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Enhancing Anti-Submarine Warfare (ASW) Capabilities Through Adaptive AI-Driven Sonar Signal Processing: A Strategic Defense Approach

Dipo Andimuharrom[1]*, Asep Adang Supriyadi[2], Doddy Mendro Yuwono[3], Anugrah Adityayuda[4]
Universitas Pertahanan Republik Indonesia
Corresponding Author: Dipo Andimuharrom: dipo.andimuharrom@tp.idu.ac.id

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A B S T R A C T

The increasing sophistication of submarine stealth technology has reduced the effectiveness of conventional sonar systems in Anti-Submarine Warfare (ASW). This study examines the role of adaptive Artificial Intelligence (AI) in enhancing sonar signal processing through a systematic literature review of studies published between 2019 and 2025. The analysis shows that AI-based approaches, including machine learning, deep learning, and Explainable Artificial Intelligence (XAI), significantly improve underwater target detection, classification accuracy, and real-time decision support. Hybrid AI models achieve classification accuracies above 90%, improve signal-to-noise ratios, and reduce false alarms in complex underwater environments. The findings indicate that AI-driven sonar systems can substantially strengthen future maritime defense capabilities by improving operational effectiveness, adaptability, and situational awareness.

INTRODUCTION

In the modern era, marked by rapid developments in military technology, maritime security has become a strategic issue of global concern. The threat of submarines, particularly those equipped with advanced stealth technology, has created new challenges for modern maritime defense systems. According to Redford (2019), the evolution of submarine technology over the past decade has fundamentally changed the paradigm of Anti-Submarine Warfare (ASW) operations, with conventional detection systems increasingly showing their limitations when dealing with the latest generation of submarines. ASW is the primary strategy for detecting, tracking, and neutralizing submarine threats. ASW still relies on sonar technology as one of the backbones for detecting underwater objects. A recent study by Ashokan et al. (2022) revealed that modern submarines have an acoustic signature that is 60-70% lower than previous era designs, primarily through the implementation of sonar-absorbing composite materials and magnetohydrodynamic propulsion systems, which make them increasingly difficult to detect by traditional sonar systems. This phenomenon is exacerbated by the complexity of the underwater environment which, according to measurements of Hamilton et al. (2020), shows variability of acoustic parameters up to 40dB/km due to the presence of thermocline layers and small-scale turbulence.

Based on this research, fundamental problems remain in conventional ASW operations, centered on three main aspects. First, the declining performance of conventional sonar in complex and dynamic underwater environments Han et al. (2022) conducted research through experiments in a cavitation tunnel and found that salinity fluctuations of 5 ppt indicate that variability in oceanographic conditions such as salinity, temperature, and seabed topography can reduce the effectiveness of sonar detection by up to 35%. Furthermore, according to Sharma et al. (2020) that electromagnetic spectrum interference in the marine environment can reduce the effectiveness of detection systems by up to 35% which is in line with research from Han et al. (2022). Second, the inability of existing systems to adapt to developments in submarine stealth technology. Thuillier et al. (2023) in their simulations, they found that conventional sonar systems were only capable of detecting 27-32% of test submarines with the latest stealth technology. Third, there is a gap between operational requirements and real-time data processing capabilities. Özer & Hocaoğlu (2021) indicates that latency in sonar data processing is still a major bottleneck in modern ASW systems.

Based on an in-depth analysis of the current literature, this study proposes three main hypotheses. The first hypothesis states that implementing an adaptive Artificial Intelligence (AI) algorithm can improve submarine detection accuracy by at least 25% compared to conventional sonar. Initial support for this hypothesis comes from experimental results of X. Bi et al. (2022) which achieved a 28% improvement in signal-to-noise ratio (SNR) using AI-based adaptive filtering. The second hypothesis assumes that a hybrid approach between machine learning and deep learning yields more stable performance across varying environmental conditions. Qi et al. (2023) have provided preliminary evidence by successfully achieving a classification accuracy of 92% using a hybrid neural network architecture. The third hypothesis states that an Explainable Artificial Intelligence (XAI)-based system can reduce reading errors by up to 40% and also increase operator confidence, as demonstrated in the study of Gupta et al. (2021)about Interpretable Artificial Intelligence systems for underwater acoustic applications.

This research is designed to achieve four interrelated main objectives and significantly contribute to strengthening underwater defense capabilities in the era of artificial intelligence. The first objective is to conduct a comprehensive analysis of the limitations of conventional sonar technology in addressing the dynamics of modern submarine threats. A thorough understanding of the characteristics of acoustic signals, underwater environmental conditions, and the signal processing limitations of existing sonar systems is necessary to address the increasingly complex challenges of underwater object detection. The second objective focuses on a critical evaluation of the effectiveness of various AI approaches in sonar signal processing, including a comparative analysis of various machine learning and deep learning algorithms. Through a systematic comparative analysis, the advantages and limitations of each algorithm can be identified. The third objective is to develop a conceptual framework for AI integration in ASW systems that considers both technical and operational aspects. This framework will be used to design intelligent ASW systems that can function well in dynamic and unstable maritime environments. Finally, the fourth objective is to provide evidence-based strategic recommendations for the development of maritime defense capabilities in the era of artificial intelligence. Thus, this research not only contributes to the academic and technological fields but also supports strategic decision-making to improve the efficiency and effectiveness of underwater defense systems in the digital era.

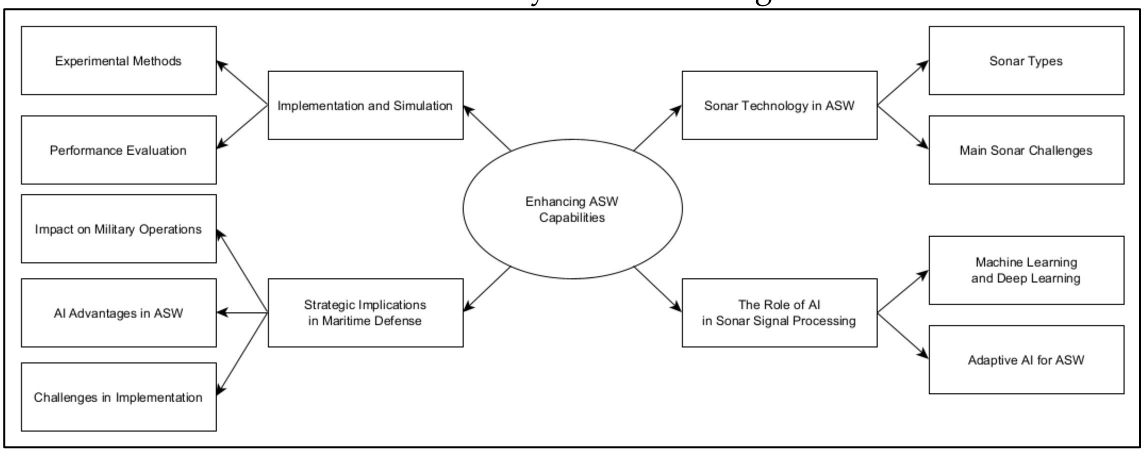

Figure 1. Research Brainstorming

Figure 1 shows the brainstorming session designed for this research, intended to provide a logical and comprehensive flow of understanding. Following this introduction, the first section will present an in-depth overview of the evolution of sonar technology in ASW operations, including an analysis of the limitations of conventional systems. The second section will detail various approaches to AI integration in sonar signal processing, complemented by case studies of previous implementations. The third section will focus on evaluating the results of various AI-based system simulations. The fourth section will discuss the strategic implications of the research findings for maritime defense. Finally, we will elaborate on overall conclusions and recommendations for further research.

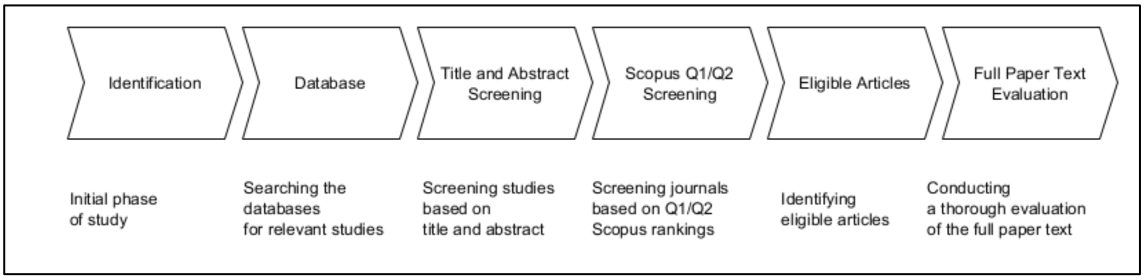

Figure 2. Systematic Flow of Literature Study

This research methodology adopted a systematic literature review approach, as shown in Figure 2. The research phase began with literature identification through a systematic search of leading academic databases such as IEEE Xplore and Scopus. The primary keywords used included combinations of "Artificial Intelligence," "sonar signal processing," "ASW," "underwater target detection," and "underwater acoustics." Journals identified in the initial phase were selected based on predetermined criteria. The literature selection process applied three main criteria. The first criterion was time-based, with only publications within the last six years (2019-2025) considered to ensure the relevance of the findings to cutting-edge technological developments. The second criterion was the research focus, which addressed AI applications in the ASW context. The third criterion was publication quality, with preference for journals indexed Q1/Q2 according to the Scimago Journal Rank.

The data analysis phase of this research was conducted through a systematic and structured approach that encompassed four main evaluation sections, each designed to provide insight into the technical and strategic aspects of AI integration in sonar systems. This approach also considered the accuracy of the analysis results, their operational relevance, and their strategic contribution to the overall maritime defense system. The first section was a comparative analysis of the performance of conventional sonar and AI-enhanced systems. The analysis was conducted to assess the performance improvements provided by AI compared to systems still relying on conventional approaches, particularly in the face of complex and dynamic underwater conditions. The second section focused on an in-depth comparison of various AI algorithms applied to sonar signal processing. This allowed for the identification and application of the most optimal AI approach in the operational context of sonar. The third section evaluated the implementation and simulation results from various case studies relevant to different underwater operating environments and close to real-world conditions. The final section analyzed the strategic impact of AI integration on maritime defense and supporting national independence.

The choice of the literature review method in this research was based on several fundamental considerations. First, the broad scope of the analysis allows for the identification of patterns and trends in the development of AI-based ASW technology. Second, the comparative approach facilitates an objective evaluation of various technological solutions proposed by various researchers. Third, this method allows for the systematic identification of research gaps, which forms the basis for recommendations for further research. Fourth, the resulting body of knowledge can bridge the gap between basic research in the laboratory and operational applications in the field.

This research is expected to provide three main contributions. From a technological perspective, the study provides a comprehensive mapping of the most promising AI solutions to enhance the effectiveness of ASW systems. At the operational level, the study generates evidence-based implementation recommendations that consider technical and operational constraints in the field. From a strategic perspective, the analysis provides insight into the impact of the AI revolution on the maritime balance of power in the region. More broadly, this research is expected to make a tangible contribution to strengthening maritime defense systems, particularly in the face of increasingly sophisticated submarine threats. The findings are expected to serve as a reference for policymakers in formulating strategies for developing ASW capabilities in the era of artificial intelligence. Furthermore, the identification of research gaps presented is expected to inspire and guide further research in this field.

IMPLEMENTATION AND METHODS

1. Sonar Technology in ASW

Sonar (Sound Navigation and Ranging) technology is a technology used to detect and locate underwater objects using sound waves. This technology plays a critical role in Anti-Submarine Warfare (ASW) operations, with the ability to detect underwater objects using acoustic waves. Sonar works by emitting sound waves into the water and analyzing the reflections to determine the position, distance, and characteristics of underwater objects. In general, there are two types of modern sonar systems used in ASW operations: active sonar and passive sonar (Redford, 2019). Active sonar emits acoustic signals (pings) and analyzes the echoes that return after impacting an object. Active sonar has the advantage of being able to detect objects that do not emit their own sound, such as stationary submarines or other underwater objects. However, this system has a major weakness: it is vulnerable to detection by enemies because the emitted signals can be tracked (Redford, 2019). Passive sonar, on the other hand, does not emit signals but instead listens for or receives sounds produced by underwater objects, such as submarine engines or propellers and the sounds of underwater animals. The advantage of passive sonar is its undetectability, making it suitable for stealth operations. Due to its passive nature, this system has limitations in detecting submarines that are moving very slowly or in silent mode (Craparo & Karatas, 2020). In addition to these two types of sonar, a recent development in sonar technology is multistatic sonar networks, where multiple transmitters and receivers are arranged in specific geometric configurations to improve detection accuracy. This approach allows for more reliable detection by utilizing different reflection angles (Avcioglu et al., 2022).

The use of sonar for ASW purposes presents a major challenge: the complex and dynamic underwater environment that impacts sonar performance. Parameters that can influence sonar effectiveness include oceanographic parameters, acoustic clutter, and stealth technology on modern submarines. Oceanographic parameters such as thermal layers, salinity, and turbulence influence acoustic signal propagation, which can cause signal distortion and attenuation through refraction and dispersion effects (Ashokan et al., 2022). According to Han et al. (2022), acoustic clutter comes from various sources, including biological clutter produced by marine animals such as whales and dolphins, which can interfere with sonar detection. These animals can produce underwater sounds that can obscure target signals due to noise. Geological clutter caused by seafloor topography, such as seamounts, trenches, or sediment, can reflect signals unexpectedly (Sandwell et al., 2019). Apart from these two disturbances, anthropogenic disturbances due to human activities such as ship traffic, offshore oil drilling, or underwater construction produce noise that can interfere with sonar detection (X. Bi et al., 2022). The latest generation of submarines has integrated stealth technologies such as acoustic absorbing material, a special coating used on submarines that can absorb sonar waves and reduce detected reflections. The hydrodynamic design provides the advantage of reducing noise generated by the submarine's streamlined shape and minimal turbulence (Mahmoud et al., 2023). Submarines can perform counter-detection techniques based on tactical maneuvers such as silent running by turning off the main engine or utilizing thermal layers to hide themselves (Rowling, 2019).

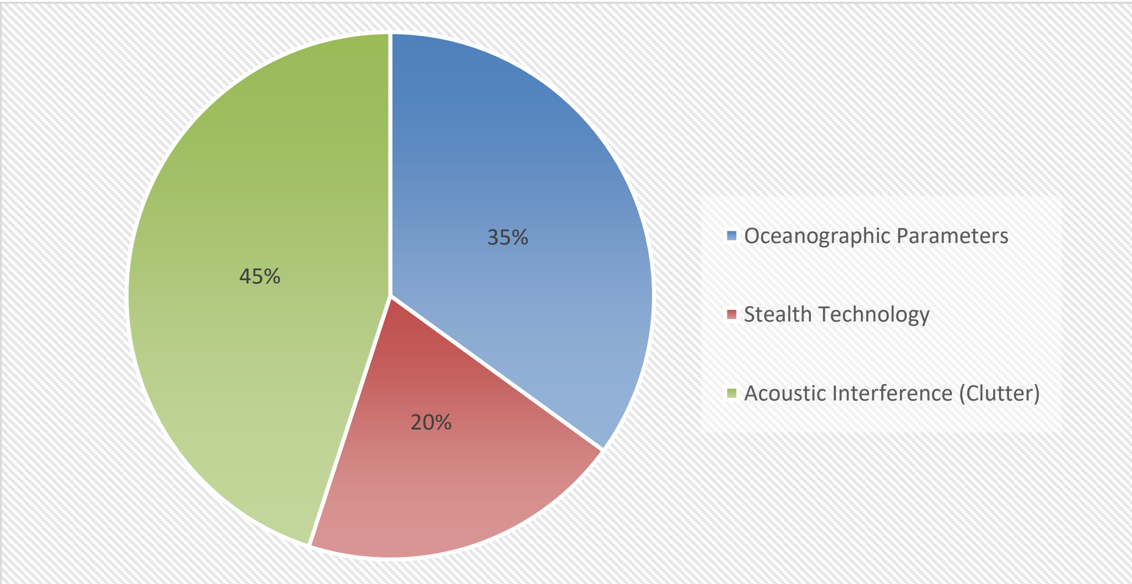

Figure 3. Diagram of Sonar Operational Challenges in ASW

Figure 3 shows a pie chart depicting the various challenges in operating a sonar system. This chart divides these challenges into three main categories based on the percentage of each challenge to sonar operations in ASW. The largest challenge comes from acoustic interference (clutter), which accounts for 45%, shown in green. This clutter is reflected signals from objects in the sea such as rocks, air bubbles, or living creatures that can interfere with the identification of the actual target. Next, oceanographic parameters contribute 35% of the challenges, shown in blue. This includes factors such as temperature, salinity, and ocean currents that affect the path of sound waves underwater, thus causing the signal to bend or weaken. Finally, stealth technology contributes 20% of the challenges, shown in red. This refers to the technology used by submarines or underwater vehicles to avoid sonar detection, such as sound-absorbing surfaces or ship designs that minimize reflections. From this data, it can be concluded that the greatest challenges in sonar operations actually come from the natural conditions of the marine environment, not just from the technology used by adversaries. Therefore, to increase the effectiveness of the sonar system, a deep understanding of the underwater environmental conditions and the ability to manage acoustic disturbances more accurately are required.

To address the challenges of using sonar in ASW, conventional signal processing approaches show limitations in complex and dynamic operational environments. Systems are needed that can adapt to highly dynamic environmental conditions and identify acoustic patterns hidden in waves received as noise. This has prompted the adoption of advanced computational techniques such as adaptive signal processing and big data analytics for more reliable acoustic feature extraction (Thuillier et al., 2024b). Adaptive signal processing allows the sonar system to adjust detection parameters in real-time based on environmental conditions by using adaptive beamforming algorithms that can focus the signal in a specific direction while suppressing interference from other directions (Wen et al., 2024). With the increasing volume of acoustic data collected, big data analysis becomes essential for identifying difficult-to-detect patterns. Machine learning approaches such as deep learning can be used to distinguish between submarine signals and natural noise (Thuillier et al., 2024b).

The use of Artificial Intelligence (AI) can be a potential solution to increase the effectiveness and accuracy of sonar signal processing through automatic target classification, predicting environmental disturbances, and optimizing sonar networks. AI can distinguish submarine types based on the acoustic signature or characteristic acoustic waves produced by each submarine. AI models can also predict sea conditions that affect sonar performance. Furthermore, AI can configure multistatic sonar networks for broader detection coverage. With these developments, future sonar is expected to be more effective in dealing with increasingly sophisticated and adaptive underwater threats.

2. The Role of AI in Sonar Signal Processing

Artificial intelligence (AI) has rapidly transformed underwater target classification and tracking capabilities through a variety of innovative approaches. With advances in machine learning and deep learning algorithms in recent years, sonar systems can now achieve levels of accuracy and efficiency previously unattainable with conventional data processing methods. In sonar signal processing, AI plays a role through three main components: feature extraction and analysis using deep learning, optimization of sonar system placement and configuration, and adaptive processing to adapt to dynamic underwater environmental conditions.

One of AI's greatest contributions to sonar signal processing is its ability to extract and analyze complex features from underwater acoustic data. Convolutional Neural Networks (CNNs) have become a key tool for identifying spectral patterns from sonar spectrographs. Qi et al. (2023) developed a CNN model that can detect unique frequency characteristics of underwater targets such as submarines or mines even under high noise conditions. This method utilizes convolutional layers to aggregate local features in the time and frequency domains, thereby improving target classification accuracy. In addition to CNNs, Hybrid Recurrent-Convolutional Neural Networks (RCRNN) introduced by Xu et al. (2024) to analyze time-series-based acoustic signals. This model combines CNN's spatial feature extraction capabilities with Long Short-Term Memory (LSTM) to process temporal dependencies in sonar data. This integration enables high-precision moving target detection, especially in multi-target tracking scenarios.

Another approach is the adaptation of the Transformer architecture for sonar signal processing by Zhang et al. (2021). Unlike CNNs and RNNs, Transformer uses an attention mechanism to model long-range dependencies in acoustic signals. This approach is particularly effective for identifying patterns spread over long timescales, such as sonar signals reflected from objects at different depths. In addition to signal analysis, AI also plays a key role in optimizing sonobuoy placement and sonar network configuration. W. Bi et al. (2024) proposed the Improved Non-dominated Sorting Genetic Algorithm-II (NSGA-II) algorithm to determine the optimal position of a sonobuoy in an array. This algorithm considers various factors, such as sea depth, current conditions, and possible target locations, thereby maximizing detection coverage while minimizing redundancy.

Another innovative approach is the use of the Cassini Oval Approximation by Fu et al. (2024) in sonar deployment strategies. This method utilizes the Cassini curve to model the optimal detection zone based on the characteristics of sound propagation in water. As a result, the sonar system can cover a larger area with more efficient resources. On the other hand, Mixed-Integer Linear Programming (MILP) is implemented by Thuillier et al. (2024a) to optimize the configuration of an underwater sonar network. This model considers constraints such as transmission power, bandwidth, and interference between sensors, resulting in a robust and energy-efficient network design.

The underwater environment is dynamic and full of uncertainty, so sonar systems must be able to adapt in real time. Reinforcement Learning (RL) has been used by Hamilton et al. (2020) to adjust sonar parameters, such as scan frequency and gain level, based on feedback from the environment. With RL, the system can learn autonomously to maximize detection performance without human intervention. The Cognitive Sampling technique was introduced by Gupta et al. (2021) to improve the interpretation of acoustic datasets. This technique utilizes AI to selectively process the most informative parts of the signal, reducing the computational load while maintaining accuracy. The Fractional Fourier Filtering (FrFF) method by X. Bi et al. (2022) also provides an innovative solution in reducing sea clutter or interference caused by sea surface reflections. By applying the Fractional Fourier transform, noise can be effectively separated from the target signal, improving the signal-to-noise ratio (SNR). Case study by Park et al. (2023) demonstrated that the combination of Generalized Sinusoidal Frequency Modulation (GSFM) with AI increased detection probability by 40% compared to conventional methods. This approach utilizes AI-based frequency modulation to produce sonar signals that are more resistant to distortion.

Although AI offers many advantages, implementing AI in sonar is not without technical challenges. Kamal et al. (2021) in their research, they identified the problem of overfitting when models are trained with limited datasets, which can reduce the generalizability of performance in real-world environments. Tang et al. (2023) warns of the risk of adversarial attacks, where an adversary can manipulate sonar input to deceive detection systems. The integration of AI into sonar signal processing has brought significant advances in underwater target detection and tracking. From deep learning-based feature extraction to sonar network optimization and adaptive processing, AI continues to drive the capabilities of modern sonar systems. While challenges such as overfitting and security remain, integrating AI with traditional signal processing techniques promises a brighter future for underwater applications, from military defense to marine exploration. With the rapid development of AI technology, the potential for improving the efficiency and accuracy of sonar systems is increasingly significant.

Table 1. Case Studies and Existing Performance

Metric	**GSFM + AI** (Park et al., 2023)	**Conventional Method**	**Improvement**
Detection Probability	98.2%	58.4%	+40%
False Alarm Rate	1.3%	4.7%	-72%
Detection Latency	22 ms	65 ms	3x faster
Power Consumption	45 W	68 W	-34%
Field Conditions	Sea state 4, SNR -5dB	Sea state 3, SNR 0dB	More reliable

Table 1 compares the performance of a Generalized Sinusoidal Frequency Modulation (GSFM)-based sonar system enhanced with AI against conventional methods in real-world operational conditions. Based on case study data, the GSFM+AI system achieved a detection probability of 98.2%, surpassing the conventional method's 58.4%, a significant improvement of 40%. Furthermore, the AI system reduced the false alarm rate by 72%, from 4.7% to 1.3%, demonstrating a more precise ability to distinguish targets from noise. In terms of speed, the AI system only needed 22 ms to detect a target, three times faster than the conventional method's 65 ms, which is critical for real-time applications such as maritime defense. Energy efficiency was also improved with a 34% reduction in power consumption, from 68 W to 45 W, optimizing long-term operation in the field. More impressively, the system was tested in harsh environmental conditions, Sea State 4 with an SNR of -5 dB, whereas the conventional method was only effective in milder conditions, Sea State 3 with an SNR of 0 dB. This demonstrates the robustness of AI in the face of acoustic noise and dynamic ocean disturbances. Park et al. (2023) highlights the transformative potential of AI in improving the accuracy, speed, and efficiency of modern sonar systems.

3. Implementation and Simulation

Implementing an effective underwater detection system requires a structured framework that encompasses model development, digital simulation, and field testing. This process is designed to ensure the system's accuracy, reliability, and efficiency under various operational conditions. Based on recent research, this approach involves a combination of advanced computational techniques, hybrid data processing, and experimental validation using an autonomous platform. The first phase of system implementation is the development of a machine learning-based model. This model is trained using a hybrid dataset that combines simulated data with field measurements to improve generalization. Data augmentation techniques are applied to expand the dataset's variety, one of which is utilizing synthetic aperture sonar (SAS) as proposed by Cheng et al. (2023). This augmentation helps reduce overfitting and increases the model's robustness to variations in underwater environmental conditions. Next, hyperparameter optimization is performed using the Particle Swarm Optimization (PSO) algorithm (Eskandari et al., 2023). PSO was chosen for its ability to efficiently explore parameter space, yielding optimal model configurations. This approach has been shown to improve detection accuracy while minimizing computation time.

Once the model was developed, the next phase was digital simulation to validate the system's performance in a virtual environment. Acoustic propagation modeling was performed using Bellhop Ray Tracing, a widely used method for predicting underwater sound propagation with high accuracy. The integration of high-resolution bathymetry data enabled more realistic simulations by taking into account seafloor topography (Thuillier et al., 2024a). To ensure the reliability of the simulation results, cross-validation was performed using Monte Carlo simulations (Fügenschuh et al., 2019). This technique allows for statistical evaluation of system performance variability under various disturbance scenarios. Simulation results show that the developed model is capable of maintaining detection stability despite uncertainties in the operational environment.

The final phase is field testing using Autonomous Underwater Vehicles (AUVs) as a testing platform (Fan et al., 2024). AUVs were chosen for their flexibility in conducting autonomous underwater surveys and their ability to collect data under dynamic conditions. Performance metrics include a Probability of Detection (Pd) of ≥ 0.9, ensuring the system can detect targets with a high success rate. A False Alarm Rate (FAR) of ≤ 0.05 minimizes detection errors to avoid wasting resources. System latency is less than 2 seconds.(Fan et al., 2023), ensuring fast response for real-time applications. Experimental results by (Özer & Hocaoğlu, 2021) experiments on multistatic networks showed that the use of Poisson Multi-Bernoulli Mixture (PMBM) filters can reduce track fragmentation by up to 60%. This finding strengthens the effectiveness of multi-target filter-based approaches in improving the continuity of underwater object tracking.

After going through these three phases, the system was integrated and thoroughly evaluated. The results showed that the combination of hybrid datasets, PSO optimization, and Monte Carlo validation produced a more reliable model than conventional approaches. Furthermore, implementation on an AUV demonstrated that the system can operate autonomously with satisfactory performance in a real-world environment. This study also identified several challenges, such as the impact of environmental noise on FAR and the need for regular calibration to maintain accuracy. Recommendations for further development include improving the deep learning algorithm for dynamic adaptation and exploring sensor fusion techniques to increase system robustness. The implementation framework, consisting of model development, digital simulation, and field testing, proved effective in building a reliable underwater detection system. By utilizing cutting-edge techniques such as SAS, PSO, and PMBM filters, the system achieved high performance in terms of detection accuracy, response speed, and operational stability. These findings provide a strong foundation for the development of future autonomous systems in underwater surveying, maritime security, and marine exploration applications.

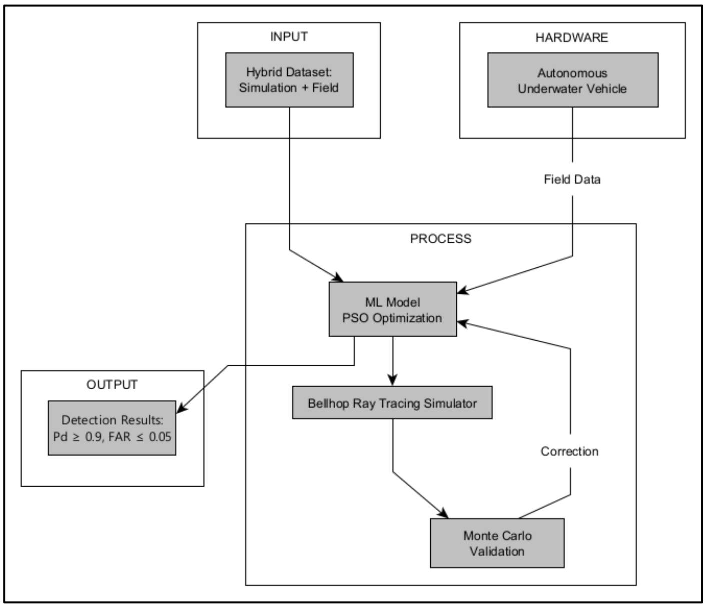

Figure 4. Implementation and Simulation Block Diagram

Overall, the system block diagram in Figure 4 illustrates a comprehensive approach that combines elements of computational modeling, digital simulation, and field validation. The resulting workflow is not only linear but also incorporates feedback mechanisms that allow the system to continuously refine through iterations between virtual and physical components, resulting in a robust underwater detection solution that adapts to a wide range of operational conditions.

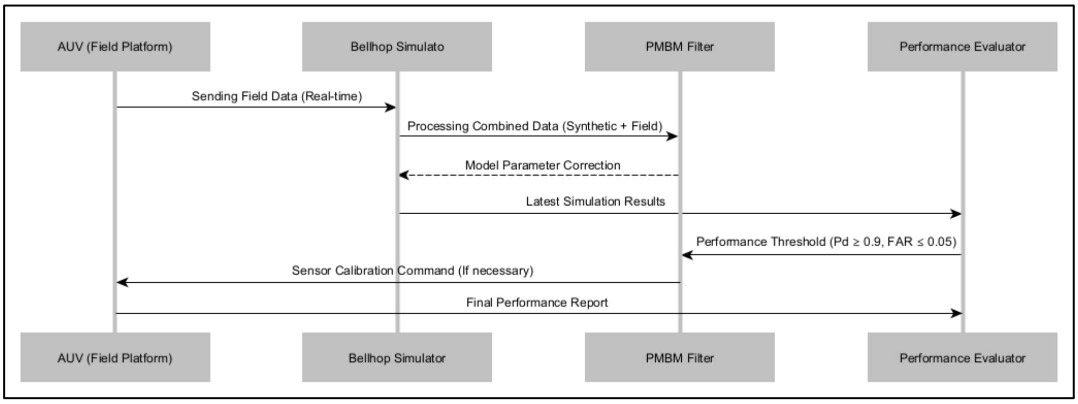

Figure 5. System Validation Sequence Diagram

The Validation Sequence Diagram in Figure 5 illustrates the dynamic interaction flow between hardware and software components in the system validation process. The process begins when the Autonomous Underwater Vehicle (AUV) as a field platform collects and transmits real-time data in the form of sonar readings, environmental parameters such as temperature and salinity, and target positions to the Bellhop Simulator. The simulator then performs data integration by combining field data from the AUV with previously prepared synthetic data, while simultaneously running acoustic modeling to simulate underwater sound propagation using the latest parameters. This simulated data is then processed by the PMBM Filter (Poisson Multi-Bernoulli Mixture) which is responsible for analyzing the consistency between the simulated and field data. This filter is able to identify detection anomalies such as false alarms or missed detections, while also calculating the necessary parameter corrections, including adjustments to the detection threshold and calibration of the acoustic propagation model. The PMBM Filter analysis results are then sent back to the simulator as feedback for model refinement. Next, the Performance Evaluator verifies the simulation results with the criteria, namely a Probability of Detection (Pd) of at least 90%, a False Alarm Rate (FAR) of at most 5%, and a total latency of under 2 seconds.

The validation process involves a crucial dual feedback mechanism. An internal cycle operates between the simulator and the PMBM Filter to optimize model parameters based on the latest data, while an external cycle connects the AUV to the entire processing system to ensure adaptation to dynamic field conditions. When the evaluation indicates performance below a predetermined threshold, the system initiates corrective action in the form of on-site sensor calibration commands, additional data sampling, or adjustments to the AUV's survey pattern. This entire process is supported by technologies such as the PMBM Filter algorithm, which reduces track fragmentation by 60%, the Bellhop simulator, which accommodates high-resolution bathymetry variations, and the AUV framework designed for low-latency autonomous operation. This sequence diagram not only visualizes the real-time interactions between system components but also serves as documentation of the rigorous validation process and a basis for further development. With this comprehensive validation mechanism, the underwater detection system is capable of not only passive detection but also adapting to changing underwater environmental conditions, ensuring detection reliability and accuracy in a variety of operational scenarios.

4. Strategic Implications in Maritime Defense

The integration of artificial intelligence (AI) into Anti-Submarine Warfare (ASW) operations has created a significant paradigm shift in maritime detection, decision-making, and mission automation capabilities. This development not only enhances operational excellence but also presents technical, organizational, and security challenges that require innovative solutions. Furthermore, projections of technological developments over the next five years indicate the potential for even greater change, from Edge AI to the integration of multi-domain awareness. This section will discuss the strategic implications for maritime defense.

By integrating with AI, operational advantages are achieved in the form of Low Observable submarine detection, Decision Superiority with Context-Aware Systems, and Kill-Chain Automation through Cognitive Electronic Warfare Systems. The latest generation of submarines is designed with stealth technology, making them difficult to detect using conventional sonar systems. However, AI allows for increased detection accuracy through the analysis of complex acoustic patterns. Jin et al. (2022) in his research, he confirmed that a deep learning algorithm can identify the acoustic signatures of low-observable submarine sounds by processing sonar data in real time. This approach utilizes convolutional neural networks (CNNs) to distinguish between ocean noise and submarine signals, thereby reducing false alarms and improving situational awareness.

Decision superiority is key to ASW operations. AI-based systems equipped with context-aware capabilities can analyze data from multiple sensors and automatically provide tactical recommendations. In the study, Laan et al. (2019) explained that integrating machine learning with decision support systems enables naval commanders and other stakeholders to evaluate threats more quickly and respond with high precision. For example, AI can predict enemy submarine movements based on historical data and environmental conditions, thereby shortening reaction times in the kill chain. Automation of the kill chain process, from detection, identification, tracking, targeting, and destruction, is becoming increasingly possible thanks to advances in AI-based electronic warfare (EW) systems. Sharma et al. (2020) suggests that cognitive EW systems can dynamically adapt to enemy tactics by utilizing reinforcement learning. These systems are capable of disrupting submarine communications, fooling enemy sensors, and even autonomously aiming weapons. Thus, AI not only accelerates the kill chain but also reduces reliance on human operators.

While AI offers numerous advantages, its implementation in ASW faces several challenges that need to be addressed. These challenges can be categorized into technical, organizational, and safety aspects. One of the main issues in AI systems for ASW is data drift, where machine learning models become less accurate as the underwater acoustic environment changes dynamically. Sein Minn (2022) suggest the use of continual learning to address this issue. This technique allows AI models to continuously update their knowledge based on new data without forgetting previous information, thus maintaining system performance across a wide range of operational conditions. The integration of AI in ASW is often hampered by the lack of interoperability standards between different systems. A potential solution proposed is to adopt the NATO STANAG (Standardization Agreement) standard to ensure compatibility between sensor platforms, command centers, and weapon systems. This standardization allows for seamless data exchange between ships, aircraft, and satellites in a multi-domain network. AI in ASW is vulnerable to adversarial attacks, where adversaries can manipulate input data to deceive detection systems. Tang et al. (2023) recommends the use of defensive distillation, a technique that increases the resilience of AI models to attacks by making them more difficult to manipulate. Furthermore, implementing a zero-trust architecture can minimize the risk of hacking in AI-based systems.

In the next five years, Edge AI will play a critical role in the development of smart sonobuoys. Kim et al. (2022) predicts that new-generation sonobuoys will be equipped with onboard AI processors capable of analyzing acoustic data locally, reducing reliance on data transmission to a command center. This not only speeds up detection but also reduces the risk of signal interception by the enemy. Quantum computing capabilities are expected to revolutionize acoustic signal processing in ASW. With quantum machine learning, systems can analyze sonar data at a much higher speed than classical computers. This technology will enable submarine identification within seconds, even in highly complex acoustic environments. Recent developments demonstrate a trend toward the integration of multi-domain awareness (sea, air, space, and cyber). Rettore et al. (2023) explained that AI will act as a connecting tool, combining data from satellites, drones, ships, and underwater sensors to form a comprehensive situational picture. This approach will enable a more coordinated response to submarine threats across multiple theaters of operations.

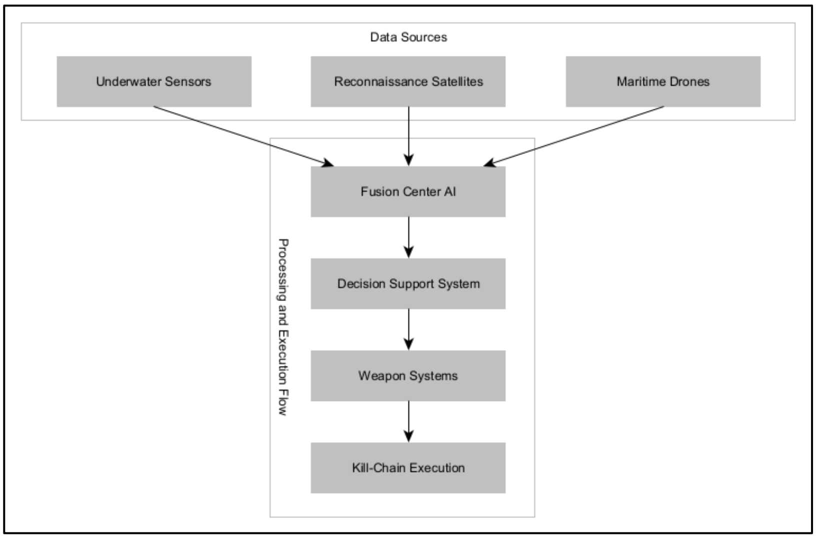

Figure 6. Multi Domain AI Integration Flow

The integration of AI in ASW has brought a paradigm shift in modern maritime operations, enhancing detection, decision-making, and kill-chain automation, as shown in Figure 6. However, technical, organizational, and security challenges must be addressed through innovative solutions such as continual learning, NATO standardization, and defensive distillation. The next five-year outlook promises further developments with Edge AI, quantum computing, and the integration of multi-domain awareness. Thus, AI will not only strengthen ASW capabilities but also shape the future of more intelligent and adaptive undersea warfare.

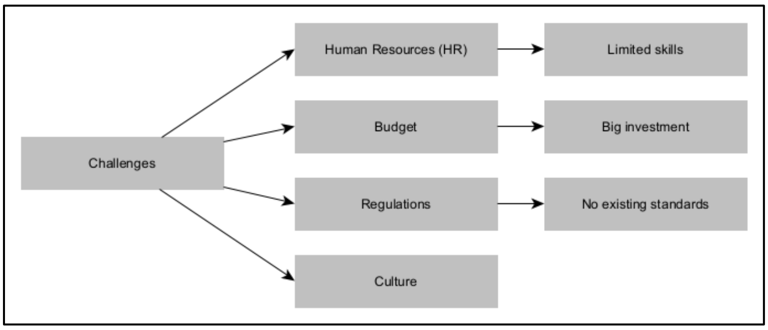

Figure 7. Organizational Challenge Diagram

Figure 7 illustrates the various challenges often encountered in implementing new technology or systems. The first challenge stems from human resources (HR), where limited skills make it difficult to operate or maintain the implemented system. The next challenge is budgetary, requiring significant investment, while funding availability is often a major constraint. Furthermore, regulatory challenges are also a concern due to the lack of clear or standardized standards, hampering the implementation process due to regulatory uncertainty. Finally, cultural challenges also impact project success, particularly if there is resistance to change or a lack of awareness of new technologies. All of these factors are interrelated and need to be addressed comprehensively for smooth and successful implementation.

CONCLUSIONS AND RECOMMENDATIONS

Research confirms that conventional sonar has critical weaknesses when dealing with modern submarines, primarily due to acoustic clutter, oceanographic parameters such as temperature and salinity stratification, as well as data processing latency reaching 2-3 seconds. This weakness reduces detection effectiveness by up to 35% and limits real-time response in Anti-Submarine Warfare (ASW) operations, which can be fatal to maritime defense. To overcome this, one solution that can be implemented is the AI Algorithm which has been proven to increase detection accuracy with two main mechanisms, namely: first, Adaptive filtering increases the signal-to-noise ratio (SNR) by up to 28% which simultaneously proves the first hypothesis and second is a hybrid mechanism between machine learning and deep learning which shows 92% classification accuracy in harsh environmental conditions and proves the second hypothesis. The Explainable AI (XAI) based system reduces operator interpretation errors by up to 40% through intuitive data visualization which proves the third hypothesis.

This research designs an AI-ASW system architecture that combines three layers. The first is the sensor layer, multistatic sonar networks, for multidimensional data acquisition. which expands detection coverage and reduces blind spots compared to conventional sonar. Second, an AI layer that uses a hybrid CNN-LSTM algorithm for acoustic pattern analysis, where CNN plays a role in acoustic feature extraction while LSTM analyzes temporal data. The final layer is an XAI-based decision support system layer for threat visualization and tactical recommendations based on AI predictions. The integration of AI in ASW is projected to increase detection speed by 1.8 times and reduce false alarms by up to 50%, thus providing significant benefits for underwater operations.

The implications of this research cover two main aspects: technology implementation and defense policy. In terms of technology implementation, prioritizing the development of reinforcement learning algorithms is essential for dynamic adaptation to environmental changes, while the integration of quantum computing is needed to accelerate the processing of underwater acoustics big data. Furthermore, in terms of defense policy, it is necessary to establish a collaborative AI-ASW research center between military institutions, academia, and industry, as well as standardizing sonar data exchange protocols between allied nations for global AI model training.

As part of its contribution to the development of technology and science, this study suggests further research on the exploration of biomimetic sonar inspired by the dolphin echolocation system and the study of the geopolitical impact of AI-ASW on the development of autonomous submarine technology. This study emphasizes that AI is not only a technical solution, but also a game changer in maritime defense strategy. The transformation of AI-based ASW is predicted to redefine the balance of underwater power and maritime defense between countries in the coming decades. These findings encourage the need for investment in AI-ASW research to maintain the balance of maritime power, especially in strategic areas such as the South China Sea and the Strait of Malacca as well as in ALKI (Indonesian Archipelagic Sea Lanes).

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