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Multi-Sensor Data Fusion for Maritime Traffic Surveillance A Systematic Review

Kiki Ambar Purwanti*, Abdul Rivai Ras, Yusnaldi
Department of Maritime Security, Faculty of National Security, Republic of Indonesia Defense University, Indonesia
*kiki.purwanti@km.idu.ac.id

Abstract

Maritime traffic surveillance requires reliable and comprehensive information to support maritime safety, security, and situational awareness. However, the limitations of individual sensing technologies have increased the need for multi-sensor data fusion to integrate complementary information from heterogeneous sources. This study aims to systematically review the types of sensors integrated for maritime traffic surveillance and the main applications of multi-sensor data fusion in this domain. A systematic literature review was conducted on 69 selected studies, followed by bibliometric analysis using VOSviewer to identify dominant research themes and their relationships. The results show that Automatic Identification System (AIS), radar, camera/visual sensors, satellite/Synthetic Aperture Radar (SAR), and meteorological sensors are among the frequently integrated sensing technologies. Maritime Situational Awareness was the dominant application, identified in 58 of the 69 reviewed studies (84.05%), followed by maritime surveillance, vessel tracking, autonomous navigation, and vessel detection and recognition. The keyword analysis indicates strong research connections among data fusion, AIS, maritime surveillance, vessel detection and tracking, remote sensing, artificial intelligence, and autonomous systems, reflecting a transition from conventional sensor integration toward increasingly intelligent and automated surveillance approaches. Despite these developments, challenges remain in real-time processing, spatiotemporal alignment, heterogeneous data integration, environmental variability, sensor reliability, and anomaly detection. Overall, multi-sensor data fusion provides an important foundation for developing more comprehensive, adaptive, and intelligent maritime traffic surveillance systems and supports the advancement of Maritime Situational Awareness and Maritime Domain Awareness.

Keywords: Multi-Sensor Data Fusion; Maritime Traffic Surveillance; Maritime Situational Awareness; Automatic Identification System; VOSviewer

1. INTRODUCTION

Maritime traffic surveillance plays an important role in supporting maritime safety, security, and situational awareness by enabling continuous monitoring of vessel movements and activities. However, maritime environments are complex and dynamic, with large surveillance areas, varying environmental conditions, dense traffic, and incomplete or uncertain information. Relying on a single sensing technology is therefore often insufficient to provide a reliable representation of the maritime domain. Different sensors have specific strengths and limitations, making the integration of heterogeneous sensing technologies increasingly important for comprehensive maritime surveillance [1],[2]. Multi-sensor data fusion refers to the integration and processing of information obtained from multiple heterogeneous sensors to produce more complete and reliable information than can be obtained from an individual sensor. In maritime surveillance, commonly integrated sources include the Automatic Identification System (AIS), radar, optical or infrared cameras, Synthetic Aperture Radar (SAR), UAV-based sensors, and other environmental or navigation sensors. The complementary characteristics of these technologies enable sensor fusion systems to compensate for limitations such as incomplete coverage, measurement uncertainty, occlusion, and temporary loss of sensor information [1], [3]. AIS–radar fusion, for example, combines vessel identification and movement information

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from AIS with the independent detection and tracking capabilities of radar, thereby supporting a more reliable maritime surveillance picture.

The application of multi-sensor data fusion has expanded beyond conventional vessel tracking toward maritime situational awareness, vessel detection and recognition, anomaly detection, collision avoidance, search and rescue, and autonomous navigation. Hadzagic et al. (2020) demonstrated the use of hard and soft data fusion for maritime traffic monitoring, while Wright (2019) highlighted the integration of multiple sensor modalities with machine learning and deep learning for autonomous ship navigation. More recent research has also explored multimodal fusion involving coastal sensors, UAV-mounted visual and infrared sensors to enhance maritime situational awareness in real-world conditions [4],[5]. The development of artificial intelligence has further strengthened the potential of multi-sensor data fusion for maritime surveillance. AI and machine-learning methods can support the extraction, association, classification, and interpretation of information from heterogeneous sensor sources, enabling more automated detection, tracking, and decision support. Recent research has increasingly emphasized AI-based maritime situational awareness and multimodal fusion, while also identifying challenges related to large data volumes, real-time processing, environmental variability, and the reliability of heterogeneous sensor information.

Despite these developments, the existing literature remains diverse in terms of sensor combinations, fusion methods, application domains, and technological approaches. This diversity makes it necessary to systematically examine how different sensing technologies are integrated and what functions they primarily support. Therefore, this systematic literature review analyzes research on multi-sensor data fusion for maritime traffic surveillance to identify (1) the types of sensors integrated in maritime traffic surveillance and (2) the main applications of multi-sensor data fusion in this domain. The review also examines emerging research themes through bibliometric keyword co-occurrence analysis to provide a broader understanding of the technological development and future direction of multi-sensor maritime traffic surveillance.

2. METHODS

2.1. Overview of the Systematic Literature Review

This study employed a Systematic Literature Review (SLR) to identify, evaluate, and synthesize previous studies related to multi-sensor data fusion for maritime traffic surveillance. The review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework to ensure a systematic and transparent study selection process [6]. The review focused on studies addressing the integration or fusion of multiple sensors and data sources to support maritime traffic surveillance activities, including vessel detection, tracking, identification, monitoring, and situational awareness. To guide the review process, two research questions (RQs) were formulated as follows RQ1: What types of sensors are integrated for maritime traffic surveillance? RQ2: What are the main applications of multi-sensor data fusion in maritime traffic surveillance?. These research questions were used to guide the literature search, study selection, data extraction, and synthesis of the selected studies.

2.2. Information Sources and Search Strategy

To perform a comprehensive literature search, the Scopus database (Elsevier) was selected as the sole bibliographic database for this systematic literature review. Scopus was selected because of its broad multidisciplinary coverage of peer-reviewed scientific literature across areas relevant to this study, including maritime technology, transportation, engineering, remote sensing, information technology, and related fields. Scopus also provides structured bibliographic metadata and advanced search functions that support reproducible literature retrieval and bibliometric analysis. Its broad coverage and standardized indexing were considered appropriate for identifying studies addressing multi-sensor data fusion and maritime traffic surveillance. The use of a single bibliographic database was also intended to maintain consistency in the search strategy, metadata structure, screening process, and subsequent bibliometric analysis. This approach enabled the literature retrieval process to be conducted using a standardized search syntax and predefined selection criteria. The search was conducted on August 30, 2026, using Boolean operators and the TITLE-ABS-KEY field to identify studies addressing multi-sensor data fusion and maritime traffic surveillance.

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Table 1. Database search strategy and Boolean syntax

Database interface /Platform	Preliminary Search	Applied filters and metadata limits
Scopus (Elsevier)	TITLE-ABS-KEY (("multi-sensor fusion" OR "multisensor fusion" OR "multi-sensor data fusion" OR "multisensor data fusion" OR "sensor fusion" OR "sensor data fusion" OR "data fusion" OR "information fusion") AND ("maritime traffic surveillance" OR "maritime surveillance" OR "vessel traffic surveillance" OR "ship traffic surveillance" OR "vessel surveillance" OR "ship surveillance" OR "vessel monitoring" OR "ship monitoring")).	Document Type: Article; Language: English; Publication Stage: Final; Database: Scopus; Search date: 30 August 2026

The search string combined terms related to multi-sensor and data fusion with terms describing maritime traffic surveillance. The use of Boolean operators (AND and OR) enabled the combination of related concepts, while the TITLE-ABS-KEY field restricted the retrieval to terms appearing in the title, abstract, or keywords of Scopus-indexed records. This approach was intended to provide sufficient retrieval sensitivity while maintaining thematic relevance to the scope of the systematic review.

A preliminary exploratory search was initially conducted using broader combinations of sensor fusion, ship or vessel, and surveillance-related terms, which retrieved 1,197 documents. The terminology was subsequently refined to improve thematic specificity and reduce the retrieval of studies unrelated to maritime traffic surveillance. The final focused search string retrieved 218 documents before the application of the predefined filters. The exact search syntax and applied selection criteria are systematically presented in Table 1 to ensure transparency and reproducibility of the literature search.

2.3. Eligibility Criteria

The inclusion criteria were as follows: (1) studies addressing the integration or fusion of two or more sensors or data sources; (2) studies related to maritime traffic surveillance, vessel detection, identification, tracking, or monitoring; (3) studies presenting a method, framework, model, or system involving multi-sensor or multimodal data fusion; (4) peer-reviewed journal articles; and (5) articles published in English. Exclusion criteria: Studies were excluded if they used only a single sensor or data source, were unrelated to maritime traffic surveillance, focused only on feature or object fusion within a single sensing modality, were review papers or conference papers, or did not provide sufficient information regarding the sensor/data fusion approach and its surveillance application.

Methodological limitations. Several methodological limitations should be acknowledged. First, the use of Scopus as the sole bibliographic database may have resulted in the omission of relevant studies indexed in other databases, such as Web of Science, IEEE Xplore, or other specialized databases. Although Scopus provides broad multidisciplinary coverage, no single bibliographic database can guarantee complete coverage of all relevant publications. Second, the restriction to English-language articles may have excluded relevant studies published in other languages, potentially introducing language-related selection bias. Third, conference papers were excluded to maintain a focus on peer-reviewed journal articles and to prioritize studies with more complete methodological and empirical descriptions. However, this restriction may have resulted in the omission of recent or emerging research presented initially at conferences, particularly in rapidly developing technological fields. These limitations should be considered when interpreting the scope and generalizability of the findings.

2.4. The screening, deduplication, and selection process

The study selection process was conducted through several stages to identify literature relevant to multi-sensor data fusion for maritime traffic surveillance. The preliminary search retrieved 1,197 records, which were refined using the focused search strategy and resulted in 218 records. Following the initial screening, 74 articles were retained for full-text eligibility assessment. After applying the language criterion, 69 English-language journal articles met the predefined inclusion and exclusion criteria and were retained for the systematic literature review. The complete study selection process is presented in the PRISMA 2020 flow diagram.

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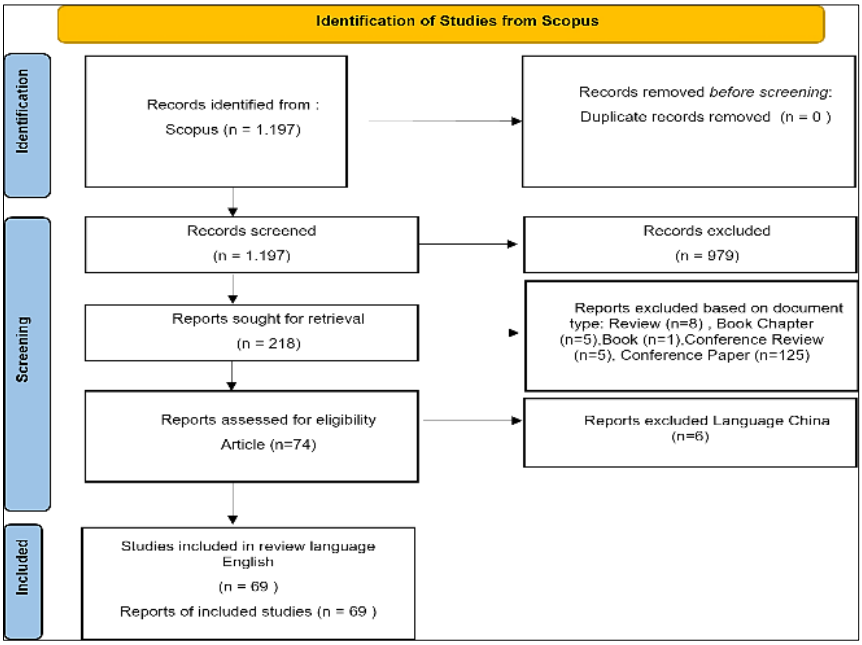


Figure 1. PRISMA 2020 Flow Diagram of the Study Selection Process for the Systematic Literature Review

The PRISMA flow diagram illustrates the systematic process of identifying, screening, assessing, and selecting the literature included in this review. The final 69 English-language journal articles were subsequently used for data extraction and further analysis.

2.5. The bibliometric mapping and VOSviewer protocol

The bibliometric mapping was performed to complement the systematic literature review by providing a visual representation of the research landscape related to multi-sensor data fusion for maritime traffic surveillance. The 69 English-language articles included in the review were analyzed using VOSviewer through keyword co-occurrence analysis. VOSviewer enables the construction and visualization of bibliometric maps and can be used to examine relationships among keywords based on their co-occurrence within the literature [7].

The analysis focused on identifying relationships among keywords and visualizing their linkages and clusters to support the identification of dominant research themes. The extracted information included publication data, sensor and data sources, fusion approaches, surveillance applications, and author keywords. The overall analytical framework integrating the systematic review and bibliometric analysis is presented in Figure 2.

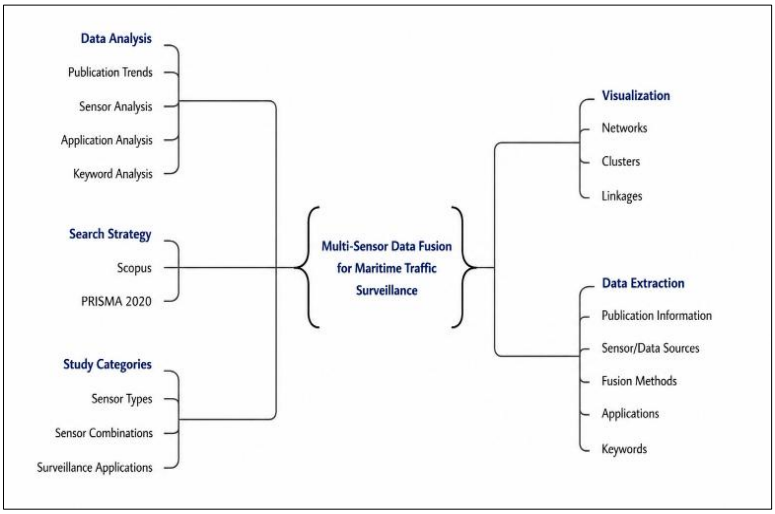


Figure 2. Analytical framework for the systematic review and bibliometric analysis of multi-sensor data fusion for maritime traffic surveillance.

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Figure 2 illustrates the analytical framework used to integrate the systematic review and bibliometric analysis. The framework links the literature search and selection process with data extraction, thematic analysis, and bibliometric mapping, providing a structured basis for analyzing sensor types, fusion approaches, and maritime surveillance applications. The results of these analyses are presented and discussed in the following section.

3. RESULTS AND DISCUSSION

3.1. Results analysis and findings

3.3.1 Publication Trends

The publication trend was analyzed to examine the temporal distribution of studies related to multi-sensor data fusion for maritime traffic surveillance. Based on the selected Scopus records, 69 articles were identified over the period from 1996 to 2026. The annual distribution of publications is presented in Figure 3.

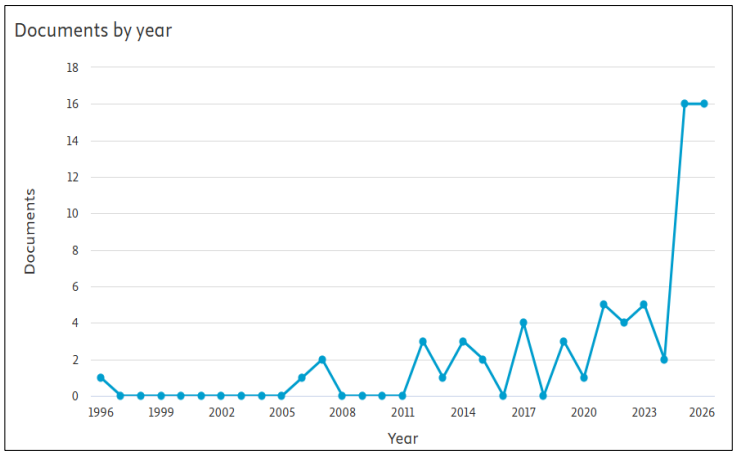


Figure 3. Publication Trends in Multi-Sensor Data Fusion for Maritime Traffic Surveillance

As shown in Figure 3, the number of publications varies across the observed period, with a relatively limited number of studies in the earlier years and a higher number of publications in the most recent period. The dataset records 16 publications in 2025 and 16 publications in 2026, representing the highest annual counts in the retrieved literature. Publications were also recorded in 1996, 2006–2007, and 2012–2024, with varying numbers of articles across the years. The 2026 records represent publications retrieved up to the search date of August 30, 2026.

The selected publications were further analyzed based on their contributing affiliations. Figure 4 presents the top contributing institutions in the reviewed literature.

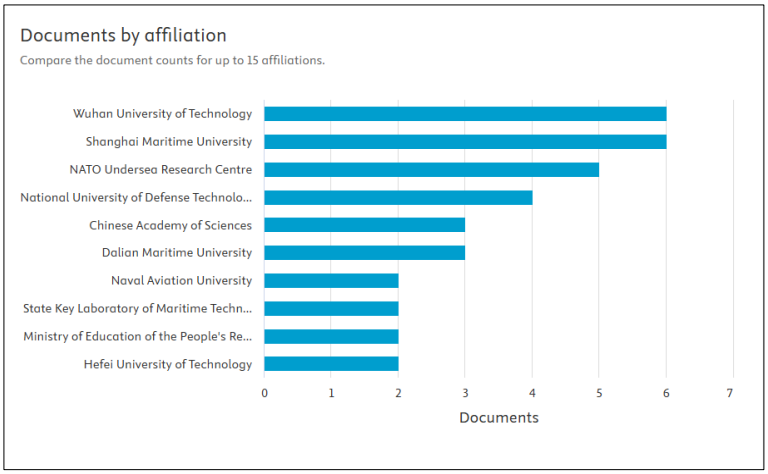


Figure 4. Top Contributing Affiliations in Multi-Sensor Data Fusion for Maritime Traffic Surveillance

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The affiliation analysis shows that Wuhan University of Technology and Shanghai Maritime University were the leading contributing institutions, with six publications each. The NATO Undersea Research Centre ranked third with five publications, followed by the National University of Defense Technology with four publications. The Chinese Academy of Sciences and Dalian Maritime University each contributed three publications. Two publications were recorded for Naval Aviation University, the State Key Laboratory of Maritime Technology, the Ministry of Education of the People's Republic of China, and Hefei University of Technology. This distribution indicates that research on multi-sensor data fusion for maritime traffic surveillance is contributed by a diverse range of universities and research institutions, reflecting the multidisciplinary nature of the field.

3.3.2 Types of sensors Integrated for Maritime Traffic

RQ1: What types of sensors are integrated for maritime traffic surveillance?

To answer RQ1, the selected studies were analyzed based on the types of sensors and data sources integrated for maritime traffic surveillance. The analysis identified several sensing modalities, including Automatic Identification System (AIS), optical/visual sensors, radar, Synthetic Aperture Radar (SAR), infrared, acoustic sensors, VHF speech, meteorological and oceanographic data, and LiDAR. The identified sensor and data sources and their frequency of occurrence in the reviewed literature are presented in Table 2.

Table 2. Sensor and Data Sources Integrated for Maritime Traffic Surveillance

No.	Sensor/Data Source	Frequency
1	AIS	30
2	Optical/Visual	19
3	Radar	14
4	SAR	12
5	Infrared	5
6	Acoustic	2
7	VHF Speech	2
8	Meteorological/Oceanographic	1
9	LiDAR	1

Note: The frequency represents the number of reviewed records in which the respective sensor or data source was identified. One study may involve more than one sensor/data source.

As shown in Table 2, AIS represents the most frequently identified data source, followed by optical/visual sensors, radar, and SAR. The reviewed studies demonstrate the use of AIS in combination with other sensing sources to provide vessel-related information for surveillance and tracking. For example, AIS has been integrated with radar for real-time vessel monitoring and data fusion [8], while other studies have combined AIS with visual data to improve vessel tracking in inland waterways [9]. The literature also includes the integration of AIS with VHF speech information to provide additional vessel identity and navigational intention information for maritime traffic surveillance [10]. These examples demonstrate the use of heterogeneous data sources to support maritime traffic surveillance functions.

Radar and optical/visual sensors also appear prominently in the reviewed literature. Radar-based studies address target detection and tracking, while optical or visual data provide complementary information on vessel appearance and target characteristics. The integration of radar, visible-light, and infrared data has also been investigated to exploit the complementary characteristics of different sensing modalities for maritime target detection and recognition [11]. In addition, AIS and SAR have been integrated for maritime surveillance, combining cooperative vessel information with satellite-based remote sensing observations [12].

The remaining sensing sources, including infrared, acoustic, VHF speech, meteorological/oceanographic data, and LiDAR, occur less frequently but represent additional modalities used in specific maritime surveillance applications. For example, AIS has been combined with meteorological and oceanographic information for multimodal ship trajectory prediction [11], while LiDAR has been integrated with AIS to support maritime object detection (2026). The reviewed literature therefore shows a heterogeneous sensor landscape in which different sensing and information sources are combined according to the surveillance requirements of each study. The sensor distribution provides the basis for the subsequent analysis of sensor integration patterns and combinations.

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3.3.3 Application of Multi-Sensor Data Fusion in Maritime Traffic Surveillance

RQ2: What are the main applications of multi-sensor data fusion in maritime traffic surveillance?

To answer RQ2, the selected studies were analyzed based on the main applications of multi-sensor data fusion in maritime traffic surveillance. The analysis identified several application areas, including Maritime Situational Awareness, maritime surveillance, vessel tracking, autonomous navigation, vessel detection and recognition, collision avoidance and safety, environmental monitoring, anomaly detection, traffic monitoring and management, risk assessment, and search and rescue. The frequency of each identified application across the reviewed studies is presented in Table 3.

Table 3. Main Applications of Multi-Sensor Data Fusion in Maritime Traffic Surveillance.

No.	Application	Articles (n)	Percentage (%)
1	Maritime Situational Awareness	58	84.05
2	Maritime Surveillance	29	42.02
3	Vessel Tracking	21	30.43
4	Autonomous Navigation	19	27.53
5	Vessel Detection/Recognition	19	27.53
6	Collision Avoidance/Safety	13	18.84
7	Environmental Monitoring	13	18.84
8	Anomaly Detection	6	8.69
9	Traffic Monitoring/Management	6	8.69
10	Risk Assessment	4	5.79
11	Search and Rescue	2	2.89

Note: Percentages are calculated based on 69 included articles. Because a study may address more than one application, the total percentage exceeds 100%

As shown in Table 3, Maritime Situational Awareness was the most frequently reported application, appearing in 58 of the 69 studies (84.05%), followed by maritime surveillance with 29 studies (42.02%) and vessel tracking with 21 studies (30.43%). Other applications included autonomous navigation and vessel detection/recognition, each reported in 19 studies (27.53%), while collision avoidance/safety and environmental monitoring were each identified in 13 studies (18.84%). More specific applications, including anomaly detection and traffic monitoring/management, were reported in 6 studies (8.69%) each, followed by risk assessment in 4 studies (5.79%) and search and rescue in 2 studies (2.89%). These findings are consistent with studies applying multi-sensor fusion to support situational awareness, vessel tracking, detection, navigation, and maritime safety [13],[9],[2].

3.3.4 Keyword Co-Occurrence Analysis

Keyword co-occurrence analysis was conducted using VOSviewer to identify the dominant research themes and relationships among the 69 selected studies. The analysis examined the frequency of keyword occurrences and the strength of their relationships with other keywords based on Total Link Strength (TLS). The keywords with the highest occurrences and total link strength are presented in Table 4.

Table 4. Dominant Keywords Based on Occurrences and Total Link Strength.

Rank	Keyword	Occurrences	Total Link Strength
1	Ships	22	147
2	Automatic identification system	21	146
3	Maritime surveillance	23	131
4	Data fusion	26	129
5	Maritime-surveillance	17	104
6	Automation	14	88
7	Ship detection	11	83
8	Information fusion	19	79
9	Automatic identification system (AIS)	11	76
10	Synthetic aperture radar	10	72
11	Tracking radar	10	71
12	Waterway transportation	11	70
13	Radar imaging	8	68
14	Automatic identification	9	64

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Rank	Keyword	Occurrences	Total Link Strength
15	Object detection	8	62
16	Sensor data fusion	11	62
17	Feature extraction	8	56
18	Monitoring	11	55
19	Object recognition	6	53
20	Remote sensing	9	52
21	Artificial intelligence	8	51
22	Target tracking	8	48
23	Optical remote sensing	6	45
24	Security systems	6	40
25	Unmanned aerial vehicles (UAV)	5	40
26	Unmanned surface vehicles	6	40
27	Deep learning	9	37
28	Synthetic aperture radar (SAR)	5	36
29	Antennas	5	35
30	Objects detection	5	35

Source: Author's analysis using VOSviewer based on keyword co-occurrence in the 69 selected studies.

As shown in Table 4, data fusion was the most frequently occurring keyword (26 occurrences), followed by maritime surveillance (23), ships (22), and automatic identification system (21), with the highest total link strengths observed for ships (147), automatic identification system (146), maritime surveillance (131), and data fusion (129). Keywords related to artificial intelligence and automated processing, such as artificial intelligence, deep learning, object detection, and automation, also appeared in the network, indicating their growing role in maritime detection, tracking, and data analysis. The relationships among these keywords are further visualized using the VOSviewer network presented in Figure 5.

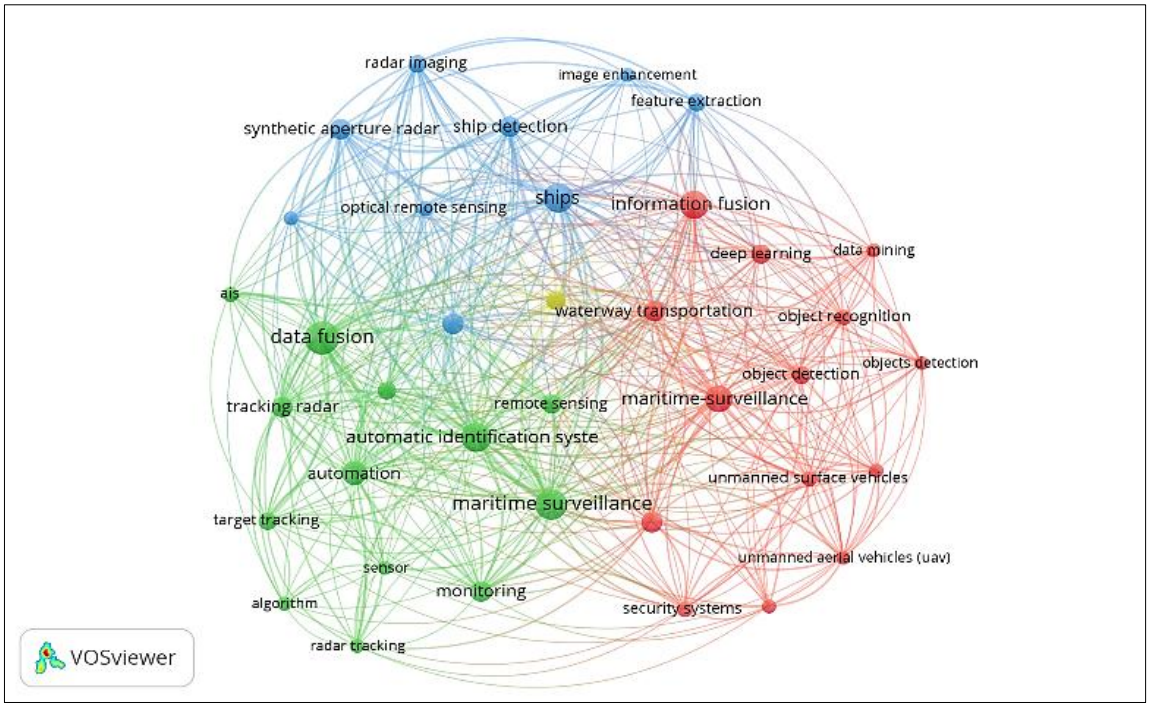


Figure 5. Network Visualization of Keyword Co-occurrence in Multi-Sensor Maritime Traffic Surveillance

Figure 5 illustrates the co-occurrence relationships among the keywords and shows several interconnected clusters representing different research themes in multi-sensor maritime traffic surveillance. The network indicates strong connections among themes related to data fusion, maritime surveillance, AIS, vessel detection and tracking, remote sensing, artificial intelligence, and autonomous systems. The identified clusters reflect the diversity and interconnection of research topics within the field. A detailed composition of the identified clusters and their associated keywords is presented in Table 5.

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Table 5. Keyword Clusters Identified from VOSviewer Network Analysis

Cluster	Main Research Theme	Representative Keywords
Cluster 1	Sensor Fusion and Vessel Tracking	Data fusion, AIS, maritime surveillance, tracking radar, target tracking, monitoring, automation
Cluster 2	AI-Based Maritime Detection and Autonomous Systems	Deep learning, object detection, object recognition, unmanned surface vehicles, UAV, security systems
Cluster 3	Remote Sensing and Image-Based Detection	Synthetic aperture radar, radar imaging, ship detection, optical remote sensing, image enhancement, feature extraction
Cluster 4	Waterway Transportation	Waterway transportation

As presented in Table 5, the identified clusters represent interconnected themes related to sensor fusion and vessel tracking, AI-based detection and autonomous systems, remote sensing, and waterway transportation. To further examine how these research themes have developed over time, an overlay visualization was generated using VOSviewer. The overlay visualization presents the temporal distribution of keywords based on their average publication year, with colors ranging from earlier research themes in blue to more recent themes in yellow. The resulting temporal evolution of the research themes is presented in Figure 6.

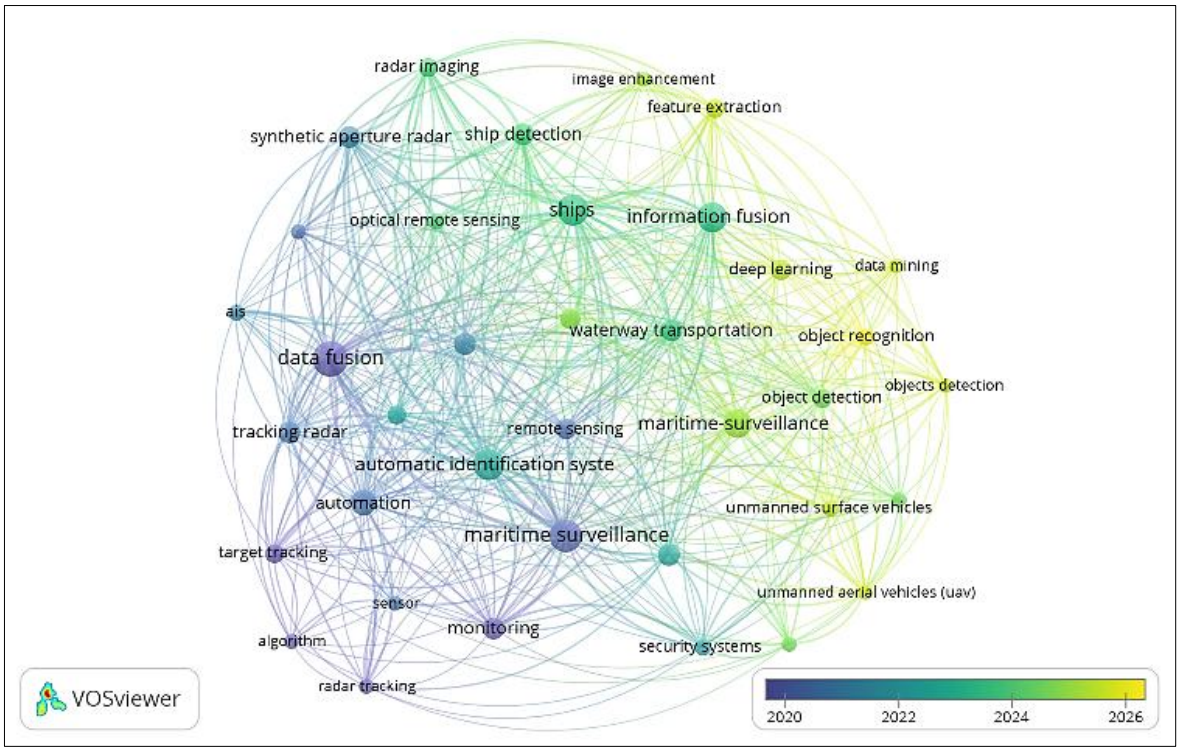


Figure 6.Overlay Visualization of Keyword Co-occurrence and Research Trends

As shown in Figure 6, the overlay visualization indicates a shift from earlier research focusing on AIS, data fusion, radar tracking, and maritime surveillance toward more recent themes involving deep learning, object detection, feature extraction, data mining, and autonomous maritime systems. This development reflects the increasing adoption of intelligent and automated approaches in maritime traffic surveillance. To further identify the most prominent and concentrated research themes within the keyword network, a density visualization was subsequently generated using VOSviewer. The density distribution of the keywords is presented in Figure 7.

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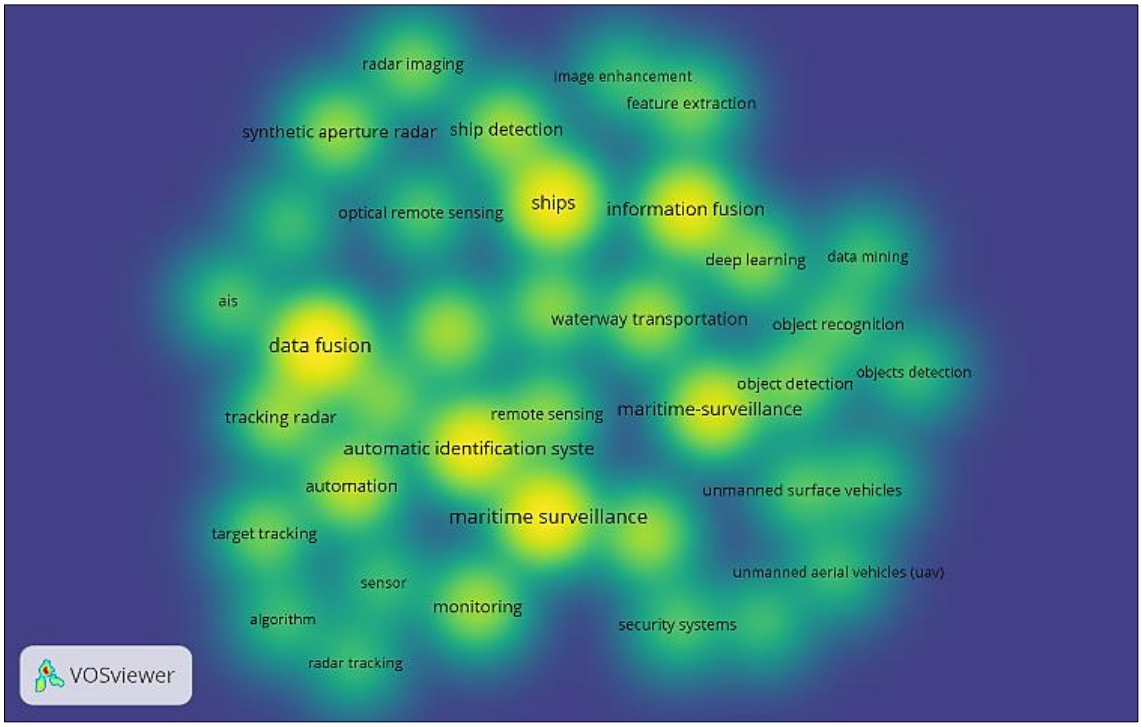


Figure 7. Density Visualization of Keyword Co-occurrence in Multi-Sensor Maritime Traffic Surveillance

Figure 7 highlights the areas with the highest concentration of keyword occurrences and link strengths, particularly around data fusion, maritime surveillance, automatic identification system, ships, and related vessel tracking themes. These dense areas indicate the core research topics that have received greater attention within the reviewed literature, while less dense areas represent more specialized or emerging themes. Overall, the network, overlay, and density visualizations collectively demonstrate the development of maritime traffic surveillance research from conventional sensor-based monitoring and fusion toward intelligent, automated, and multi-modal surveillance approaches.

3.2. Discussion

3.2.1 Sensor Integration and Technological Complementarity

The findings indicate that multi-sensor integration is primarily driven by the complementary capabilities of heterogeneous sensing technologies. AIS provides vessel identity and dynamic information, while radar offers continuous target detection and tracking, and camera/visual sensors provide information on vessel appearance and spatial characteristics. The integration of these sources therefore enables one sensor to compensate for the limitations of another, particularly in situations involving incomplete AIS information, visual occlusion, or differences in spatial and temporal observations. The study demonstrated that AIS-visual fusion can improve vessel tracking by combining AIS-based identity and movement information with visual observations, while also showing that AIS–radar fusion can enhance maritime target tracking through the complementary characteristics of the two sensing sources [14]. Similarly, SAR–AIS integration extends surveillance capabilities by combining wide-area remote sensing with vessel identification and movement information, supporting the detection and identification of vessels that may not be adequately represented by AIS alone [15]. These findings are consistent with Bal Şahin et al. (2026), who emphasized that integrating heterogeneous sensors such as AIS, radar, optical systems, and SAR can overcome the limitations of individual sensors and provide a more comprehensive maritime surveillance capability. Overall, the literature suggests that sensor integration is not merely a technological combination, but a complementary strategy for improving the completeness, reliability, and robustness of maritime situational awareness.

The reviewed literature also indicates an evolution from conventional sensor fusion toward increasingly intelligent and AI-based approaches. Conventional sensor fusion primarily focuses on integrating and associating observations obtained from heterogeneous sensing technologies to construct a more complete representation of maritime traffic. In this approach, the complementary characteristics of AIS, radar, optical/visual sensors, and SAR are exploited to improve target detection, identification, tracking, and

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monitoring. Such approaches remain important because they provide the fundamental mechanism for combining heterogeneous maritime observations and mitigating the limitations of individual sensors. In contrast, artificial intelligence (AI)-based approaches extend the role of multi-sensor fusion from information integration toward automated interpretation and higher-level analysis. Machine learning (ML) methods can support tasks such as vessel classification, trajectory analysis, anomaly detection, pattern recognition, and risk assessment, while deep learning (DL) methods provide additional capabilities for image-based vessel detection, object recognition, feature extraction, and the analysis of complex maritime data. The keyword analysis in this review identified artificial intelligence, deep learning, object detection, object recognition, and data mining among the relevant research themes, indicating the increasing incorporation of intelligent data-processing techniques into maritime traffic surveillance.

The distinction between conventional and AI-based approaches can therefore be understood in terms of their analytical roles. Conventional sensor fusion primarily seeks to improve the completeness, consistency, and reliability of maritime information by combining complementary observations, whereas ML and DL approaches can further process the integrated information to identify patterns, classify targets, detect anomalies, and support prediction. For example, AIS and visual data can provide complementary vessel identity, movement, and appearance information, while AI-based image analysis can subsequently support automated vessel detection or recognition. Similarly, AIS–SAR integration can provide complementary information over wider surveillance areas, while AI-based analytical methods can potentially be applied to the resulting data to identify patterns or anomalous vessel behavior.

Nevertheless, AI-based approaches should not be regarded as a replacement for conventional sensor fusion. Rather, the findings suggest that conventional fusion provides an important foundation for integrating heterogeneous maritime observations, while ML and DL provide additional analytical capabilities for interpreting the integrated information. The combination of these approaches can support a transition from conventional sensor-based monitoring toward more intelligent maritime surveillance, in which heterogeneous data are not only collected and integrated but also processed to support automated detection, tracking, classification, anomaly identification, prediction, and operational decision support. This integrated approach is particularly relevant for maritime surveillance environments in which large volumes of heterogeneous data must be processed continuously and where timely identification of relevant vessel activities is required.

3.2.2 Applications of Multi-Sensor Data Fusion

The findings indicate that multi-sensor data fusion is primarily applied to support maritime situational awareness, which was identified in 58 of the 69 reviewed studies (84.05%). This dominant application reflects the role of multi-sensor integration in providing a more comprehensive representation of vessel movements and surrounding maritime conditions. Beyond situational awareness, the reviewed studies also addressed maritime surveillance, vessel tracking, autonomous navigation, vessel detection and recognition, collision avoidance and safety, and environmental monitoring. These applications demonstrate that sensor fusion extends beyond basic target detection by supporting continuous monitoring, navigation, safety assessment, and operational decision-making. For example,previous research demonstrated the use of AIS and visual data fusion to improve maritime traffic surveillance and vessel tracking while the study also applied multi-sensor fusion to support integrated ship motion perception in inland waterways [16]. In addition, Wolsing et al. (2022) highlighted the importance of AIS-based analysis for detecting anomalous vessel behavior, indicating the potential of fused maritime data to support anomaly detection and safety-related applications. These applications demonstrate that the value of multi-sensor fusion is not limited to improving the accuracy of individual sensing tasks, but also lies in its ability to provide complementary information for different operational requirements.

The dominance of MSA as an application also indicates that multi-sensor data fusion functions as a foundational capability for other maritime surveillance activities. Vessel tracking, detection and recognition, collision avoidance, autonomous navigation, and environmental monitoring require reliable information regarding vessel position, movement, identity, and surrounding conditions. By integrating complementary information from multiple sensing sources, these applications can obtain a more complete operational representation than would generally be available from an individual sensor. Overall, the results show that multi-sensor data fusion has developed into an enabling technology for a broad range of maritime surveillance functions, with MSA serving as a central application that supports other operational tasks such as tracking, detection, navigation, safety assessment, and collision avoidance.

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3.2.3 Emerging Research Themes and Technological Development

The reviewed literature indicates a growing emphasis on the integration of heterogeneous sensors, intelligent data processing, and automated maritime surveillance. Recent studies increasingly combine AIS with radar, visual/optical sensors, SAR, LiDAR, GNSS/IMU, and environmental sensors to improve the completeness and reliability of maritime information. This development is accompanied by the increasing application of artificial intelligence and machine-learning techniques for vessel detection, tracking, anomaly detection, and maritime situational awareness. Qu et al. (2023) demonstrated the benefits of combining AIS and visual data for maritime traffic surveillance, while Bal Şahin et al. (2026) highlighted multi-sensor data fusion as an important approach for overcoming the limitations of individual sensing technologies. Similarly, the increasing use of AIS–SAR and multimodal AIS–SAR–optical fusion demonstrates a shift toward wider-area and more automated maritime surveillance capabilities. Overall, the research trend suggests that maritime traffic surveillance is moving from single-sensor monitoring toward heterogeneous, intelligent, and increasingly autonomous sensing architectures, with data fusion serving as a key foundation for Maritime Domain Awareness and advanced maritime safety and security applications.

The reviewed studies also indicate a gradual transition from conventional sensor fusion toward AI-supported maritime surveillance. Conventional fusion approaches primarily focus on integrating observations from heterogeneous sensors to improve the completeness, consistency, and reliability of maritime information. In contrast, artificial intelligence (AI), machine learning (ML), and deep learning (DL) approaches provide additional capabilities for interpreting the integrated data and extracting higher-level information. ML methods can support vessel classification, trajectory analysis, anomaly detection, and pattern recognition, while DL methods can facilitate automated vessel detection, object recognition, feature extraction, and analysis of complex maritime data. Thus, conventional sensor fusion provides the information integration foundation, whereas AI-based methods extend the analytical capability of the surveillance system. This development suggests that conventional sensor fusion and AI-based analytics should be considered complementary rather than competing approaches. Heterogeneous sensor integration can provide a more complete representation of vessel activities, while AI-based methods can subsequently process the integrated information to identify patterns, classify vessels, detect anomalous behavior, and support prediction and decision-making. The combination of these approaches therefore represents an emerging direction for maritime traffic surveillance, particularly in environments where large volumes of heterogeneous and continuously generated data must be processed in a timely manner.

3.2.4 Research Gaps and Future Directions

Despite the extensive adoption of multi-sensor fusion, several research gaps remain. In the reviewed dataset, data or sensor fusion was identified in 26 of the 69 studies (37.68%), while AI and deep-learning approaches were reported in 21 studies (30.43%). However, anomaly detection was addressed in only 6 studies (8.69 %), indicating that research remains more strongly focused on general maritime situational awareness than on the identification of anomalous or non-cooperative vessels. Autonomous navigation was reported in 19 studies (27.53%), further indicating a growing transition toward intelligent and automated maritime operations.

Beyond these quantitative patterns, the literature highlights several technical challenges that require further investigation, particularly spatial and temporal alignment, real-time processing, sensor reliability, and robustness under complex environmental conditions. AIS and visual data, for example, may have different temporal resolutions and spatial representations, while vessel occlusion can further reduce fusion reliability. Recent research has addressed these challenges through trajectory matching, coordinate transformation, and anti-occlusion methods [9]. Recent review evidence also identifies large data volumes, real-time processing, environmental variability, and sensor limitations as continuing challenges in AI-supported maritime multi-sensor fusion [2]. These gaps indicate the need for future research to develop adaptive fusion architectures capable of integrating heterogeneous and asynchronous data while maintaining reliable performance under incomplete, noisy, or degraded sensor observations. Greater attention should also be given to open and representative real-world maritime datasets, real-time implementation, and the detection of non-cooperative or anomalous vessels to support more robust Maritime Domain Awareness.

Emerging technologies also provide opportunities to address these research gaps. Edge artificial intelligence (edge AI) could enable data processing closer to maritime sensing sources, such as VTS stations, surveillance cameras, smart buoys, and coastal monitoring systems, thereby reducing processing latency and

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supporting near-real-time vessel detection, classification, and anomaly identification. Digital twin technology could further integrate real-time multi-sensor observations with dynamic virtual representations of vessels, waterways, and maritime traffic environments to support continuous monitoring, trajectory prediction, risk assessment, and scenario-based analysis. Federated learning (FL) represents another potential direction for collaborative maritime AI, particularly when surveillance data are distributed across vessels, ports, VTS centers, coastal surveillance stations, and maritime authorities. By enabling collaborative model training without requiring the underlying data to be centralized, federated learning could support applications such as vessel classification, anomaly detection, and trajectory analysis while addressing data-sharing and privacy constraints. In parallel, explainable artificial intelligence (XAI) could improve the interpretability of AI-based maritime surveillance by providing operational users with understandable information regarding the basis of vessel classifications, anomaly alerts, or other analytical outputs.

Real-time multimodal maritime analytics also represents an important future research direction. The integration of AIS, radar, SAR, optical imagery, environmental sensors, vessel trajectories, and contextual information could enable continuous analysis of maritime activities for vessel detection, tracking, classification, anomaly identification, and risk assessment. The combination of conventional sensor fusion with AI-based analytics, edge computing, digital twins, federated learning, and explainable AI could therefore support the development of more adaptive, predictive, and intelligent maritime surveillance architectures. Future research should prioritize validation using representative real-world datasets and evaluation under diverse environmental and operational conditions while maintaining interoperability, cybersecurity, computational efficiency, and appropriate human oversight.

3.2.5 Practical Implications for Maritime Traffic Surveillance

The findings have practical implications for maritime authorities, Vessel Traffic Services (VTS), and Maritime Domain Awareness (MDA) systems. Multi-sensor data fusion can provide a more comprehensive maritime operational picture by integrating information from AIS, radar, visual/optical sensors, satellite/SAR, and other available sensing technologies. Maritime Situational Awareness was reported in 58 of the 69 reviewed studies (84.05%), indicating the importance of integrated maritime information for understanding vessel movements and surrounding maritime conditions. By combining complementary information from multiple sensors, surveillance systems can improve vessel detection, identification, tracking, and monitoring, particularly when information from an individual sensor is incomplete, unavailable, or affected by environmental conditions.

For maritime authorities, multi-sensor data fusion can support maritime safety, traffic management, surveillance, and security-related activities by providing more comprehensive information about vessel movements and maritime conditions. The integration of cooperative information, such as AIS, with independently observed information from radar, SAR, optical sensors, and other surveillance technologies can also support the identification of discrepancies between reported vessel information and independently observed vessel behavior. This capability is particularly relevant for identifying potential anomalies and non-cooperative vessels. For VTS, the integration of heterogeneous surveillance sources can strengthen continuous vessel traffic monitoring and provide operators with a more complete operational picture. AIS can provide vessel identity and navigational information, while radar can provide independent target detection and tracking. Optical and other sensing technologies can provide additional information regarding vessel characteristics and surrounding conditions. The combination of these sources can therefore assist VTS operators in monitoring complex traffic conditions and identifying situations that require further assessment.

The incorporation of machine learning and deep learning can provide an additional decision-support capability for maritime surveillance and VTS operations. AI-based methods can assist with automated vessel detection, classification, trajectory analysis, anomaly identification, and risk assessment. These capabilities may help operators process large volumes of heterogeneous information and identify potentially significant events more efficiently. However, AI-generated outputs should be considered decision-support information rather than a complete replacement for human operational judgment, particularly in safety-critical maritime operations. At the MDA level, multi-sensor data fusion provides an opportunity to integrate information from different surveillance domains to develop a broader understanding of maritime activities. The combination of AIS with radar, SAR, optical sensors, and other surveillance sources can provide complementary perspectives on vessel activity and contribute to more persistent maritime monitoring. This integrated approach can support the development of a more comprehensive maritime picture and strengthen the information basis for maritime safety and security operations.

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The practical implementation of these findings requires attention to interoperability between surveillance systems, temporal and spatial synchronization of sensor data, communication latency, sensor reliability, data quality, cybersecurity, computational requirements, and the reliability and explainability of AI-based outputs. Therefore, future maritime surveillance architectures should combine conventional sensor fusion with AI-based analytics within an integrated human–machine decision-support framework. Such an approach can support more responsive VTS operations, assist maritime authorities in surveillance and safety-related functions, and contribute to more comprehensive Maritime Domain Awareness.

4. CONCLUSION

This systematic literature review examined the types, applications, technological development, and research gaps associated with multi-sensor data fusion for maritime traffic surveillance based on 69 selected studies. The findings show that AIS, radar, camera/visual sensors, satellite/SAR, and meteorological sensors are among the technologies frequently integrated in maritime surveillance applications, reflecting the complementary role of heterogeneous sensing technologies in improving the completeness and reliability of maritime information. In terms of applications, Maritime Situational Awareness (MSA) was the dominant application, identified in 58 of the 69 reviewed studies (84.05%) followed by maritime surveillance, vessel tracking, autonomous navigation, and vessel detection and recognition. The scientific contribution of this review lies in synthesizing the development of multi-sensor data fusion in maritime traffic surveillance and identifying the transition from conventional sensor integration toward increasingly intelligent and AI-supported approaches. The review demonstrates that conventional sensor fusion provides an important foundation for combining heterogeneous observations, while artificial intelligence, machine learning, and deep learning provide additional capabilities for automated detection, classification, trajectory analysis, anomaly identification, and higher-level maritime data interpretation. The review also identifies persistent research gaps related to heterogeneous and asynchronous data integration, spatial-temporal alignment, real-time processing, sensor reliability, environmental variability, data availability, and the detection of anomalous or non-cooperative vessels.

From a practical perspective, the findings indicate that multi-sensor data fusion can support the development of more comprehensive maritime surveillance systems for maritime authorities, Vessel Traffic Services (VTS), and Maritime Domain Awareness (MDA). The integration of AIS, radar, optical/visual sensors, SAR, and other sensing technologies can provide complementary information for vessel detection, identification, tracking, and monitoring. The incorporation of AI-based analytics can further support operational decision-making by assisting with automated vessel analysis, anomaly identification, trajectory assessment, and risk-related information processing. However, effective operational implementation requires interoperability between surveillance systems, reliable data synchronization, real-time processing capabilities, cybersecurity, and appropriate human oversight. Future research should therefore adopt multidisciplinary approaches that integrate maritime science and operations with artificial intelligence, sensor engineering, data science, communication systems, cybersecurity, and human–machine interaction. Emerging technologies such as edge AI, digital twins, federated learning, explainable artificial intelligence (XAI), and real-time multimodal maritime analytics provide opportunities to develop more adaptive, predictive, and intelligent maritime surveillance architectures. Future studies should prioritize validation using representative real-world maritime datasets and evaluation under diverse environmental and operational conditions to ensure that proposed approaches can be effectively transferred to operational maritime environments.

Overall, multi-sensor data fusion represents an important technological foundation for the continued development of maritime traffic surveillance and Maritime Situational Awareness. The integration of conventional sensor-fusion techniques with AI-based analytical capabilities provides opportunities to improve the completeness, timeliness, and intelligence of maritime information processing, while supporting the operational needs of VTS, maritime authorities, and broader Maritime Domain Awareness systems.

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