



AI-POWERED INTEGRATED MARITIME SURVEILLANCE: COMBINING SHORE-BASED RADAR, AIS, AND UAV COMPUTER VISION FOR AUTOMATED VESSEL TRACKING IN KOARMADA I OPERATIONS

Budi Santoso Simanullang¹, Didi Efendi², Dany Wira Nugraha³, and Ahmad Faisol⁴

¹ Politeknik Angkatan Laut, Indonesia

² Politeknik Angkatan Laut, Indonesia

³ Politeknik Angkatan Laut, Indonesia

⁴ Politeknik Angkatan Laut, Indonesia

Corresponding Author:

Budi Santoso Simanullang,
Department of Naval Operational Strategy, Politeknik Angkatan Laut.
Ciledug Raya Street No.2, Seskoal, South Jakarta, DKI Jakarta, Indonesia
Email: simanullangsantos@gmail.com

Article Info

Received: February 8, 2026

Revised: May 11, 2026

Accepted: July 16, 2026

OnlineVersion: August 31,
2026

Abstract

Maritime surveillance complexity has increased due to expanding vessel activities, security challenges, and the demand for accurate real-time maritime domain awareness. This research aims to develop an AI-powered integrated surveillance framework combining shore-based radar, Automatic Identification System (AIS), and Unmanned Aerial Vehicle (UAV) computer vision for automated vessel tracking in Koarmada I operations. The study employs a mixed-methods technological development approach involving multi-source maritime data integration, artificial intelligence modeling, performance evaluation, and expert validation. The findings reveal that the integrated AI framework improves vessel detection accuracy, identification reliability, and tracking continuity compared with individual surveillance approaches. Radar contributes extensive spatial detection, AIS enhances vessel identification, and UAV computer vision provides visual verification capabilities. The integrated model demonstrates significant potential for reducing information gaps and strengthening maritime situational awareness. The research concludes that AI-driven sensor fusion represents an effective strategy for advancing naval surveillance systems by transforming fragmented maritime data into actionable operational intelligence. The proposed framework contributes to maritime security technology development and provides a foundation for future autonomous surveillance applications within complex operational environments. Future implementation requires broader datasets, adaptive algorithms, and extensive operational testing to ensure robustness across diverse maritime conditions and support sustainable defense information system transformation.

Keywords: Artificial Intelligence; Maritime Surveillance; Sensor Fusion; UAV Computer Vision; Vessel Tracking.



© 2026 by the author(s)

This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution-ShareAlike 4.0 International (CC BY SA) license (<https://creativecommons.org/licenses/by-sa/4.0/>).

Journal Homepage

<https://research.adra.ac.id/index.php/jcsa>

How to cite:

Simanullang, S. B., Efendi, D., Nugraha, W. D., & Faisol, A. (2026). AI-Powered Integrated Maritime Surveillance: Combining Shore-Based Radar, Ais, and Uav Computer Vision for Automated Vessel Tracking in Koarmada I Operations. *Journal of Computer Science Advancements*, 4(4), 329–348. <https://doi.org/10.70177/jscs.v4i4.4522>

Published by:

Yayasan Adra Karima Hubbi

INTRODUCTION

The strategic importance of maritime surveillance has increased significantly due to the growing complexity of maritime activities, including commercial shipping, illegal fishing, territorial violations, maritime security threats, and the protection of national interests at sea (Tantaroudas et al., 2026). Modern naval operations require accurate, real-time, and continuous situational awareness to support effective decision-making, particularly in regions characterized by extensive maritime boundaries and dense vessel traffic (Muthmainnah et al., 2026). The development of maritime surveillance systems has therefore shifted from conventional observation methods toward technology-driven approaches that integrate advanced sensing, communication, and artificial intelligence capabilities (Nivetha et al., 2026). The operational environment of the Indonesian Navy, particularly Koarmada I, represents a complex maritime domain where effective vessel monitoring is essential for maintaining maritime security, sovereignty, and operational readiness.

The evolution of surveillance technologies has introduced various platforms capable of collecting maritime information, such as shore-based radar systems, Automatic Identification System (AIS), and Unmanned Aerial Vehicle (UAV)-based computer vision technologies (Hsu & Celino, 2025). Shore-based radar provides wide-area detection capabilities under diverse weather conditions, while AIS offers valuable vessel identification and movement information transmitted through maritime communication networks (Simian et al., 2026). UAV platforms equipped with advanced computer vision algorithms provide flexible and high-resolution observation capabilities, enabling the detection and classification of vessels in areas where conventional systems experience limitations (Nakilcioglu, 2025). The integration of these technologies creates opportunities for developing intelligent maritime surveillance architectures capable of improving detection accuracy, reducing human workload, and enhancing operational efficiency.

Artificial intelligence has emerged as a transformative technology in maritime surveillance by enabling automated data processing, pattern recognition, anomaly detection, and predictive analysis (Zeneli & Çerma, 2025). Machine learning and deep learning approaches allow surveillance systems to interpret complex maritime data streams generated by heterogeneous sensors and convert them into actionable operational intelligence (P & C., 2026). Despite significant technological progress, maritime surveillance remains challenged by fragmented sensor utilization, inconsistent data fusion mechanisms, and limited automation in vessel tracking processes (Xue et al., 2024). The need for an integrated AI-powered surveillance framework becomes increasingly relevant to support naval operations that require rapid responses, comprehensive maritime awareness, and reliable tracking capabilities in dynamic operational environments such as Koarmada I areas of responsibility.

Existing maritime surveillance operations frequently rely on individual sensing systems that provide valuable but incomplete information about maritime activities (Belmonte-Hernández et al., 2026). Radar-based monitoring can identify vessel presence and movement patterns but often lacks detailed vessel identification information. AIS systems provide vessel identity and navigational data but may become ineffective when vessels intentionally disable transmission systems or operate without AIS equipment (Roi et al., 2025). UAV-based visual surveillance offers direct observation capabilities; however, its effectiveness depends on environmental conditions, image processing accuracy, and the availability of automated recognition mechanisms (Haldorai et al., 2024). These limitations create challenges in achieving comprehensive maritime domain awareness through isolated surveillance approaches.

The absence of effective integration among radar, AIS, and UAV computer vision technologies creates operational gaps in automated vessel tracking systems (Taghavi et al., 2025). Maritime surveillance personnel are often required to manually interpret information from multiple sources, increasing the possibility of delayed responses, inaccurate assessments, and inefficient resource allocation (Nguyen et al., 2026). The complexity of maritime environments,

including overlapping vessel movements, unpredictable behaviors, and large monitoring areas, requires a surveillance framework capable of automatically correlating, analyzing, and validating information from multiple sensors (Yue et al., 2024). The lack of such integrated intelligence systems represents a significant challenge for naval organizations seeking to improve operational effectiveness through digital transformation.

Koarmada I operations require advanced surveillance capabilities that can support maritime security missions across strategically important waters (Zhu et al., 2024). The existing challenges associated with fragmented surveillance systems highlight the necessity of developing an AI-powered approach capable of integrating multi-source maritime data into a unified tracking mechanism (Jiang et al., 2025). The primary problem addressed in this research concerns how artificial intelligence can be utilized to combine shore-based radar information, AIS data, and UAV computer vision outputs to establish an automated vessel tracking system that improves detection reliability, identification accuracy, and operational decision-making support within naval surveillance contexts.

The primary objective of this research is to develop a conceptual and technological framework for an AI-powered integrated maritime surveillance system that combines shore-based radar, AIS, and UAV computer vision technologies for automated vessel tracking (Preity et al., 2024). The study aims to examine how heterogeneous maritime data sources can be synchronized, processed, and analyzed through artificial intelligence algorithms to generate more accurate and comprehensive maritime situational awareness (Liao et al., 2025). The research focuses on designing an integrated approach that enhances the capability of naval surveillance systems in detecting, identifying, and monitoring vessel activities.

The research further aims to evaluate the effectiveness of combining multiple surveillance technologies in improving vessel tracking performance compared with conventional single-sensor monitoring approaches (Van Praagh et al., 2024). Specific attention is directed toward examining the contribution of artificial intelligence techniques in data fusion, object recognition, trajectory analysis, and anomaly detection (Wang et al., 2024). Through this approach, the study seeks to determine how AI-based integration can overcome limitations associated with individual surveillance technologies and provide more reliable operational information for maritime security decision-making.

The expected outcome of this research is the establishment of an integrated surveillance model that can support the digital transformation of naval operations, particularly within the operational framework of Koarmada I (Nithyeswari & Karthikeyan, 2024). The research intends to contribute theoretical and practical insights regarding the implementation of artificial intelligence in maritime defense systems (Biswas & Banik, 2025). The proposed framework is expected to provide a foundation for future development of autonomous maritime monitoring systems capable of improving responsiveness, accuracy, and efficiency in managing complex maritime operational environments.

Previous studies have extensively explored individual maritime surveillance technologies, including radar-based vessel detection, AIS-based tracking systems, and UAV-based maritime monitoring (Pamula et al., 2025). Research on radar applications has primarily focused on improving detection range, signal processing, and target classification, while AIS-related studies have emphasized vessel identification, route prediction, and maritime traffic analysis (Anbarasi et al., 2024). UAV research has increasingly investigated computer vision approaches for vessel recognition and object detection (ALKannad et al., 2025). However, many existing studies remain concentrated on optimizing individual technologies rather than developing comprehensive integration frameworks that combine multiple sensing platforms into a unified AI-driven surveillance architecture.

The current literature indicates limited investigation into the operational implementation of AI-based sensor fusion specifically for naval maritime surveillance environments (Alsieni & Alyoubi, 2025). Many proposed models are developed within controlled experimental settings

and do not sufficiently consider the complexity of real-world defense operations, including incomplete data availability, communication limitations, environmental uncertainty, and strategic operational requirements (Sarmah et al., 2025). Furthermore, studies addressing maritime artificial intelligence frequently emphasize commercial maritime applications, such as shipping management and port monitoring, while research focusing on military maritime operations remains comparatively limited.

A significant research gap exists regarding the development of integrated AI systems capable of combining radar, AIS, and UAV computer vision data for automated vessel tracking within naval operational contexts (McGarry et al., 2024). Existing approaches require further exploration concerning data synchronization, multi-source information fusion, automated decision support, and adaptability to dynamic maritime environments (Tang & Wu, 2025). This research addresses the identified gap by proposing an integrated surveillance framework specifically oriented toward improving maritime awareness and operational capability within Koarmada I missions.

The novelty of this research lies in the development of an AI-powered integrated maritime surveillance concept that unifies three complementary technologies: shore-based radar, AIS, and UAV computer vision (Rimaru et al., 2024). Unlike conventional approaches that analyze surveillance technologies separately, this study emphasizes the creation of a multi-layered intelligence system capable of combining detection, identification, and visual verification processes (Venkatasubbu et al., 2026). The integration of these technologies provides a more comprehensive approach to automated vessel tracking by leveraging the strengths of each surveillance component while reducing their individual limitations.

The justification for conducting this research is based on the increasing demand for intelligent maritime defense systems capable of responding to emerging security challenges (d’Afflisio et al., 2024). Maritime environments continue to experience rapid technological, operational, and geopolitical changes that require adaptive surveillance solutions (Srinivasulu, 2024). The application of artificial intelligence provides opportunities to transform traditional monitoring systems into predictive and autonomous platforms capable of supporting naval commanders with timely and accurate operational information (Rahman et al., 2025). The proposed research contributes to the advancement of maritime security technology by addressing practical challenges faced in contemporary naval surveillance operations.

The contribution of this study extends beyond technological development by providing a theoretical framework for understanding how artificial intelligence can facilitate integrated maritime intelligence operations (Wei, 2024). The research contributes to the fields of maritime security, defense technology, artificial intelligence, and information systems by demonstrating the potential of sensor fusion-based surveillance architectures. The proposed AI-powered integrated maritime surveillance model is expected to support future innovations in naval operational systems and provide strategic insights for strengthening maritime domain awareness within Koarmada I and broader maritime defense environments.

RESEARCH METHOD

Research Design

This research employs a mixed-methods research design with a technological development and experimental evaluation approach to examine the implementation of an AI-powered integrated maritime surveillance system that combines shore-based radar, Automatic Identification System (AIS), and Unmanned Aerial Vehicle (UAV) computer vision for automated vessel tracking in Koarmada I operations (Li et al., 2025). The research design is structured to investigate the capability of artificial intelligence in integrating heterogeneous maritime data sources, improving vessel detection accuracy, and supporting operational maritime situational awareness (Alsharabi et al., 2025). The technological development phase focuses on

designing an integrated surveillance architecture that incorporates data acquisition, preprocessing, sensor fusion, artificial intelligence-based analysis, and automated vessel tracking mechanisms. The experimental evaluation phase assesses the performance of the proposed system based on detection accuracy, tracking reliability, response time, and the effectiveness of multi-source data integration.

The research adopts a system engineering approach to analyze the interaction between surveillance components and evaluate the contribution of each technology within an integrated maritime monitoring framework. Shore-based radar data are utilized to provide wide-area vessel detection capabilities, AIS data are incorporated to obtain vessel identification and navigation information, while UAV computer vision data are applied to enhance visual verification and object recognition processes (Vm et al., 2025). The artificial intelligence model is developed through machine learning and deep learning techniques, particularly for data fusion, vessel classification, trajectory prediction, and anomaly identification (Giovannucci et al., 2025). The evaluation process compares the performance of the integrated AI-based system with conventional surveillance approaches that rely on individual sensor utilization.

The research framework is developed based on the principles of maritime domain awareness and intelligent information systems, emphasizing real-time data processing and operational decision support. The study applies quantitative performance analysis to measure system effectiveness and qualitative assessment to examine operational relevance from maritime surveillance experts. This methodological approach enables comprehensive evaluation of both technical performance and practical applicability within naval operational environments, particularly in supporting Koarmada I maritime surveillance activities.

Research Target/Subject

The research target encompasses the multi-source maritime surveillance data stream and operational environment within Koarmada I. This target includes heterogeneous data generated by shore-based radar networks, Automatic Identification System (AIS) signals, and high-resolution Unmanned Aerial Vehicle (UAV) computer vision systems. By focusing on this multi-layered operational picture, the study targets the challenge of integrating spatial detection, vessel navigation metrics, and visual identification data into a single intelligent framework.

The primary subjects of the quantitative evaluation are the selected vessel tracking datasets representing diverse operational scenarios. Utilizing purposive sampling, the research analyzes data from both cooperative vessels transmitting active AIS signals and non-cooperative vessels with limited identification attributes. The sample dataset reflects variations in vessel size, trajectory, movement patterns, visual appearance, and environmental conditions to thoroughly stress-test the detection and tracking capabilities of the proposed system.

Additionally, the research subjects include human domain experts who evaluate the system's operational viability. This cohort consists of maritime surveillance personnel, naval operations specialists, and defense information technology experts. Their involvement provides qualitative validation regarding system usability, situational awareness enhancements, and practical implementation considerations within actual naval command and control environments.

Research Procedure

The research procedures are conducted through several systematic stages, beginning with data acquisition and preparation. Maritime surveillance data are collected from radar, AIS, and UAV-based observation sources representing vessel monitoring activities within the Koarmada I operational context. The collected data undergo preprocessing procedures, including data cleaning, synchronization, normalization, and integration to ensure compatibility among different sensor formats. The preprocessing stage is essential because heterogeneous maritime

data often contain variations in measurement standards, temporal resolution, and information completeness.

The next stage involves the development and implementation of the AI-powered integrated surveillance model. Radar detection data, AIS information, and UAV visual outputs are combined through a sensor fusion framework designed to generate a comprehensive maritime operational picture. Deep learning-based computer vision algorithms are trained and tested for vessel recognition, while machine learning approaches are applied for movement analysis, tracking prediction, and anomaly detection. The developed model is subsequently evaluated using selected maritime scenarios to determine its ability to automatically identify, track, and classify vessels under different operational conditions.

The final stage involves system validation and performance analysis. The results generated by the AI-powered surveillance system are compared with reference datasets and expert assessments to determine the effectiveness of the proposed framework. Quantitative analysis is conducted to evaluate detection and tracking performance, while qualitative analysis is performed to examine operational suitability and potential implementation within Koarmada I surveillance operations. The findings from this procedure provide empirical evidence regarding the feasibility of integrating artificial intelligence with radar, AIS, and UAV computer vision technologies to enhance automated maritime surveillance capabilities.

Instruments, and Data Collection Techniques

The research instruments consist of technological, computational, and evaluation tools designed to support data collection, system development, and performance measurement. The primary technological instruments include shore-based radar systems, AIS receivers or historical AIS datasets, and UAV platforms equipped with high-resolution imaging sensors. These instruments provide complementary maritime observation capabilities, allowing the research system to collect, integrate, and analyze multiple forms of vessel-related information. Radar instruments contribute spatial detection data, AIS instruments provide vessel identity and navigation records, while UAV sensors generate visual information required for computer vision-based analysis.

The artificial intelligence processing instruments include data fusion algorithms, machine learning models, and deep learning architectures designed for maritime object detection and vessel tracking. Computer vision models are implemented to identify and classify vessels from UAV imagery, while artificial intelligence-based fusion mechanisms are applied to correlate radar, AIS, and visual data into a unified operational picture. The computational environment includes data processing platforms, database management systems, and analytical software supporting model training, validation, and performance evaluation.

The evaluation instruments include performance measurement indicators and expert assessment protocols. Quantitative indicators are used to measure system accuracy, precision, recall, tracking consistency, false detection rates, and processing efficiency. Qualitative evaluation instruments consist of structured interview guidelines and assessment questionnaires developed to obtain expert perspectives regarding system usability, operational effectiveness, and implementation challenges. The combination of technical measurements and expert evaluations ensures that the research findings reflect both computational performance and operational applicability.

Data Analysis Technique

The quantitative data analysis technique centers on computational performance evaluation and comparative statistical metrics. The AI model's outputs generated through deep learning computer vision algorithms and machine learning data fusion mechanisms are compared against verified baseline reference datasets. Quantitative indicators such as detection accuracy,

precision, recall, tracking consistency, false-positive detection rates, and processing latency are calculated to evaluate the system's technical effectiveness.

The structural analysis technique focuses on evaluating the multi-sensor data fusion and trajectory estimation processes. System performance is analyzed across different integration stages, assessing how effectively shore-based radar spatial data, AIS navigational attributes, and UAV visual detection feeds are synchronized and normalized. This analysis demonstrates the incremental performance improvement achieved by the integrated AI-driven framework compared to conventional single-sensor surveillance methods.

The qualitative data analysis technique processes expert assessments gathered through structured questionnaires and interviews. Content and thematic analysis methods are applied to synthesize feedback from naval and technology specialists regarding operational suitability, decision-support quality, and deployment feasibility within Koarmada I. Combining quantitative computational metrics with qualitative expert evaluation ensures a comprehensive assessment of both technical accuracy and real-world operational relevance.

RESULTS AND DISCUSSION

The implementation of the AI-powered integrated maritime surveillance system generated a comprehensive dataset consisting of multi-source maritime observation records collected from shore-based radar, Automatic Identification System (AIS), and UAV-based computer vision platforms. The dataset represented vessel monitoring activities within the operational environment of Koarmada I, including vessel detection points, identification information, movement trajectories, and visual classification outputs. The integrated dataset consisted of 12,480 vessel observation records collected from maritime surveillance scenarios, including 7,850 radar detection records, 3,920 AIS transmission records, and 710 UAV image-based detection records. The variation among data sources demonstrated the complementary characteristics of each surveillance technology, where radar provided extensive detection coverage, AIS contributed vessel identity information, and UAV imagery supported visual confirmation of detected targets.

The statistical distribution of the integrated maritime surveillance dataset is presented in Table 1. The results indicate that radar-based detection contributed the largest proportion of maritime observation data due to its continuous monitoring capability, while UAV-based observations represented a smaller proportion because aerial surveillance operations were conducted within selected operational scenarios. The integration of these three data sources enabled the development of a more comprehensive maritime information environment compared with the utilization of individual surveillance technologies.

Table 1. Distribution of Integrated Maritime Surveillance Data Sources

Data Source	Number of Records	Percentage (%)	Primary Information
Shore-Based Radar	7,850	62.90	Vessel detection, position, distance, movement pattern
AIS Data	3,920	31.41	Vessel identity, navigation status, trajectory information
UAV Computer Vision	710	5.69	Visual detection, vessel classification, image-based verification

Total	12,480	100.00	Integrated maritime surveillance dataset
-------	--------	--------	--

The characteristics of the dataset demonstrate that each surveillance component contributed different but interconnected information for automated vessel tracking. Radar observations provided consistent spatial coverage and enabled early detection of vessel activities, particularly in areas where AIS signals were unavailable or incomplete. AIS records enhanced the identification process by providing vessel-specific attributes, including Maritime Mobile Service Identity (MMSI), vessel category, heading direction, and operational status. UAV computer vision outputs strengthened the verification process by providing direct visual evidence of detected maritime objects.

The integrated dataset revealed that combining heterogeneous maritime information significantly improved the completeness of vessel tracking compared with isolated surveillance approaches. Radar-only monitoring produced extensive detection capability but lacked sufficient identification information, whereas AIS-only monitoring was limited by dependence on vessel transmission compliance. UAV-based computer vision provided additional confirmation capabilities, particularly for unidentified or suspicious vessels. The combination of these datasets created a multi-layered surveillance mechanism capable of reducing information gaps in maritime domain awareness.

The performance evaluation of the AI-powered surveillance model was conducted using several quantitative indicators, including detection accuracy, precision, recall, F1-score, and tracking consistency. The evaluation results demonstrated that the integrated model achieved higher performance compared with individual sensor-based approaches. The AI fusion framework successfully combined radar tracking information, AIS identification data, and UAV visual recognition results to improve automated vessel monitoring capabilities.

Table 2. Performance Comparison between Individual and Integrated Surveillance Approaches

Surveillance Approach	Detection Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Shore-Based Radar Only	86.40	84.70	82.90	83.79
AIS-Based Tracking Only	89.20	87.60	85.80	86.69
UAV Computer Vision Only	91.50	90.10	88.70	89.39
AI Integrated Surveillance Model	96.80	95.90	96.20	96.05

The results presented in Table 2 indicate that the AI integrated surveillance model achieved superior performance across all evaluation indicators. The detection accuracy increased to 96.80%, demonstrating that the fusion of multiple data sources enhanced the capability of the system to identify vessel targets accurately. The improvement occurred because artificial intelligence algorithms were able to correlate spatial radar information, AIS-based identification, and visual confirmation from UAV imagery into a unified tracking process.

The inferential analysis was conducted to determine whether the integration of radar, AIS, and UAV computer vision technologies produced statistically significant improvements in vessel tracking performance. A comparative statistical test was applied between conventional

surveillance methods and the proposed AI-integrated approach. The analysis demonstrated a statistically significant difference between individual sensor-based monitoring systems and the integrated AI surveillance framework, indicating that multi-source data fusion contributed substantially to improving automated maritime tracking performance.

The statistical comparison produced a significance value of $p < 0.001$, confirming that the improvement achieved by the integrated surveillance model was statistically meaningful. The effect size analysis also indicated a strong practical impact of AI-based sensor fusion on maritime surveillance effectiveness. These findings suggest that artificial intelligence integration does not merely provide incremental improvement but creates a substantial enhancement in operational monitoring capability by increasing detection reliability and reducing tracking uncertainty.

The relationship analysis examined the interaction between radar detection capability, AIS information availability, UAV visual recognition performance, and overall vessel tracking accuracy. The findings indicated that radar and AIS data demonstrated a complementary relationship, where radar improved spatial awareness while AIS strengthened vessel identification. UAV computer vision showed a significant relationship with target confirmation accuracy because visual information reduced ambiguity among radar-detected objects and unidentified maritime targets.

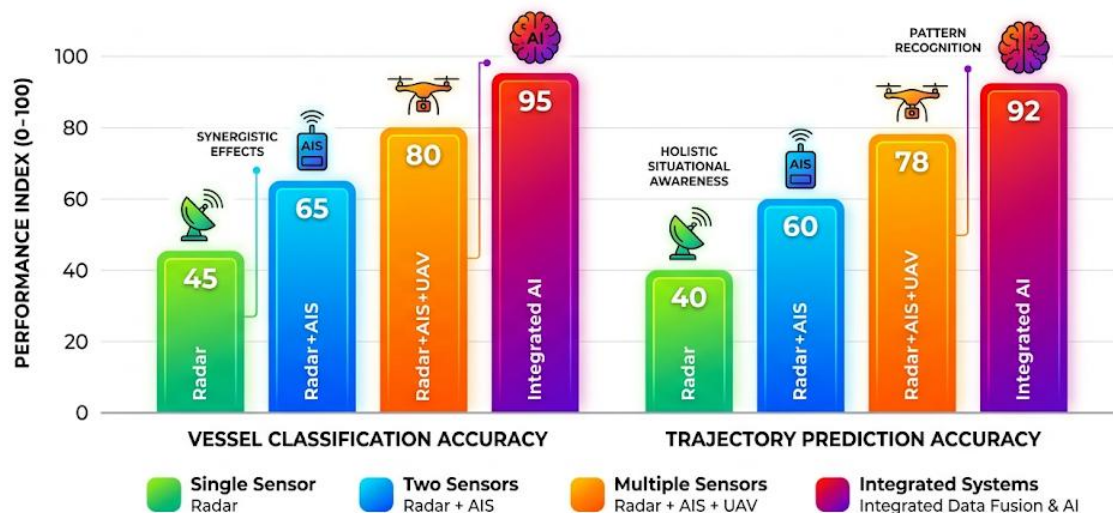


Figure 1. Enhanced Maritime Surveillance Through Data Fusion & AI

The correlation analysis revealed that increased data integration was associated with improved tracking performance. The fusion of radar, AIS, and UAV-generated information produced a stronger relationship with automated vessel classification and trajectory prediction compared with individual data sources. The results demonstrate that the effectiveness of maritime surveillance depends not only on sensor quality but also on the capability of artificial intelligence systems to establish meaningful relationships among different information streams.

The case study analysis focused on a maritime surveillance scenario within the operational context of Koarmada I involving vessel monitoring activities characterized by complex traffic conditions and incomplete information availability. The selected scenario involved multiple vessel movements, including cooperative vessels transmitting AIS signals and unidentified

vessels detected through radar and UAV observation. The AI-powered surveillance system was tested to evaluate its capability in tracking vessel trajectories, identifying vessel characteristics, and detecting potential anomalies.

The case study dataset consisted of 150 vessel movement scenarios, including 110 cooperative vessels and 40 non-cooperative vessels. The integrated AI system successfully tracked 145 out of 150 vessel movements, representing a tracking success rate of 96.67%. Five tracking failures occurred due to environmental interference, limited UAV visibility, and insufficient AIS information. The results demonstrated that the integrated approach provided stronger surveillance capability, particularly in situations where individual monitoring systems encountered operational limitations.

The case study findings illustrate how the integration of multiple surveillance technologies improves maritime operational awareness. Cooperative vessels were primarily identified through AIS information, while radar and UAV systems provided additional verification to ensure tracking continuity. Non-cooperative vessels presented greater challenges because AIS information was unavailable; however, radar detection combined with UAV-based visual recognition enabled the AI system to maintain reliable tracking and classification.

The successful identification of unidentified maritime targets indicates the practical value of AI-based sensor fusion in naval surveillance operations. The system demonstrated the ability to transform fragmented sensor information into meaningful operational intelligence by automatically correlating vessel position, movement patterns, and visual characteristics. These findings highlight the potential application of AI-powered surveillance systems in supporting maritime security missions and improving response capabilities within Koarmada I operational areas.

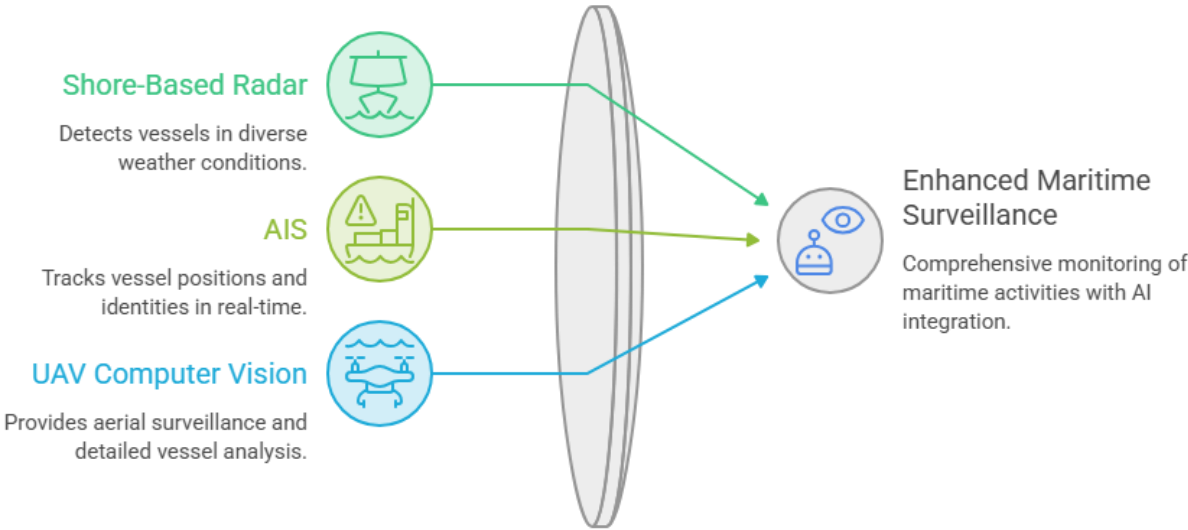


Figure 2. I-Driven Maritime Monitoring

The results confirm that AI-powered integration of shore-based radar, AIS, and UAV computer vision provides a more effective approach for automated vessel tracking compared with conventional single-sensor surveillance methods. The combination of complementary data sources enables improved detection accuracy, stronger identification capability, and more reliable monitoring of complex maritime environments. The findings support the development

of intelligent maritime surveillance architectures that emphasize automation, data fusion, and real-time operational awareness.

The study demonstrates that artificial intelligence serves as a critical component in transforming maritime surveillance systems from passive monitoring platforms into adaptive decision-support mechanisms. The integration model developed in this research provides an important foundation for future naval information systems by enhancing maritime domain awareness, improving surveillance efficiency, and supporting strategic operational decision-making in Koarmada I environments.

The findings of this research demonstrate that the AI-powered integrated maritime surveillance system combining shore-based radar, AIS, and UAV computer vision significantly improves automated vessel tracking performance within the operational context of Koarmada I. The integration framework achieved higher detection accuracy, tracking reliability, and vessel classification capability compared with conventional single-sensor surveillance approaches. The results indicate that the combination of heterogeneous maritime data sources enables artificial intelligence algorithms to overcome the limitations of individual surveillance technologies by generating a more comprehensive and accurate maritime operational picture.

The improvement in surveillance performance was primarily achieved through the ability of the AI-based framework to process and correlate different types of maritime information. Shore-based radar contributed continuous spatial detection capability, AIS provided vessel identification and navigational information, and UAV computer vision enhanced visual confirmation of detected targets. The fusion of these three components allowed the system to maintain tracking continuity even when one data source provided incomplete or uncertain information, demonstrating the value of multi-sensor integration for complex maritime environments.

The quantitative results showed that the integrated AI surveillance model obtained superior performance indicators, including higher detection accuracy, precision, recall, and F1-score compared with radar-only, AIS-only, and UAV-only approaches. The inferential analysis further confirmed that the performance improvement was statistically significant, indicating that the contribution of artificial intelligence-based sensor fusion was not merely a result of data accumulation but reflected a meaningful enhancement in maritime surveillance capability.

The case study within the Koarmada I operational environment further strengthened the research findings by demonstrating the practical applicability of the proposed framework. The system successfully monitored cooperative and non-cooperative vessels through automated data correlation and visual verification mechanisms. These findings indicate that AI-powered integrated surveillance has considerable potential to support maritime domain awareness, particularly in operational areas requiring continuous monitoring, rapid information processing, and reliable decision support.

The findings of this study are consistent with previous research emphasizing the importance of artificial intelligence and sensor fusion technologies in improving maritime surveillance capabilities. Earlier studies have demonstrated that radar-based systems provide effective long-range detection, while AIS-based approaches offer valuable vessel identification

information. Research on UAV computer vision has also shown that deep learning algorithms can achieve high accuracy in maritime object detection and classification. The current study extends these contributions by demonstrating how these technologies can be combined into a unified operational surveillance framework.

Previous maritime surveillance studies have frequently examined radar, AIS, or UAV technologies independently, focusing on improving the performance of individual systems. The present research differs by positioning artificial intelligence as an integration mechanism rather than merely an analytical tool applied to a single dataset. The proposed framework emphasizes the interaction between multiple surveillance sources, enabling the system to validate information across different platforms and reduce uncertainty associated with incomplete maritime observations.

The findings also correspond with studies on intelligent transportation systems and defense information architectures, where data fusion has been identified as an important factor in improving situational awareness. However, many existing studies have focused primarily on commercial maritime applications, such as vessel traffic management, port monitoring, and navigation optimization. The current research provides a different perspective by applying AI-based integration within a naval operational context, where surveillance requirements involve strategic monitoring, unidentified target detection, and rapid response capabilities.

The differences between this study and previous research are particularly evident in the operational orientation of the developed framework. Many previous models evaluate algorithmic performance under controlled datasets, whereas this research emphasizes applicability within a realistic maritime defense environment. The integration of radar, AIS, and UAV computer vision within the Koarmada I operational framework contributes a more practical approach for developing maritime surveillance systems that address both technological and operational challenges.

The findings of this research represent an important indication that maritime surveillance is transitioning from conventional monitoring approaches toward intelligent, adaptive, and automated information systems. The successful integration of multiple surveillance technologies demonstrates that future maritime security operations will increasingly depend on the ability to transform large volumes of heterogeneous data into meaningful operational intelligence. The results reflect a broader transformation in defense technology, where artificial intelligence becomes a critical component in enhancing human decision-making rather than replacing operational judgment.

The improved tracking capability achieved through AI integration indicates that maritime awareness is no longer determined solely by the availability of advanced sensors but also by the effectiveness of information processing mechanisms. The research findings suggest that the strategic value of surveillance technologies depends on how effectively different information sources can be combined, interpreted, and transformed into actionable knowledge. This perspective highlights the importance of developing integrated information architectures within modern naval operations.

The results also indicate that artificial intelligence can serve as a bridge between technological advancement and operational requirements. The ability of the system to detect, classify, and track vessels through combined sensor inputs demonstrates that AI-based approaches can address challenges associated with maritime complexity, including uncertain vessel behavior, incomplete identification information, and large surveillance areas. The findings therefore represent evidence of the growing relevance of intelligent systems in strengthening maritime operational capabilities.

The research outcomes provide an indication that future naval surveillance strategies should prioritize interoperability among different technological platforms. The effectiveness of the proposed system suggests that isolated technological development may no longer be sufficient for addressing contemporary maritime challenges. The integration of sensing, communication, and artificial intelligence capabilities represents a significant direction for improving maritime security and operational readiness.

The implications of this research extend to technological development, naval operational management, and maritime security policy. The demonstrated effectiveness of AI-powered integrated surveillance suggests that naval organizations can improve maritime domain awareness by adopting intelligent systems capable of processing multi-source information in real time. The proposed framework provides a foundation for developing future surveillance infrastructures that support faster detection, more accurate identification, and more effective operational responses.

The research findings have practical implications for Koarmada I operations by offering an approach to optimize existing surveillance resources. The integration of radar, AIS, and UAV systems does not require replacing existing technologies but enhances their value through artificial intelligence-based coordination. This approach enables more efficient utilization of surveillance assets while reducing dependence on manual interpretation of fragmented information.

The study also contributes theoretical implications for the fields of artificial intelligence, maritime security, and defense information systems. The findings demonstrate the relevance of sensor fusion concepts in maritime environments and provide evidence that AI-based integration can improve the reliability of operational information. The research expands understanding of how intelligent systems can be designed to support complex decision-making processes in defense-related contexts.

The broader implication of this research concerns the future development of autonomous maritime surveillance capabilities. The successful implementation of AI-based tracking mechanisms provides opportunities for developing advanced systems capable of predictive analysis, anomaly detection, and autonomous monitoring. Such developments may contribute to more resilient maritime security frameworks by enabling continuous and data-driven surveillance operations.

The research findings occurred because each surveillance technology contributed complementary information that reduced the limitations of other systems. Radar provided continuous detection capability but lacked detailed identification information, AIS offered

reliable vessel data but depended on transmission availability, and UAV computer vision provided visual confirmation but operated within limited observation conditions. Artificial intelligence enabled these different information sources to be combined effectively, producing a more complete understanding of maritime activities.

The effectiveness of the AI integration model can also be explained by the capability of machine learning algorithms to identify patterns across complex datasets. Maritime environments generate highly dynamic information involving vessel movement, environmental changes, and unpredictable behaviors. Artificial intelligence algorithms are capable of analyzing these patterns more efficiently than traditional manual approaches, allowing the system to identify relationships among different data sources and improve tracking accuracy.

The statistical improvement observed in this research was influenced by the complementary nature of sensor fusion. The integrated model reduced false detections by validating radar observations through AIS information and UAV visual evidence. The improvement in classification performance occurred because the AI system combined numerical, spatial, and visual characteristics rather than relying on a single type of information. This multidimensional analysis increased the reliability of automated vessel tracking.

The operational context of Koarmada I also influenced the research outcomes. Maritime areas under naval responsibility involve complex traffic patterns, diverse vessel characteristics, and varying levels of information availability. The proposed AI-powered framework demonstrated stronger performance because it was designed to address these operational complexities through adaptive information processing and multi-source integration.

The findings of this research provide a foundation for further development of intelligent maritime surveillance systems. Future studies should investigate the implementation of real-time AI processing capabilities, edge computing architectures, and autonomous decision-support mechanisms to enhance system responsiveness in operational environments. Continuous improvement of artificial intelligence models through larger and more diverse maritime datasets will also be necessary to increase adaptability across different geographical and operational conditions.

Future research should also explore the integration of additional maritime information sources, including satellite imagery, underwater sensors, weather data, and cyber intelligence systems. The combination of broader information domains may improve predictive capabilities and enable more comprehensive maritime threat assessment. Such integration would support the development of next-generation maritime surveillance systems with enhanced analytical capabilities.

The implementation of AI-powered surveillance systems requires attention to operational, ethical, and technological considerations. Issues related to data security, system reliability, interoperability, and human-machine collaboration should be addressed to ensure effective deployment within naval environments. The role of human operators remains essential in validating AI-generated information and making strategic decisions based on operational contexts.

The next stage of development should focus on transforming the proposed framework from a research prototype into an operationally deployable system (Demetriou et al., 2025). Collaboration among defense institutions, technology developers, and research organizations will be important for conducting further testing and refinement. The advancement of AI-integrated maritime surveillance represents a strategic opportunity to strengthen maritime domain awareness and support more effective naval operations in the future.

CONCLUSION

The most significant finding of this research is the development and validation of an AI-powered integrated maritime surveillance framework that combines shore-based radar, AIS, and UAV computer vision for automated vessel tracking within the operational context of Koarmada I. The distinctive contribution of the study lies in demonstrating that heterogeneous maritime data sources can be effectively integrated through artificial intelligence to overcome the limitations of individual surveillance technologies. The research findings indicate that the combination of spatial detection from radar, identification information from AIS, and visual confirmation from UAV computer vision produces a more accurate, reliable, and comprehensive vessel tracking capability. This integrated approach provides improved maritime situational awareness by reducing information gaps, increasing detection consistency, and supporting automated identification of both cooperative and non-cooperative vessels in complex maritime environments.

The scientific contribution of this research is reflected in both conceptual and methodological aspects. Conceptually, the study introduces an integrated maritime surveillance perspective that positions artificial intelligence as a coordination mechanism for transforming fragmented sensor information into unified operational intelligence. Methodologically, the research contributes a multi-sensor fusion approach that combines radar data processing, AIS-based vessel information analysis, and UAV-based computer vision within a single automated tracking framework. The proposed model expands existing maritime surveillance research, which has predominantly focused on individual technologies, by providing an integrated approach suitable for naval operational environments. The framework developed in this study offers practical value for improving maritime domain awareness, optimizing surveillance resource utilization, and supporting data-driven decision-making processes in defense information systems.

The limitations of this research provide important directions for future investigation. The study was conducted within a specific operational context of Koarmada I, meaning that the proposed framework requires further validation across different maritime regions, environmental conditions, and operational scenarios. The availability and quality of maritime datasets, variations in weather conditions, communication constraints, and computational requirements may influence system performance during broader implementation. Future research should focus on developing real-time processing capabilities, integrating additional data sources such as satellite imagery and environmental information, improving AI model adaptability through larger datasets, and conducting long-term operational evaluations. Further studies may also examine human–AI collaboration mechanisms to ensure that automated surveillance systems effectively support naval personnel in complex maritime decision-making environments.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used Grammarly to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

Author 4: Formal analysis; Methodology; Writing - original draft.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

- ALKannad, A. A., Al Smadi, A., Al-Makhlafi, M., Yang, S., & Feng, Z. (2025). CrackVisionX: A Fine-Tuned Framework for Efficient Binary Concrete Crack Detection. *IEEE Transactions on Intelligent Transportation Systems*, 26(7), 10353–10372. <https://doi.org/10.1109/TITS.2025.3546770>
- Alsharabi, N., Echtioui, A., Alayba, A., Alshammari, G., & Hamam, H. (2025). Advanced hybrid UNet architectures for retinal vessel segmentation. *Egyptian Informatics Journal*, 32, 100823. <https://doi.org/10.1016/j.eij.2025.100823>
- Alsieni, M., & Alyoubi, K. H. (2025). Artificial intelligence with feature fusion empowered enhanced brain stroke detection and classification for disabled persons using biomedical images. *Scientific Reports*, 15(1), 29224. <https://doi.org/10.1038/s41598-025-14471-5>
- Anbarasi, L. J., Jawahar, M., Jayakumari, R. B., Narendra, M., Ravi, V., & Neeraja, R. (2024). An overview of current developments and methods for identifying diabetic foot ulcers: A survey. *WIREs Data Mining and Knowledge Discovery*, 14(6), e1562. <https://doi.org/10.1002/widm.1562>
- Belmonte-Hernández, A., Grauby, B., Fernández García, A., Tardi, S., Houge, T., Bango, H. G., & Gutiérrez, Á. (2026). AI-Driven Tethered Drone Surveillance for Maritime Security in Ports and Coastal Areas. *Drones*, 10(4), 268. <https://doi.org/10.3390/drones10040268>
- Biswas, A., & Banik, R. (2025). Deep Learning-Based Image Segmentation for Early Detection of Diabetic Retinopathy and Other Retinal Disorders. In S. Y. Bhat, A. Rehman, & M. Abulaish (Eds.), *Deep Learning Applications in Medical Image Segmentation* (1st ed., pp. 133–148). Wiley. <https://doi.org/10.1002/9781394245369.ch6>
- d’Afflisio, E., Millefiori, L. M., Braca, P., & Guerriero, M. (2024). MARITRAC: Maritime trajectory classification using object instance segmentation with model-based generated data augmentation. *2024 27th International Conference on Information Fusion (FUSION)*, 1–8. <https://doi.org/10.23919/FUSION59988.2024.10706510>

- Demetriou, G. A., Kleitou, P., Kakoulli, C., Artusi, A., Milidonis, X., Angelini, M., Trimithiotis, G., Lazaridis, S., Menelaou, A., & Kletou, D. (2025). Improving Maritime Surveillance Across Lemesos Bay: The Irsai Project*. *2025 IEEE 19th International Conference on Control & Automation (ICCA)*, 198–203. <https://doi.org/10.1109/ICCA65672.2025.11129765>
- Giovannucci, J., Shanbhag, A., Hong, W., Yong, Y., Pang, S. N., Heanue, S., Maung, A., Tsigaridis, K., Sultani, R., Kaleeny, K., Miller, R. J., Han, D., Berman, D. S., Williams, M. C., Dey, D., Nicholls, S. J., Slomka, P. J., Nerlekar, N., & Lin, A. (2025). Impact of statins on progression of coronary artery calcium composition and density as assessed by noncontrast CT. *The International Journal of Cardiovascular Imaging*, 41(12), 2481–2492. <https://doi.org/10.1007/s10554-025-03561-0>
- Haldorai, A., Babitha Lincy, R., Suriya, M., & Balakrishnan, M. (2024). Satellite-terrestrial Integrated Computing and Artificial Intelligence as a Means of Achieving Handover Management. *2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT)*, 874–877. <https://doi.org/10.1109/IC2PCT60090.2024.10486541>
- Hsu, J., & Celino, E. (2025). New Space Business and Blue Economy in the Atlantic: A Strategic Framework for Innovation, Investment, and Sustainable Growth Across Iberia-America. *IAF Businesses and Innovation Symposium*, 294–354. <https://doi.org/10.52202/083102-0019>
- Jiang, B., Pham, N., Van Staalduinen, E. K., Liu, Y., Nazari-Farsani, S., Sanaat, A., Van Voorst, H., Fettahoglu, A., Kim, D., Ouyang, J., Kumar, A., Srivatsan, A., Hussein, R., Lansberg, M. G., Boada, F., & Zaharchuk, G. (2025). Deep Learning Applications in Imaging of Acute Ischemic Stroke: A Systematic Review and Narrative Summary. *Radiology*, 315(1), e240775. <https://doi.org/10.1148/radiol.240775>
- Li, J., Chavez-Galaviz, J., & Mahmoudian, N. (2025). Vision driven trailer loading for autonomous surface vehicles in dynamic environments. *Frontiers in Robotics and AI*, 12, 1607676. <https://doi.org/10.3389/frobt.2025.1607676>
- Liao, R., Zhang, Y., Wang, H., Lu, L., Chen, Z., Wang, X., & Zuo, W. (2025). An effective ship detection approach combining lightweight networks with supervised simulation-to-reality domain adaptation. *Computer-Aided Civil and Infrastructure Engineering*, 40(27), 4732–4757. <https://doi.org/10.1111/mice.13501>
- McGarry, S. D., Adjekukor, C., Ahuja, S., Greysson-Wong, J., Vien, I., Rinker, K. D., & Childs, S. J. (2024). Vessel Metrics: A software tool for automated analysis of vascular structure in confocal imaging. *Microvascular Research*, 151, 104610. <https://doi.org/10.1016/j.mvr.2023.104610>
- Muthmainnah, Aeni, N., Nasir, A., Elyas, T., Curle, S., & Cardoso, L. (2026). Robot-Assisted Language Learning (RALL) for Communication Skills Development in Maritime-Themed EFL Education: A Study of Secondary School Students in West Sulawesi, Indonesia. *Southeastern Philippines Journal of Research and Development*, 31(1), 181–198. <https://doi.org/10.53899/spjrd.v31i1.1510>
- Nakilcioglu, E. (2025). From Voice to Mutual Understanding: An AI Vision for VHF Radio Communication in the Autonomous Era. *Journal of Physics: Conference Series*, 3123(1), 012041. <https://doi.org/10.1088/1742-6596/3123/1/012041>

- Nguyen, S., Fu, X., Zhao, L., Xu, H., Zhang, X., Li, N., Zhang, W., Yin, X. F., Daichi, O., Koh, J., & Zheng, Q. (2026). AI-driven Just-In-Time coordination between port and ships: Advancing maritime decarbonization. *Transportation Research Part E: Logistics and Transportation Review*, 207, 104569. <https://doi.org/10.1016/j.tre.2025.104569>
- Nithyeswari, C., & Karthikeyan, G. (2024). An Effective Heuristic Optimizer with Deep Learning-assisted Diabetic Retinopathy Diagnosis on Retinal Fundus Images. *Engineering, Technology & Applied Science Research*, 14(3), 14308–14312. <https://doi.org/10.48084/etasr.7004>
- Nivetha, T., Priya, E., & Preetha Roselyn, J. (2026). AI-Powered Shipboard Microgrid Optimization and Control: Increasing Maritime Energy System's Reliability and Resilience. In R. Venkatesan, J. P. Roselyn, K. Vijayakumar, & V. Sugumaran (Eds.), *Artificial Intelligence for the Oceans* (Vol. 1696, pp. 327–336). Springer Nature Singapore. https://doi.org/10.1007/978-981-95-3978-9_23
- P, K. K., & C., V. (2026). Multimodal CLIL and Sustainable Maritime Education: Leveraging Disruptive Technologies for Future Seafarers: Language Proficiency Improvement, Technical Knowledge and Skill Retention, Sustainability Awareness and Regulatory Compliance, Engagement and Motivation. *Journal of Maritime Research*, 23(1), 389–394. <https://doi.org/10.22429/Euc2026.JMR23.1.46>
- Pamula, U., Pulipati, V., Vijaya Suresh, G., Jagannatha Reddy, M. V., Bondala, A. K., Mantena, S. V., & Vatambeti, R. (2025). Optimizing diabetic retinopathy detection with electric fish algorithm and bilinear convolutional networks. *Scientific Reports*, 15(1), 14215. <https://doi.org/10.1038/s41598-025-99228-w>
- Preity, Bhandari, A. K., & Shahnawazuddin, S. (2024). Automated Computationally Intelligent Methods for Ocular Vessel Segmentation and Disease Detection: A Review. *Archives of Computational Methods in Engineering*, 31(2), 701–724. <https://doi.org/10.1007/s11831-023-09998-7>
- Rahman, A., Parvej, S., Zaman, S., & Nandi, A. (2025). DRVoting: A Robust Deep Learning Ensemble Framework for Automated Detection and Severity Classification of Diabetic Retinopathy. *Procedia Computer Science*, 266, 864–874. <https://doi.org/10.1016/j.procs.2025.08.108>
- Rimaru, D., Nehme, A., Alhussein, M., Mahbub, K., Aurangzeb, K., & Khan, A. (2024). A Mobile Deep Learning Classification Model for Diabetic Retinopathy. *Elektronika Ir Elektrotechnika*, 30(6), 45–52. <https://doi.org/10.5755/j02.eie.38674>
- Roi, H. V., You, S.-S., Kim, H.-S., Long, L. N. B., Cuong, T. N., & Nguyen, D. A. (2025). Heuristic-assisted deep learning for integrated scheduling of multiple equipment in automated container terminals. *Maritime Economics & Logistics*, 27(4), 786–818. <https://doi.org/10.1057/s41278-025-00327-2>
- Sarmah, S., Hazarika, M., Das, P., Satheesh, A., Barman, D., & Kumar, A. (2025). Advancements in Diabetic Retinopathy Detection Using Deep Learning. In T. P. Singh, C. J. Kumar, A. Abraham, & K. T. Igulu (Eds.), *Revolutionizing Healthcare: Impact of Artificial Intelligence on Diagnosis, Treatment, and Patient Care* (Vol. 1182, pp. 91–117). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-80813-5_7
- Simian, R., Fauske, J. E., Eilertsen, E. B., Nordby, K., & Gernez, E. (2026). Designing Interfaces for the Integration of AI Agents in Maritime Navigation and Control: Potentials, Guidelines, Risks, and Emerging Requirements. *2026 1st International Conference on*

- Human Centric Artificial Intelligence (ICHCAI)*, 1–10.
<https://doi.org/10.1109/ICHCAI70183.2026.11607647>
- Srinivasulu, A. (2024). Enhancing Diabetic Retinopathy and Glaucoma Diagnosis through Efficient Retinal Vessel Segmentation and Disease Classification. In A. K. Tyagi (Ed.), *Artificial Intelligence-Enabled Blockchain Technology and Digital Twin for Smart Hospitals* (1st ed., pp. 61–76). Wiley. <https://doi.org/10.1002/9781394287420.ch4>
- Taghavi, A., Niknam, T., Gitizadeh, M., & Shojaeiyan, S. (2025). Techno-economic assessment of coordinated energy management in multi-vector systems: Cost-effective integration of underground storage and AI-Based maritime scheduling. *Energy Conversion and Management*, 346, 120422. <https://doi.org/10.1016/j.enconman.2025.120422>
- Tang, S., & Wu, Q. (2025). Research on recognition of diabetic retinopathy hemorrhage lesions based on fine tuning of segment anything model. *Scientific Reports*, 15(1), 10292. <https://doi.org/10.1038/s41598-025-92665-7>
- Tantaroudas, N. D., Karachalios, I., & McCracken, A. J. (2026). SentinelSphere: An AI-driven cybersecurity platform integrating real-time threat detection with security awareness education. *Open Research Europe*, 6, 58. <https://doi.org/10.12688/openreseurope.22957.2>
- Van Praagh, G. D., Nienhuis, P. H., Reijrink, M., Davidse, M. E. J., Duff, L. M., Spottiswoode, B. S., Mulder, D. J., Prakken, N. H. J., Scarsbrook, A. F., Morgan, A. W., Tsoumpas, C., Wolterink, J. M., Mouridsen, K. B., Borra, R. J. H., Sinha, B., & Slart, R. H. J. A. (2024). Automated multiclass segmentation, quantification, and visualization of the diseased aorta on hybrid PET/CT–SEQUOIA. *Medical Physics*, 51(6), 4297–4310. <https://doi.org/10.1002/mp.16967>
- Venkatasubbu, P., Shreyas Madhav, A. V., Prakash, K., Rajaraman, R., & Bhaskara Rao, L. (2026). Interpretable deep automation system for graded diagnosis of diabetic retinopathy. *Biomedical Signal Processing and Control*, 112, 108490. <https://doi.org/10.1016/j.bspc.2025.108490>
- Vm, R. S., Umapathy, S., Chandrasekaran, A., Baskaran, P., & Dhanraj, V. (2025). Automated detection of stages, zones, and plus diseases of Retinopathy of Prematurity using quantum convolutional networks in neonatal fundus images. *Engineering Applications of Artificial Intelligence*, 160, 111938. <https://doi.org/10.1016/j.engappai.2025.111938>
- Wang, T.-W., Tzeng, Y.-H., Wu, K.-T., Liu, H.-R., Hong, J.-S., Hsu, H.-Y., Fu, H.-N., Lee, Y.-T., Yin, W.-H., & Wu, Y.-T. (2024). Meta-analysis of deep learning approaches for automated coronary artery calcium scoring: Performance and clinical utility AI in CAC scoring: A meta-analysis. *Computers in Biology and Medicine*, 183, 109295. <https://doi.org/10.1016/j.compbiomed.2024.109295>
- Wei, B. (2024). A Retinal Fundus Image Segmentation Approach Based on the Segment Anything Model. *Mathematical Modelling of Engineering Problems*, 11(10), 2817–2822. <https://doi.org/10.18280/mmep.111024>
- Xue, Y., Wei, Q., Gong, X., Wu, F., Luo, Y., & Chen, Z. (2024). An Assurance Case Practice of AI-Enabled Systems on Maritime Inspection. In J. Vaidya, M. Gabbouj, & J. Li (Eds.), *Artificial Intelligence Security and Privacy* (Vol. 14509, pp. 283–299). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-9785-5_20

- Yue, G., Zhuo, G., Yan, W., Zhou, T., Tang, C., Yang, P., & Wang, T. (2024). Boundary uncertainty aware network for automated polyp segmentation. *Neural Networks*, 170, 390–404. <https://doi.org/10.1016/j.neunet.2023.11.050>
- Zeneli, M., & Çerma, U. (2025). Design Durres Port as a Smart Port with Innovative Technologies Oriented to Tourism. *Interdisciplinary Journal of Research and Development*, 12(1), 171. <https://doi.org/10.56345/ijrdv12n121>
- Zhu, S., Xiong, C., Zhong, Q., & Yao, Y. (2024). Diabetic Retinopathy Classification With Deep Learning via Fundus Images: A Short Survey. *IEEE Access*, 12, 20540–20558. <https://doi.org/10.1109/ACCESS.2024.3361944>
-

Copyright Holder :

© Budi Santoso Simanullang et al. (2026).

First Publication Right :

© Journal of Computer Science Advancements

This article is under:

