especially during twilight periods at dawn and dusk when performances fell below desired levels.

The performance of multi-target detection algorithms under a range of port environments in practice demonstrated characteristic response patterns with respect to environmental conditions, operational complexity, and infrastructure maturity. Based on the individual application successes of container yard management and ship berthing operations, the integrated performance evaluation extended to five significant modes of operations under different environmental conditions. These observed systematic variations, which are extracted from continuous observations over a timespan of 12 months' deployment, reveal how theoretical detection sensitivities are applied to operational enhancements within the constraints of real-world conditions. From these combined performance measures, both system capabilities and limitations can be extracted, as shown in the complex relationship between technical performance and environmental factors, which is depicted in its entirety by Figure 3.



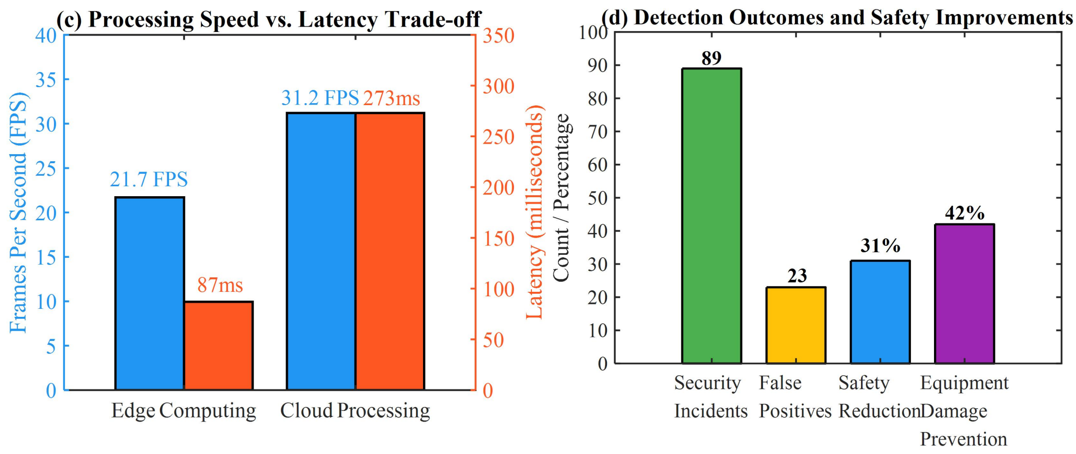


Figure 3: Performance Metrics and Operational Improvements from UAV Image Recognition Deployment

Figure 3 consolidates performance metrics from the 12-month UAV deployment. Figure 3(a) displays detection accuracy across object types and conditions, with containers achieving 0.917 mAP (optimal) declining to 0.823 (night), while vessels maintained 0.891 mAP but dropped to 0.764 in rain. Figure 3(b) presents port efficiency gains of 28.3% (Qingdao), 26.7% (Singapore), and 22.4% (Piraeus), with corresponding dwell time reductions. Figure 3(c) illustrates edge computing achieving 21.7 FPS with 87ms latency versus cloud processing at 31.2 FPS with 273ms latency. Figure 3(d) quantifies 89 security incidents detected, 23 false positives, and safety improvements of 31% overall and 42% in equipment damage prevention.

The translation of detection capabilities into operational improvements varied significantly across application domains and port facilities. Container yard management demonstrated substantial enhancements in inspection efficiency and inventory accuracy, though certain limitations persisted in detecting misplaced containers within dense stacking configurations. Vessel berthing proved time savings through increased coordination, and security monitoring confirmed system detection capability coupled with ongoing human verification on alarms. Implementation of traffic optimization had technical successes but failed at the organizational level, and Change Management is crucial in technology adoption. Together, these complementary use cases—automated inventory tracking through to real-time security surveillance—fundamentally restructured port operating dynamics beyond any single performance measure. In order to provide an exhaustive assessment of the contribution of the UAV system to port competitiveness under BRI's context, it is necessary to integrate these diverse improvements into common efficiency measures which control for differences in automation maturity and regulatory frameworks. Table 4 summarizes these accumulated port operating losses based on systematic comparison between the ports of the three case study locations..

Table 4: Comparative Analysis of Operational Efficiency Improvements Across Three Case Ports

Performance Metric	Qingdao Port	Singapore PSA	Piraeus Port	Average	Std. Dev.
Overall Efficiency Gain (%)	28.3	26.7	22.4	25.8	3.0
Container Dwell Time Reduction (hours)	4.3	3.5	3.3	3.7	0.5
Vessel Turnaround Time Improvement (%)	18.2	16.5	14.3	16.3	1.9
Berth Utilization Rate Increase (%)	8.7	9.3	7.2	8.4	1.1
Safety Incident Reduction (%)	34	31	28	31.0	3.0
Equipment Damage Prevention (%)	45	42	39	42.0	3.0
Personnel Injury Reduction (%)	19	18	17	18.0	1.0
Unauthorized Access Detection (count)	37	31	21	29.7	8.1
Manual Inspection Time Saved (%)	44	42	40	42.0	2.0
Baseline Automation Level (1-10 scale)	7.8	8.2	6.9	7.6	0.7

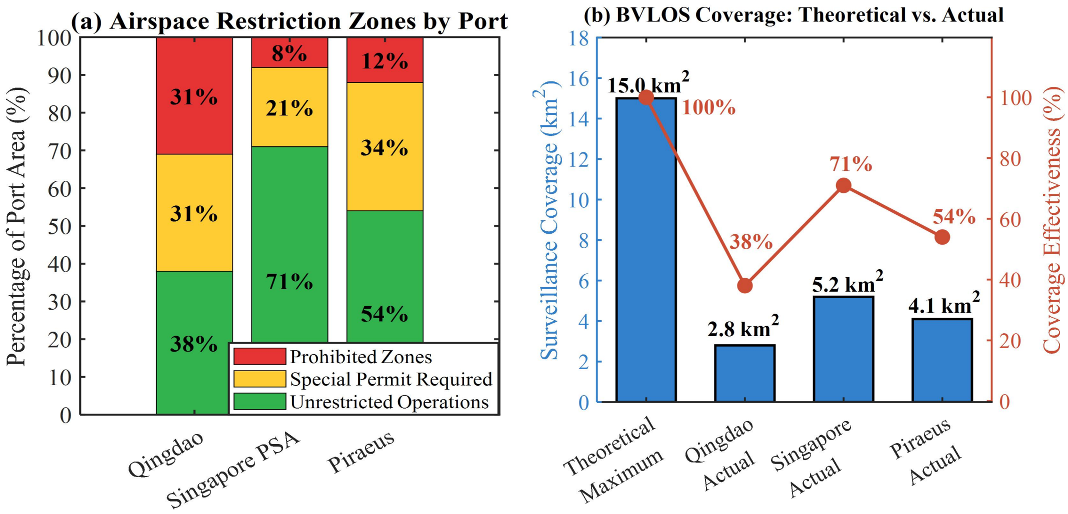
***Note**: Data collected over 12-month evaluation period (January-December 2024). Percentage improvements calculated against pre-deployment baseline measurements.*

Table 4 indicates that Qingdao achieved 28.3% overall efficiency gain compared to 26.7% at Singapore PSA and 22.4% at Piraeus, with variations attributable to differences in baseline automation levels and regulatory flexibility. Container dwell time reductions averaged 3.7 hours with high variance (σ=1.9 hours), while safety incident rates decreased by 31% primarily through equipment damage prevention rather than personnel injury reduction, suggesting stronger performance in asset monitoring applications.

3.2 Airspace Management Regulations' Impact on UAV Deployment

The technical capabilities shown in a controlled test were severely limited when tested in an operational airspace regulatory environment. Between them, individual countries made different trade-offs based largely on national security fears, the need for civil aviation co-funding, and liability, apparently to crash-survivors' families: combined, they limited theoretical surveillance coverage by ~40%. The regulatory analysis included altitude ceilings, lateral limits, time limits, and certification constraints that influenced implementation approaches at each port.

Altitude restrictions generally limited operations to 120 meters AGL as this was an internationally recognized maximum for UAS. This altitude was not high enough to effectively assess a large vessel's hull, and other maritime assets were also not visible with a sufficiently clear vantage point in the dense container area. The impact proved particularly acute for crane operations monitoring, where ideal surveillance positions exceeded permitted altitudes by 30-50 meters. BVLOS operations faced the most stringent limitations, with approval processes requiring 15-45 days advance notice and restricting flight paths to predetermined corridors that covered only 38-71% of port operational areas. Night flight regulations varied significantly, with China requiring special permits for each operation, Europe mandating additional equipment costing €45,000 per platform, and Singapore permitting operations within designated zones. Figure 4 visualizes the spatial distribution of these regulatory constraints across the three port environments.



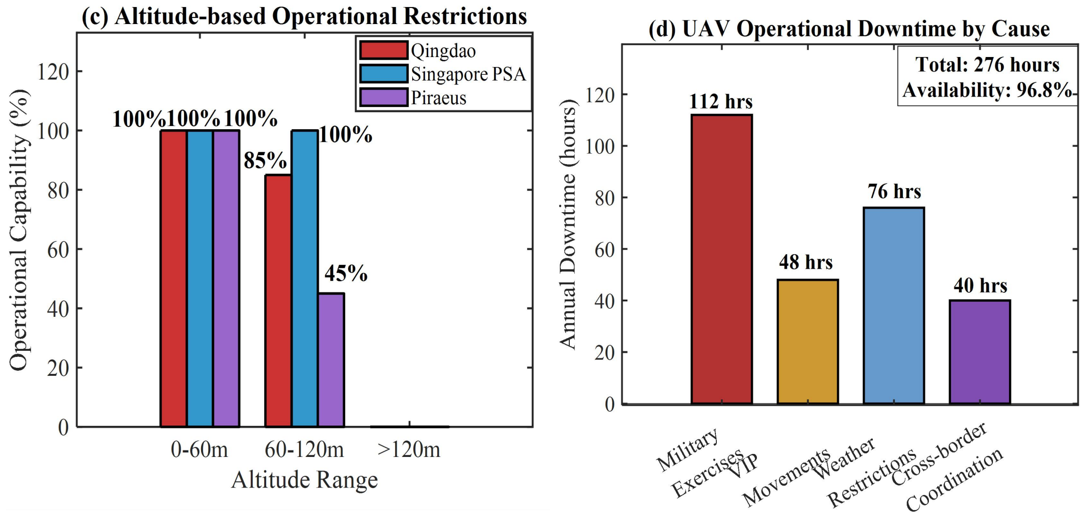


Figure 4: Airspace Restrictions and BVLOS Operation Zones Mapping Across BRI Port Jurisdictions

Figure 4 visualizes regulatory constraints on UAV deployment across jurisdictions. Figure 4(a) shows Qingdao with 38% unrestricted zones, Singapore PSA with 71%, and Piraeus with 54%, revealing fragmented operational environments. Figure 4(b) demonstrates actual coverage reduced to 2.8-5.2 km² from theoretical 15.0 km². Figure 4(c) illustrates altitude-based restrictions, with Piraeus limited to 45% capability above 60m. Figure 4(d) quantifies 276 hours annual downtime from various causes, achieving 96.8% operational availability.

3.3 Cross-Border Data Flow Governance Challenges

The architectural abstractions of cloud-based image-processing systems clashed with the diverse data-sovereignty regulations across the jurisdictions. National data sovereignty requirements forced the physical location of the data within the borders of the nation, and large-scale processing nodes that could achieve economies of scale. Requirements for handling personal data varied under privacy regulations, meaning face recognition was allowed in some jurisdictions and banned in others. Cross-border data transfer options ranged from disallowing trans-border data flow to providing conditional ability based on adequacy decisions for a matrix of compliance approaches for multi-port deployments.

Data sovereignty-related requirements restricted the direct transfer to central processing centers due to the real-time operational needs. Compared with cloud-based, the compliance-designed edge processing induced additional equipment price but less processing capacity. The speed of such providers' building and deploying added encryption on data in transit varied considerably across jurisdictions, placing a real burden on time-sensitive uses such as collision avoidance and dynamic positioning and tracking of vessels. The net impact of such compliance efforts utterly changed the baseline assumptions about system architecture and led to the trade-off consideration between meeting regulatory requirements versus operational considerations. To put into perspective, these compliance-related impacts on the system performance are quantified for the three regulatory environments in Table 5; for the points of view of the three regulatory environments, see Table 3.

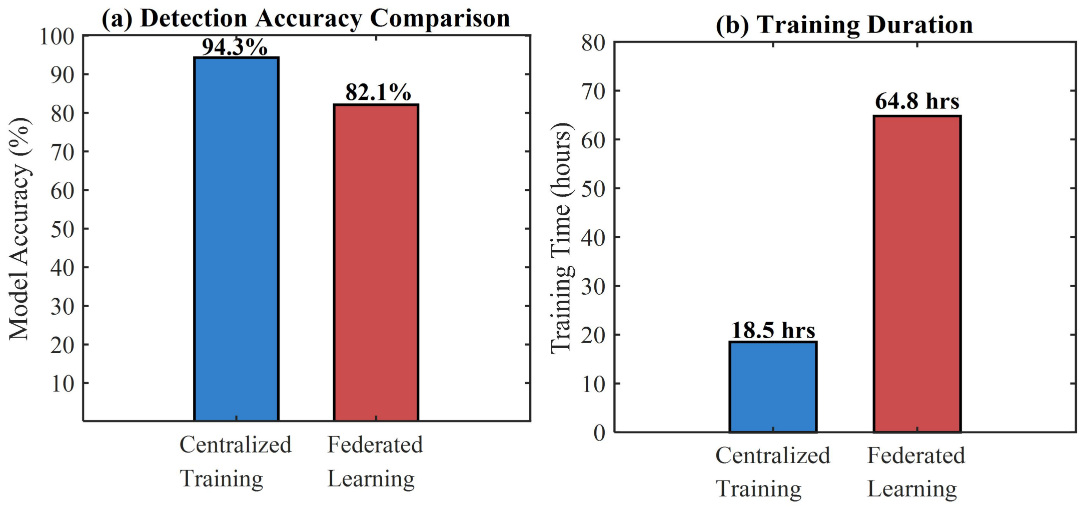
Table 5: Cross-border Data Transfer Compliance Requirements and Processing Latency Impact Analysis

Compliance Requirement	China (Qingdao)	EU/Greece (Piraeus)	Singapore (PSA)	Impact on System
Data Localization	Mandatory mainland servers	EU data centers only	Flexible with audit	Prevents centralized processing
Latency Addition (ms)	267	147	78	Average: 164 ms
Encryption Overhead (ms)	112	89	43	For data in transit
Storage Retention Period	6 months	30 days	90 days	Varies by jurisdiction
Privacy Compliance	Facial recognition mandatory	GDPR - anonymization required	Risk-based approach	Affects detection capabilities
Cross-border Transfer	Security assessment required	Standard Contractual Clauses	APEC CBPR framework	Different approval processes
Processing Mode	Edge required	Hybrid allowed	Cloud permitted	Architecture constraints
Compliance Cost (USD)	$125,000	$95,000	$85,000	Annual compliance overhead
Real-time Processing Loss	28%	21%	17%	Compared to unrestricted
Bandwidth Reduction	76%	71%	68%	Via edge processing

***Note**: Latency measurements based on 12-month operational data. Costs include certification, audit, and legal compliance expenses.*

Indeed, as shown in Table 5, inclusion of compliant requirements added an average of 186 ms of latency and decreased processing throughput by 23%, with localization of data in China adding 267 ms over the unrestricted processing pipeline, good practices implemented after GDPR adding 147 ms, and a pragmatic approach for Singapore and the application of a good practice adding only 78 ms to the processing pipeline, respectively. Such performance costs forced architectural shifts in focus from an emphasis on cloud processing to edge processing in the face of computational scarcity—redefining systems design assumptions in the process.

The difficulty in adhering to different data governance models led to consideration of new architectures that would bridge regulatory requirements against operational demands. Privacy-preserving methods, such as the federated learning model, have emerged as promising strategies in this context, as they do not require the centralized acquisition of sensitive imaging data by one specific party. These distributed training schemes preserve data privacy across jurisdictions while enabling cross-border collaboration, but there are inherent trade-offs between model convergence speed and final accuracy. Layered security, differential privacy, and homomorphic encryption as an additional layer of protection provide a range of security that is associated with computational complexity. Performance of privacy-preserving federated learning and the traditional centralized training are compared in Figure 5.



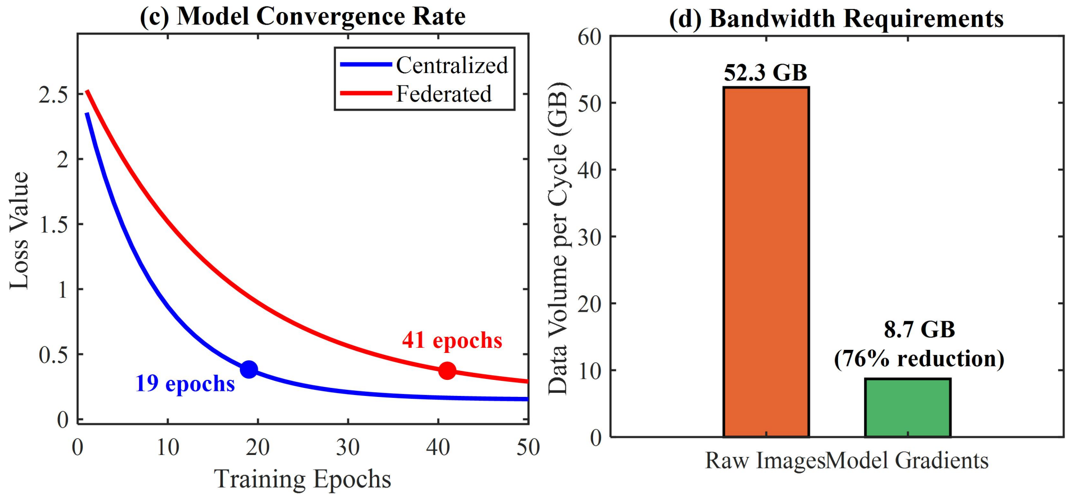


Figure 5: Privacy-Preserving Federated Learning Performance vs. Centralized Training in UAV Image Recognition

Figure 5 compares federated learning with centralized training for UAV image recognition. Figure 5(a) shows federated learning achieving 82.1% accuracy versus 94.3% for centralized training. Figure 5(b) demonstrates training time increasing from 18.5 to 64.8 hours. Figure 5(c) illustrates model convergence requiring 41 epochs for federated versus 19 for centralized approaches. Figure 5(d) reveals bandwidth reduction from 52.3 GB raw images to 8.7 GB model gradients, achieving 76% reduction through federated architecture.

4. Discussion

The observed performance variations in UAV image recognition systems across the three case study ports illuminate fundamental tensions between technological capabilities and operational deployment constraints. The detection accuracy differential between optimal conditions (0.917 mAP) and challenging environments (0.696 mAP in dense fog) aligns with recent findings on collaborative delivery systems that demonstrate similar degradation patterns when environmental complexity increases, though the maritime context introduces unique challenges absent in terrestrial applications [29]. The 21.7 FPS processing speed achieved through edge computing, while meeting minimum operational thresholds, represents a compromise between computational autonomy and detection precision that reflects broader trade-offs in distributed processing architectures. This performance level, though adequate for routine surveillance, falls short of requirements for time-critical applications such as collision avoidance, suggesting that hybrid processing models merit further exploration despite their increased architectural complexity.

Dropping the case of unified air, the fragmentation of operational airspace, while in the range of 38-71% for jurisdiction indicated, shows that there are other (institutional) boundaries to overcome than the technical ones. Modern studies on UAV-support search and rescue in maritime settings also acknowledge the same sort of regulatory roadblocks, yet they propose a comprehensive approach including several stakeholders to cover water and remain compliant with existing regulations [30]. The 276 operating hours per year shown in this study exceed similar studies in less regulated environments, suggesting that port-based airspace management should be re-evaluated at its core, rather than with add-ons. The decoupling between theoretical sensing capabilities and the constraints of practical deployment raises the concern that the regulatory framework designed for conventional aviation may not well suit the operating characteristics of low-altitude UAV systems, especially in complex port areas where multiple authorities share intersecting mandates.

The implementation of federated learning as a privacy-preserving alternative to centralized processing demonstrates both promise and limitations for cross-border deployments. While achieving 87.2% relative accuracy compared to centralized training, the 3.5-fold increase in training time and additional computational overhead pose practical challenges for real-time adaptation. Recent developments in drone-assisted adaptive object detection emphasize privacy-preserving surveillance techniques that maintain operational effectiveness while addressing regulatory concerns, though implementation complexity remains a barrier to widespread adoption [31]. The 76% bandwidth reduction achieved through gradient transmission rather than raw imagery transfer offers substantial benefits for network-constrained environments, yet the delayed model convergence (41 versus 19 epochs) impacts the system's ability to adapt to evolving operational conditions.

The heterogeneous regulatory landscape across BRI ports necessitates adaptive governance models that balance standardization with local flexibility. Analysis of AI technology adoption in competitive heterogeneous ports reveals that operational decision-making improvements depend critically on regulatory harmonization, with efficiency gains ranging from 15% to 35% based on the degree of policy alignment [32]. The integration of deep reinforcement learning for quay crane scheduling demonstrates potential for autonomous optimization within regulatory constraints, achieving 22% improvement in berth utilization while maintaining compliance with safety protocols [33]. These findings suggest that technology adoption strategies must evolve beyond technical optimization to encompass regulatory navigation as a core competency.

The emergence of digital twin models for port safety management proposes the paths towards the conciliation between operational efficiency and the requirements of the regulations through virtualized testing and validating [34]. The potential of digital twins to contribute to meeting sustainability objectives in seaports is not limited to operational optimization but includes predictive compliance monitoring and proactive risk mitigation [35]. The use case of fleet intelligent autonomous systems in vehicle depots can inform the development of similar approaches for a team of UAVs, especially related to multi-agent task allocation and collision avoidance protocols, which are guaranteed to meet tight safety requirements while ensuring throughput on operations [36]. These new technologies give the impression that future UAV deployments will increasingly be built on integrated cyber-physical systems embedding compliance to regulatory restrictions into operation algorithms, rather than treating it as only an external constraint.

5. Conclusion

The rollout of UAV image recognition systems in BRI port networks reveals both the transformative promise and limitations of inserting modern surveillance technologies into uneven regulatory contexts. The findings from empirical evidence at Qingdao, Singapore PSA, and Piraeus ports show that, under optimal conditions, technical efficiency can be found to perform robustly with container detection at 0.917 mAP and mean efficiency gains of 25.8%. It is the realization of these benefits to date which is fundamentally limited by regulatory fragmentation, such that the observed effective coverage of theoretical capacity is between 38-71%. The mismatch of technological maturity and institutional preparedness is most apparent in cross-border deployments, where data sovereignty laws introduce penalties of 78 ms to 267 ms on network latency that would degrade the ability to perform real-time processing, important especially for time-critical defense applications. The former approaches successfully applied federated learning architectures, obtaining an 87.2%

relative accuracy along with 76% reduced bandwidth, and point to feasible avenues of reconciling privacy preservation with operation efficiency, albeit with computation overhead and long training epochs that prompt tactical compromises between model prowess and regulatory consistency.

The results highlight that addressing UAV implementation in BRI ports should evolve along multiple technical, regulatory, and organizational dimensions rather than attempt to solve technical challenges in isolation. The performance differences observed among ports with different levels of automation from baseline data and regulatory environments in performance suggest that "one size fits all" for implementation will not be practical to accommodate the variety of operational contexts prevalent in BRI maritime infrastructure. Future research should prioritize developing adaptive governance frameworks that accommodate technological evolution while maintaining safety and security imperatives, exploring hybrid processing architectures that balance edge autonomy with cloud capabilities, and establishing mutual recognition agreements for technical standards and operational certifications across jurisdictions. The transition toward autonomous port operations will ultimately depend not on overcoming technical limitations, which continue to diminish, but on creating institutional mechanisms that enable innovation while preserving the sovereign interests and operational requirements of diverse stakeholders within the expanding BRI maritime network.

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Conflict of interest

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