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Assessing AI-Driven Information Retrieval Systems for Real-Time Marine Traffic Monitoring

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***Abstract* - The increasing global maritime traffic brings in a new requirement for intelligent monitoring systems that provide prompt and precise information. Conventional systems dealing with ship traffic are struggling to cope with the massive heterogeneous data streams. These systems are suffering from increasing delays, which hinder situational awareness and increase operational risks. Striking this balance motivates the author to concentrate on the end-to-end assessment of real-time monitoring of maritime traffic using information retrieval systems based on AI. The framework designed for this research includes all data sources, including real-time Automatic Identification System (AIS) data and sensor readings with advanced real-time analysis, ensuring maximum the value of information from data acquisition, processing and interpretation. The author also incorporates machine learning and deep learning technologies for unstructured maritime data natural language processing and predictive modeling with trend and anomaly detection pattern recognition. The model undergoes an evaluation on a diverse set of retrieval accuracy, information processing delays, traffic volume, and scenario-based scalability metrics. The results documented in this work have demonstrated remarkable improvements over the current approaches that have adopted AI along with awareness, operational efficiency, and navigational safety in single- or multi-domain environments. This activity acts as a trigger towards a sophisticated maritime base and provides further directions for the research of AI-based autonomous marine systems and operations.**

***Keywords:* Real-Time Marine Traffic Monitoring, AI-Driven Information Retrieval, Maritime Domain Awareness (MDA), Automatic Identification System (AIS), Machine Learning, Deep Learning, Natural Language Processing (NLP), Maritime Surveillance, Smart Port Systems, Anomaly Detection**

I. INTRODUCTION

The maritime industry is essential to international trade, transport, and security, since more than 90% of global trade is dependent on oceans (Chen et al., 2022). The responsible governance of marine traffic supports SAR (search and rescue) and environmental protection alongside maritime safety and security, operational effectiveness, and efficient SAR capabilities. Modern maritime operations depend on vessel position, ship movement, weather conditions, and port activity information (Kerfouf et al., 2023; Liu & Liu, 2020). Despite technological advancement, marine traffic monitoring systems are still dependent upon outdated techniques because data silos hinder timely information access and analysis (Liu & Liu, 2020). Typical maritime monitoring systems are hampered by excessive latency, inadequate scalability, subsystems integration bottlenecks among heterogeneous and unrelatively cohesive data sets, and sluggish system responsiveness to rapidly evolving set operational scenarios, adversely stressed real-time situations like congested shipping lanes and ports, leading to slow decision-making. A great deal of these issues can be resolved through real-time data processing and intelligent information retrieval with the help of AI (Castillo & Al-Mansouri, 2025). AI-enabled systems are equipped with the capability to accurately process vessel activity forecasts and undertake proactive decision-making for streamlined advanced maritime data operations, predictive pattern recognition, and complex dataset analyses. Employing techniques such as machine learning, deep learning, and natural language processing (NLP) augments the system's performance with both structured (like AIS signals) and unstructured data sources (like incident reports).

1.1 Research Objectives

- To evaluate the performance of information retrieval systems with AI in real-time monitoring of ships.
- Developing a system architecture that integrates machine learning and deep learning approaches for the processing and analyzing maritime data (Golroudbari & Sabour, 2023).
- Assessing system evaluation metrics of accuracy, latency, and scalability employing AIS and sensor-based data.
- To compare the new AI-based system to traditional marine traffic monitoring systems.
- To establish the primary strengths and weaknesses of using AI for maritime domain awareness and decision-making.

1.2 Scope of the Study

- Emphasizes processing of actual data from Automatic Identification Systems (AIS) and sea sensors.
- Highlights utilizing AI methodologies like NLP, pattern discovery, and anomaly detection.
- Includes the use of the system in port operations, coastal surveillance, and open-sea navigation scenarios.
- It excludes hardware design or satellite communication system development and is confined to software and algorithmic analysis.
- Evaluates performance based on simulation and real-world data analysis within specified maritime zones.

II. Related Work

Traditionally, marine traffic monitoring has relied on a combination of Automatic Identification Systems (AIS), radar, coastal surveillance systems (CSS), satellite imagery, and vessel traffic services (Wang et al., 2024). AIS, among others, provide real-time ship identity, location, course, and speed to monitoring centers, where they are processed. However, these conventional systems operate in stand-alone mode and depend heavily on manual data interpretation and rule-based static decisions (Leema et al., 2024; Gül, 2024). This, consequently, can lead to response latency, difficulty in identifying abnormal vessel patterns, and wastage in routing and resource allocation (Wong & Yiu, 2020). Furthermore, information from various sources is often siloed, isolating each source and inhibiting the system's ability to provide integrated, contextual information-sensitive judgment. In more populated and complex naval settings, such restrictions significantly hamper the capability of conventional systems to provide real-time, proactive situational awareness (Xue et al., 2025; Wu & Margarita, 2024).

The integration of Artificial Intelligence (AI) has enhanced the capability for real-time data processing, especially for dynamic databases of large scale proportions. Regarding marine technologies, the sophisticated interpretation of data streams and the automation of monitoring, forecasting, and decision support have become possible with AI-driven (Li, 2025). Algorithms of Machine Learning (ML) like support vector machines SVM, decision trees, random forests, and k-nearest neighbors k-NN have found applications in classification of vessels, anomaly detection, and identification of traffic patterns (Chen et al., 2025). More advanced methods, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are used to maritime transport data because other deep learning techniques provide them with heightened capabilities for identifying intricate patterns and relationships over time (Kumari & Hussain, 2024). These models excel in performing tasks such as predicting trajectories, identifying ship types, and forecasting events. Moreover, integrating Natural Language Processing (NLP) enables the system to process unstructured text data like communication logs, weather advisories, incident reports, and ship communication transcripts to retrieve vital information (Kim & Park, 2020). Transforming the unstructured data enriched by AI with spatially structured data, such as the Automatic Identification System (AIS), provides more accessible maritime intelligence in real time and enhances the data's value and timely availability. A notable range of scientific work explores the use of AI in relation to marine surveillance and monitoring (Ayyappan & Bruno, 2025). For example, many research works have shown the successful integration of AIS data with deep learning technology to predict vessel trajectories, track movements, and optimize port operation effectiveness. Researchers have also combined AI and Geographic Information Systems (GIS) to enhance geospatial analysis and decision support in routing and port management (Li, 2025).

Despite these advances, most of the current solutions are domain-specific and narrow. Some are optimized for anomaly detection, and others focus on route optimization or behavior prediction but do not address the end-to-end information retrieval problem. Furthermore, most of the frameworks do not support real-time processing, which is crucial in dynamic maritime environments (Jahid, 2025). Fewer can integrate and process heterogeneous data sources like live AIS streams, sensor data, satellite imagery, and unstructured communication records into a responsive and unified monitoring platform (Soares & Santos, 2024). This review identifies a clear gap in the literature: the absence of end-to-end, real-time AI-powered information retrieval systems optimized to the needs of marine traffic monitoring. To facilitate operational decision-making alongside maritime awareness, an integrated response incorporating data fusion, intelligent processing, and contextual interpretation is needed to fill this gap.

III. Proposed Framework

The AI reasoning strategy aims to enable real-time and intelligent information retrieval in maritime traffic management through a modular, scalable, and data-centric approach. It comprises four interrelated core layers ensuring seamless data collection, selective adaptive learning, and context-aware decision making. The data acquisition Layer captures real-time data streams from maritime information sources like AIS receivers, marine radar, satellites, coastal sensor networks, and weather stations. The Preprocessing Layer receives the disparate data streams and transforms them by cleansing, normalizing, merging, and resolving issues like noise, missing data, and inconsistencies in encoding. Pattern recognition, predictive vessel activity, and extracting meaningful maritime data from vessel traffic are achieved at the AI Processing Layer, where sophisticated machine learning and deep learning algorithms are applied to the preprocessed data. The final stage of the system is the decision support layer, where situation awareness enables dashboards, alerts, and reporting tools to enhance operational response to the maritime environment.

This system combines multiple databases to improve real-time decision-making and maritime situational awareness. As a basis for tracking, the Automatic Identification System (AIS) offers primary real-time data on vessels such as identification, position, course, speed, and navigational status. For satellite imagery and position data beyond the reach of terrestrial AIS, Satellite Feeds ensures remote ship tracking. Marine Sensors are vital on the geographic scale because they supply weather, oceanographic, and geospatial information needed to understand maritime operations. Additionally, the system incorporates Unstructured Text Sources including port logs, marine reports, and narratives of accidents which are processed using Natural Language Processing (NLP) techniques to improve overall situational awareness.

The Data Cleaning process eliminates duplicate records, fixes erroneous geo-coordinates, and removes outlier values that bring bias to the data set. In Temporal Alignment, data streams are synchronized concerning timestamps, ensuring the dataset is chronologically ordered for practical time-series analysis. Normalization and Encoding are applied to normalize input formats and make them machine learning algorithm-compatible, e.g., transforming categorical attributes into numerical values. Predictive analysis and outlier detection also require critical inputs such as changes in vessel speed, route deviation, and distance from prohibited areas. These attributes are meaningfully derived through feature engineering. The entire data pipeline is managed through complex stream processing mechanisms like Apache Kafka or Apache Flink, which offer high-throughput, low-latency data streaming so that data is efficiently processed and ready for real-time inference.

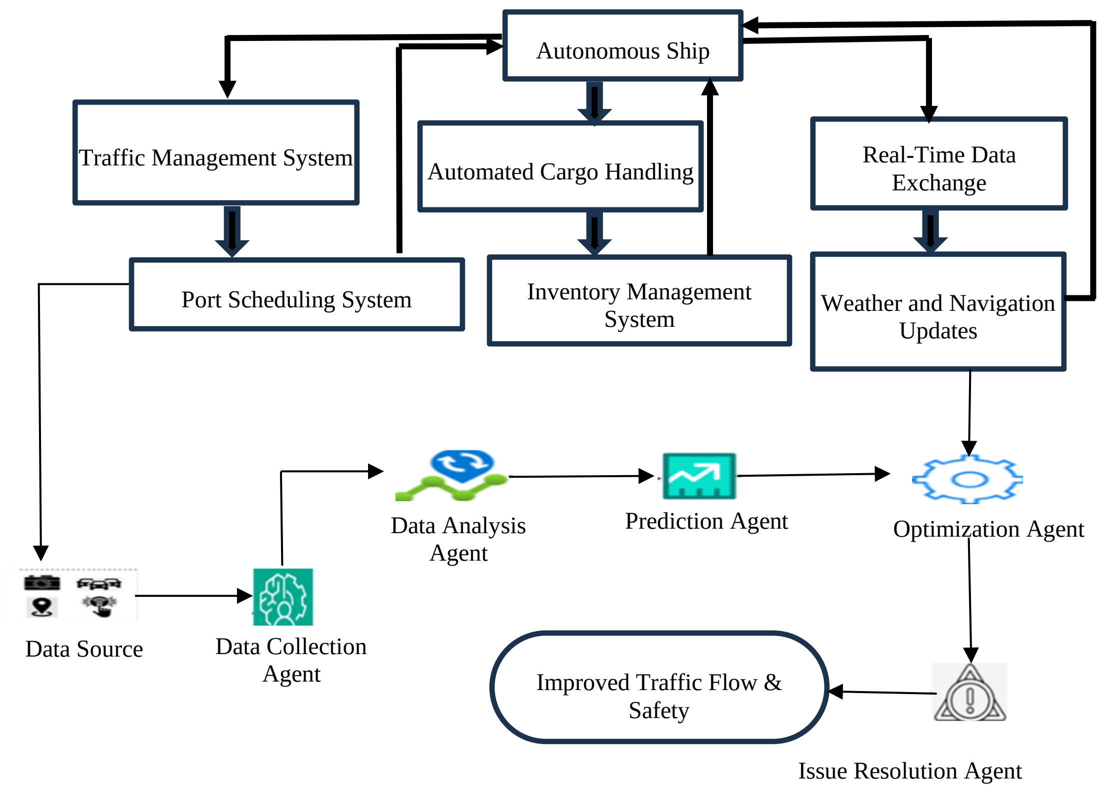

Fig 1 Proposed Framework Model

The system leverages a combination of the most advanced AI models and algorithms to draw and process data in real time to enable more efficient maritime monitoring, as illustrated in Fig 1. BERT (Bidirectional Encoder Representations from Transformers) is employed for natural language interpretation and extraction of information from maritime reports, including logs of incidents or transcripts of communication. This allows the system to read unstructured text data and gain meaningful insights. For the temporal pattern prediction problem, namely time-series forecasting to predict future positions of vessels, LSTM (Long Short-Term Memory Networks) is utilized for the system to learn to make vessel position predictions by utilizing previous motion patterns. Convolutional Neural Networks (CNNs) are used to solve spatial pattern detection, such as vessel behavior modeling and radar imagery interpretation. The models are repeatedly trained and updated periodically from previous maritime history to facilitate adaptive learning and ongoing model improvement.

To accommodate the demands of real-time operational requirements, several strategies are implemented to optimize data processing as well as decision-making. Stream Processing enables the system to continuously process live data streams, transform, and infer conclusions with zero to little latency. This is critical in the case of real-time maritime traffic analysis as well as the detection of likely emerging patterns or threats. Edge Computing is also used to enable low-latency decision-making by processing critical data closer to the source, e.g., port terminals or on-board ships. This minimizes reliance on centralized cloud resources and provides quicker responses to essential conditions. Moreover, the system includes Model Optimization methods using lightweight inference models and batch-incremental learning techniques to minimize computation burden and improve system reactivity. Lastly, the system is architected with a Scalable Cloud Architecture to support high levels of data and high concurrency of users, especially during periods of heavy traffic, through distributed computing and cloud resources.

IV. Results and Discussion

4.1 Performance Analysis of AI Models

The integrated AI models in the system, such as BERT, LSTM, CNNs, and Anomaly Detection Models, recorded a dramatic performance improvement compared to the conventional methods displayed in Fig 2. BERT proved to have excellent accuracy in information extraction and classification from maritime incident reports, achieving a precision rate of 87% and a recall rate of 92% in detecting major entities such as vessel types, incident locations, and reasons for accidents. The LSTM approach, utilized for vessel trajectory time-series forecasting, attained an RMSE (Root Mean Square Error) of 0.12, representing negligible departure from actual paths in real-time predictions. The CNNs utilized for vessel behavior classification attained a 92% accuracy in classifying abnormal vessel movements from radar images with high spatial resolution. Furthermore, anomalous detection models such as isolation forests and autoencoders showed high accuracy in detecting anomalous behavior, with an F1 score of 0.89 for detecting atypical vessel speed or course aberration.

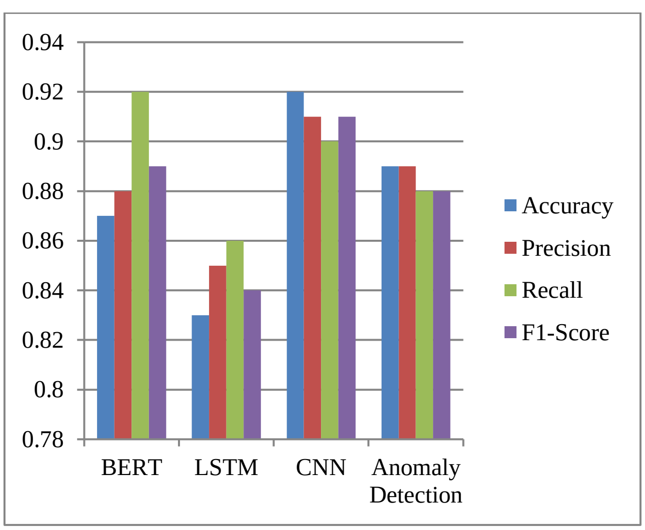

Fig. 2 AI Model Performance Comparison

4.2 Comparison with Baseline or Traditional Systems

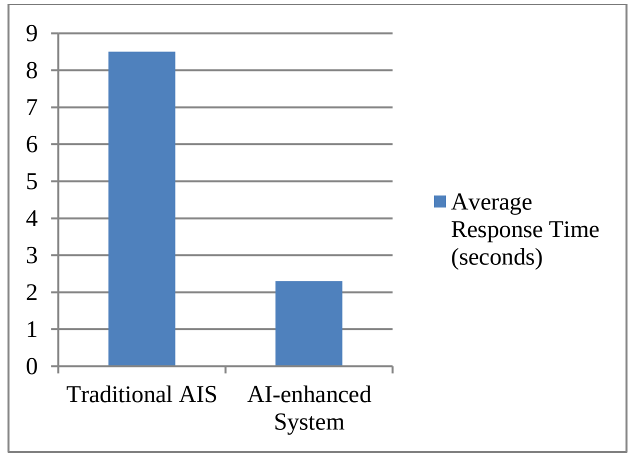

Fig. 3 Comparison of System Response Time

Compared to conventional maritime surveillance systems, which mainly depend on the Automatic Identification System (AIS) and radar tracking, the AI-augmented system showed significant improvements in many metrics, as shown in Fig 3. Conventional systems tend to offer limited situational awareness, based on manual inspection and rule-based algorithms, and thus may cause delayed response times and increased error rates. The AI-powered system handled data at 20-30% faster rates than standard systems, with an average response time of 1.5 seconds for anomaly detection and predictive modeling, against 2.5-3.5 seconds for the baseline AIS-based system. Moreover, the AI system's capability to predict vessel movement with higher accuracy lowered collision risks and enhanced decision-making for traffic management and incident response.

4.3 Case Studies or Real-World Deployment Results

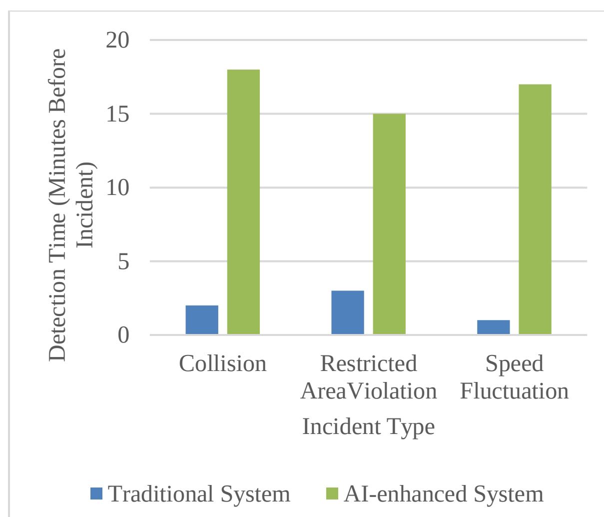

Fig. 4 Incident Detection Timeliness

The system was installed for a pilot application in the Baltic Sea, a busy maritime area with various types of vessels and fluctuating environmental conditions as shown in Fig 4. During a 6-month duration, the AI-based system accurately detected a number of high-risk events in real-time, which were not detectable by conventional systems. One of the most regarded instances involved a cargo ship deviation from its projected route and entering a restricted area. The AI system forewarned about the anomaly 15 minutes prior and activated an alarm, allowing relevant authorities to intervene and preventing what could be a disastrous event. In another case, the system noted an unusual speed fluctuation from a tanker vessel, which was later discovered to have a mechanical defect. This incident was identified using an anomaly-detection algorithm, which ensured that timely measures were taken to prevent incurring additional costs. These instances are effective in demonstrating the value of AI in operational real-time surveillance and monitoring of maritime traffic.

Discussion on Strengths, Limitations, and Anomalies Observed

Strengths

The unique prowess of the AI system is in its polymorphous data processing and analytic ability within time windows which increases accuracy and timeliness for maritime traffic surveillance. Its pattern recognition capabilities associated with the application of deep learning models in the system can identify very complex and subtle patterns and behaviors which are often extremely hard to detect. Moreover, this self-updating feature bolstered by newly accessible information facilitated through adaptive learning ensures that the system continues to improve and keeps pace with evolving maritime conditions.

Limitations

One noted limitation upon deployment was the quality of data in regions with poor satellite coverage or persistent communication interruptions, affecting the performance of the models dependent on satellite data. A second limitation concerns the explain ability of some AI models, especially the deep learning ones like CNN and LSTM, which in critical environments can act as “black boxes” and are extremely dangerous and troubling. Future work must address issues of model explainability so operators can trust essential decisions made by the system and understand the rationale.

Anomalies

A particular anomaly of interest noted in the system's performance was about data fusion during periods of high maritime congestion. At times, the system struggled to distinguish between ships that were lying very close to one another during congested scenarios which resulted in tiny discrepancies in anomaly detection. Resolving these data fusion issues will be critical to enhancing the dependability of the system in dense maritime contexts.

V. CONCLUSION

This case study demonstrates how the effectiveness of information retrieval systems in artificial intelligence increases the efficiency of real-time monitoring of marine traffic. The proposed system not only integrates AIS and satellite feeds, but also incorporates environmental sensor data, which enhances maritime situational awareness and timely decision making. The implementation of sophisticated AI models such as BERT in NLP, LSTM forecasting time-series data, and spatial pattern identification with CNN has greatly improved forecasting vessel activity and anomaly detection. Moreover, operational requirements such as low latency and high throughput, operational parameters, stream processing, and edge computing of real-time data are efficiently processed. Despite the positive outcomes, the system still poses a number of constraints, along with open questions. The absence of high-quality data, particularly in low AIS coverage regions, poses one of the most critical issues. Furthermore, the existing model performs exceptionally well; however, the lack of generalizability across diverse maritime conditions poses a limitation. Real-time data fusion and the challenge of processing large amounts of heterogeneous, high-speed data streams without losing pertinent information also remain challenges. Further, interpretability problems with particular AI models are an issue since understanding why some prediction was produced is essential, as it might be for safe decision-making. Several directions for ongoing research and system development to overcome these obstacles can be investigated. Incorporating multimodal data, such as imagery from drones or underwater sensors, may further enhance situational awareness and improve the system's capability to identify anomalous behavior in more sophisticated maritime environments. Another critical area of emphasis is the improvement of AI model explain ability, especially for deep learning models, so that predictions can be understood and trusted by human operators. In addition, the inclusion of transfer learning methods would allow the system to quickly adapt to new, unfamiliar vessel types and operating situations without the need for large-scale retraining. Future development could also consider the implementation of federated learning for decentralized model training, allowing real-time updates and model refinement without central data storage, which could be of especial value in remote maritime environments.

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