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NEURAL NETWORK-BASED PREDICTIVE STEERING CONTROL INTEGRATED WITH REAL-TIME COMPUTER VISION FOR SAFE AUTONOMOUS SHIP NAVIGATION

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Abstract

The rapid advancement of autonomous maritime transportation has intensified the demand for intelligent steering control systems capable of ensuring accurate vessel maneuverability, reliable obstacle detection, and collision-free navigation under complex environmental conditions. This study presents an advanced neural network-based predictive steering control framework integrated with real-time computer vision for improving autonomous ship navigation, trajectory optimization, and operational safety. The proposed framework combines Convolutional Neural Networks (CNNs) for hierarchical visual feature extraction, Bidirectional Long Short-Term Memory (BiLSTM) networks for temporal vessel-motion modeling, and an attention-guided Model Predictive Control (MPC) strategy for adaptive rudder-angle prediction and dynamic trajectory regulation. The research considers a multimodal maritime navigation dataset comprising 125,000 synchronized observations collected across 2,500 simulated navigation scenarios, incorporating vessel heading, steering angles, ship velocity, GPS coordinates, maritime imagery, obstacle distances, wind disturbances, wave characteristics, and surrounding vessel movements. The experimental design encompasses open-sea navigation, congested maritime corridors, restricted visibility, sharp-turn maneuvers, and dynamic obstacle avoidance. The reported performance values indicate that the proposed CNN–BiLSTM–MPC architecture achieves 98.4% obstacle detection accuracy, 97.6% collision avoidance success, and 96.8% trajectory tracking accuracy. Furthermore, the framework attains a mean heading error of 1.24°, cross-track deviation of 0.38 m, and steering response time of 0.21 s, corresponding to improvements of 42.7%, 38.5%, and 35.6%, respectively, compared with conventional MPC-based steering control. The integrated visual perception module achieves a processing speed of 42 frames per second, supporting real-time navigation decisions while reducing estimated navigation-related energy consumption by 18.9%. Comparative evaluation against conventional Proportional–Integral–Derivative controllers, standalone MPC, and neural network-based steering

architectures indicates improved navigation precision, disturbance rejection, and collision avoidance performance. These findings demonstrate the potential of integrating deep learning-driven visual perception with predictive steering control to advance intelligent maritime navigation, strengthen autonomous decision-making, and support the development of safer and more energy-efficient autonomous ship systems.

1- INTRODUCTION:

The rapid advancement of artificial intelligence (AI), intelligent transportation technologies, and autonomous control systems has significantly transformed the maritime industry, creating new opportunities for developing safer, more efficient, and intelligent ship navigation systems. Maritime transportation plays a fundamental role in international trade and global logistics; however, conventional navigation systems continue to face operational challenges associated with unpredictable environmental disturbances, complex vessel interactions, restricted visibility, navigational uncertainties, and human-dependent decision-making. These challenges become particularly critical in congested maritime corridors, coastal waterways, and dynamically changing ocean environments, where inaccurate steering decisions and delayed responses may increase collision risks and operational inefficiencies [1]. Consequently, intelligent autonomous ship navigation systems integrating environmental perception, predictive motion modeling, and adaptive steering control have emerged as an important research direction in modern maritime engineering. Autonomous ship navigation requires the coordinated operation of multiple subsystems responsible for environmental sensing, obstacle identification, vessel-state estimation, trajectory planning, steering regulation, and collision avoidance. Traditional maritime steering systems primarily employ Proportional–Integral–Derivative (PID) controllers, adaptive autopilot mechanisms, and conventional Model Predictive Control (MPC) strategies. Although these approaches provide satisfactory performance under relatively stable operating conditions, their effectiveness may decrease when vessels encounter nonlinear hydrodynamic behavior, rapidly changing environmental disturbances, and complex maritime traffic. Conventional PID controllers may experience reduced tracking accuracy under substantial variations in vessel dynamics, while classical MPC approaches depend heavily on accurate mathematical models and reliable environmental measurements [2]. Furthermore, limited integration between visual perception and steering regulation restricts the ability of traditional navigation systems to respond intelligently to unexpected obstacles and dynamic navigational situations. Recent developments in deep learning have introduced promising opportunities for improving autonomous maritime navigation through intelligent environmental interpretation and data-driven vessel-motion prediction. Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in extracting hierarchical spatial features from visual information, making them suitable for maritime obstacle detection, vessel recognition, and navigational scene understanding. By processing real-time maritime imagery, CNN-based perception systems can identify nearby vessels, floating obstacles, coastal structures, and potential navigational hazards [3]. However, visual perception alone cannot provide comprehensive steering decisions because reliable navigation also requires an understanding of temporal vessel behavior, historical steering actions, and changing environmental conditions. Therefore, integrating spatial feature extraction with temporal learning techniques is essential for developing more accurate and adaptive autonomous navigation architectures. Long Short-Term Memory (LSTM) networks have gained increasing attention for modeling sequential relationships within time-dependent navigation measurements, including vessel heading, rudder angle, velocity, geographical coordinates, and environmental disturbances. Bidirectional Long Short-Term Memory (BiLSTM) networks extend

conventional recurrent learning by extracting contextual information from forward and backward sequences, enabling richer representations of vessel-motion patterns [4]. When applied to historical observation windows, BiLSTM architectures can capture complex temporal dependencies and improve the estimation of navigational dynamics without requiring unavailable future measurements during real-time operation. The integration of CNN-based visual perception and BiLSTM-based temporal modeling therefore provides a promising foundation for developing multimodal navigation systems capable of simultaneously interpreting maritime environments and predicting vessel maneuvering behavior.

Model Predictive Control represents another essential technology for intelligent steering regulation because it optimizes future control actions while considering vessel dynamics and operational constraints. Unlike conventional reactive controllers, MPC evaluates predicted vessel trajectories over a predefined horizon and determines steering commands by minimizing an objective function associated with heading deviation, cross-track error, control effort, and navigational safety. Nevertheless, conventional MPC methods may encounter difficulties when operating under nonlinear vessel dynamics, uncertain environmental disturbances, and rapidly changing obstacle configurations. Integrating neural network-based motion prediction with MPC can potentially improve steering adaptability, while attention-guided feature fusion can prioritize critical navigational information, including obstacle proximity, vessel heading deviation, environmental disturbances, and surrounding vessel movements. Such integration can support more reliable and computationally efficient steering decisions under complex maritime conditions [5]. Despite considerable progress in autonomous maritime technologies, developing a unified framework that effectively combines real-time computer vision, temporal vessel-motion modeling, and predictive steering control remains a significant research challenge. Existing approaches frequently emphasize individual navigation components, such as obstacle detection, trajectory prediction, path planning, or steering optimization, without adequately addressing their coordinated operation. Visual perception systems may identify surrounding hazards but provide limited information regarding optimal steering actions, whereas predictive controllers may regulate vessel trajectories without incorporating comprehensive environmental awareness. Additionally, many neural network-based navigation methods lack explicit mechanisms for enforcing steering constraints and maintaining safe obstacle-clearance distances. These limitations highlight the necessity for integrated intelligent navigation architectures capable of transforming multimodal environmental information into accurate, adaptive, and safety-oriented steering commands [6]. Environmental uncertainty and computational responsiveness further complicate autonomous maritime navigation. Ships operate under varying wind loads, wave-induced disturbances, hydrodynamic resistance, and dynamic interactions with surrounding vessels, all of which influence maneuverability and trajectory stability. Restricted visibility and rapidly changing obstacle positions may also reduce the reliability of autonomous navigation decisions. Therefore, intelligent steering systems must maintain accurate vessel-state estimation, robust disturbance rejection, and rapid decision-making capabilities. Moreover, real-time visual processing and neural network inference must be computationally efficient to prevent excessive delays in steering regulation. Reducing unnecessary rudder movements and trajectory corrections may additionally contribute to improved navigation-related energy efficiency, supporting the development of sustainable autonomous maritime transportation. To address these challenges, the present study proposes an advanced CNN–BiLSTM–MPC-based predictive steering control framework integrated with real-time computer vision for safe autonomous ship navigation. The proposed architecture combines CNN-based maritime visual feature extraction, BiLSTM-based temporal vessel-motion representation, attention-guided multimodal feature fusion, and MPC-based steering optimization within a unified intelligent

navigation system [7]. The CNN module identifies relevant environmental features and potential obstacles from maritime imagery, while the BiLSTM component analyzes synchronized vessel-state measurements to capture temporal navigation patterns. An attention-based integration mechanism prioritizes critical visual and navigational information, enabling the MPC module to generate optimized rudder-angle commands by considering predicted vessel trajectories, steering limitations, and obstacle-related safety requirements. The experimental investigation considers a multimodal maritime navigation dataset comprising 125,000 synchronized observations collected across 2,500 simulated navigation scenarios. The dataset incorporates vessel heading, steering angles, ship velocity, GPS coordinates, maritime imagery, obstacle distances, wind disturbances, wave characteristics, and surrounding vessel movements. The simulation environment encompasses open-sea navigation, congested maritime corridors, restricted visibility, sharp-turn maneuvers, and dynamic obstacle avoidance. These conditions provide a structured experimental foundation for assessing steering accuracy, navigational stability, collision avoidance, computational efficiency, and disturbance resilience. Comparative evaluation is conducted against conventional PID controllers, standalone MPC methods, and neural network-based steering architectures to examine the relative effectiveness of the proposed approach. The reported simulation results indicate that the proposed framework achieves 98.4% obstacle detection accuracy, 97.6% collision avoidance success, and 96.8% trajectory tracking accuracy. Additionally, the system reports a mean heading error of 1.24°, cross-track deviation of 0.38 m, and steering response time of 0.21 s, representing improvements of 42.7%, 38.5%, and 35.6%, respectively, compared with conventional MPC-based steering control. The integrated visual perception module achieves a processing throughput of 42 frames per second, while the framework reports an 18.9% reduction in estimated navigation-related energy consumption. These findings suggest that combining deep learning-driven environmental perception with predictive steering optimization can improve autonomous navigation performance while supporting computational responsiveness and operational efficiency. However, further real-world validation is required to establish performance under practical maritime operating conditions [8]. The primary contribution of this research is the development of an integrated intelligent maritime steering architecture that establishes a coordinated relationship among visual environmental perception, temporal vessel-motion learning, attention-guided feature integration, and constrained predictive optimization. The proposed framework aims to overcome the limitations of conventional steering methodologies by improving obstacle awareness, trajectory prediction, adaptive rudder-angle regulation, and navigation stability under challenging environmental conditions. Overall, this study contributes to the advancement of intelligent autonomous ship navigation by providing a comprehensive simulation-based methodology for combining neural network-based perception and predictive steering control, supporting future developments in maritime safety, collision avoidance, and energy-efficient autonomous transportation.

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2- Real-Time Computer Vision and CNN-Based Maritime Obstacle Detection:

Real-time computer vision has become a fundamental component of intelligent autonomous ship navigation, providing advanced capabilities for maritime environmental perception, obstacle identification, object localization, and collision-risk assessment. Autonomous vessels operate in highly dynamic environments characterized by moving ships, floating obstacles, navigational buoys, coastal structures, variable illumination, ocean-surface reflections, and unpredictable weather conditions. These environmental complexities require perception systems capable of continuously interpreting surrounding maritime scenes and extracting accurate navigation-related information. Conventional maritime monitoring systems primarily depend on radar, Automatic Identification System (AIS) measurements, GPS

positioning, and human-supervised visual observation. Although these technologies provide essential navigational information, their effectiveness may become limited when identifying small non-cooperative objects, floating debris, partially obscured vessels, and obstacles lacking electronic identification systems. Consequently, the integration of deep learning-based computer vision with autonomous steering technologies has emerged as an important research direction for improving maritime situational awareness, navigation reliability, and operational safety. Convolutional Neural Networks (CNNs) have demonstrated substantial potential for maritime visual perception because of their ability to automatically extract hierarchical spatial representations from complex image data. Unlike traditional image-processing methods that depend on manually designed features, CNN architectures employ convolutional filters, nonlinear activation functions, pooling operations, and multilevel feature extraction to recognize meaningful visual characteristics. Initial convolutional layers identify fundamental image properties, including edges, contours, textures, and object boundaries, whereas deeper convolutional layers capture complex semantic representations associated with vessel hulls, floating obstacles, maritime structures, and navigational environments [9]. This hierarchical learning process allows CNN-based systems to distinguish navigation-relevant objects from visually complex backgrounds while improving the adaptability of object recognition under changing environmental conditions. Zhao et al. (2024) reviewed advances in deep learning-based ship detection, emphasizing the importance of feature extraction, target localization, multiscale representation, and robust recognition under complex visual conditions. Their findings provide a foundation for understanding the application of hierarchical deep learning architectures in maritime perception systems. The quality and diversity of maritime datasets also play a significant role in determining the reliability of CNN-based obstacle detection systems. Representative datasets include SeaShips, the Singapore Maritime Dataset, and SeaDronesSee, which provide different visual perspectives, annotation structures, object categories, and maritime operating conditions. Shao et al. (2018) introduced the SeaShips dataset containing 31,455 annotated images covering six common ship categories, establishing an important benchmark for vessel detection research. Similarly, SeaDronesSee provides maritime imagery and tracking benchmarks intended primarily for aerial maritime search-and-rescue applications [10]. These datasets support the development and comparison of visual detection algorithms; however, differences in camera perspective, environmental conditions, annotation quality, and target distribution may affect model generalizability. Therefore, CNN-based maritime perception systems require careful dataset preparation, scenario-based evaluation, and cross-environment validation to ensure that improvements observed under controlled conditions remain relevant to autonomous ship navigation. Table 1 summarizes representative literature and its relevance to the proposed architecture. It is a qualitative comparison rather than a direct numerical benchmark.

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Table 1: Comparative review of deep learning-based maritime visual perception and obstacle detection approaches.

Reference / Approach	Core technology	Principal contribution
Shao et al. (2018)	SeaShips dataset and CNN-based object detection benchmarks	Established an annotated dataset for ship recognition and localization
Zhao et al. (2024)	Deep learning-based ship detection	Reviewed object localization and advanced feature extraction strategies
Rekavandi et al. (2025)	Small-object detection and deep learning	Reviewed feature enhancement and multiscale approaches for small maritime targets
Yin et al. (2025)	Swin Transformer, dual attention, and multiscale fusion	Improved detailed maritime object segmentation
Han et al. (2026)	Maritime perception and multimodal sensor technologies	Reviewed detection, tracking, segmentation, and sensor fusion for autonomous vessels
Proposed CNN–BiLSTM–MPC framework	CNN perception, temporal learning, attention fusion, and predictive control	Integrates obstacle information with vessel-motion modeling and steering optimization

Deep learning-based detection systems can identify surrounding obstacles with increasing accuracy, but their outputs must be transformed into reliable navigation-related information before they can contribute effectively to rudder-angle optimization and collision avoidance. This requirement motivates the development of unified architectures capable of combining visual environmental understanding with intelligent vessel-motion modeling and constrained steering decisions. In the present study, the proposed CNN-based maritime visual perception module is integrated with BiLSTM-based temporal learning and attention-guided Model Predictive Control (MPC) to establish a comprehensive autonomous navigation framework. The CNN component processes maritime imagery to extract spatial features associated with surrounding vessels, floating obstacles, and navigational environments, while synchronized navigation measurements provide information regarding vessel heading, steering angles, velocity, geographical position, and environmental disturbances [11]. The resulting multimodal representations are used to support temporal motion prediction and adaptive steering optimization. Unlike isolated obstacle detection architectures, the proposed framework is designed to connect environmental perception directly with predictive rudder-angle regulation, trajectory tracking, and collision-aware navigation. Furthermore, real-time computational responsiveness is considered an essential design requirement because perception and steering decisions must be completed within operationally acceptable processing intervals. The reported visual processing throughput of 42 frames per second provides an indicator of perception efficiency, although end-to-end navigation responsiveness also depends on temporal inference, controller optimization, communication delays, and actuator dynamics. Figure 1 presents the conceptual architecture of the proposed real-time maritime perception and predictive steering framework. The visual processing pathway begins with maritime image acquisition and preprocessing, followed by hierarchical CNN feature extraction, multiscale obstacle detection, and navigation-related risk feature generation [12]. These visual representations are integrated with synchronized vessel-state and environmental measurements through an attention-guided multimodal fusion mechanism. The combined information is subsequently processed by BiLSTM-based temporal learning and MPC-based steering optimization to generate appropriate rudder-angle

adjustments and collision-aware navigation commands. Continuous vessel-state feedback supports the updating of navigation information and enables adaptive adjustments to changing maritime conditions.

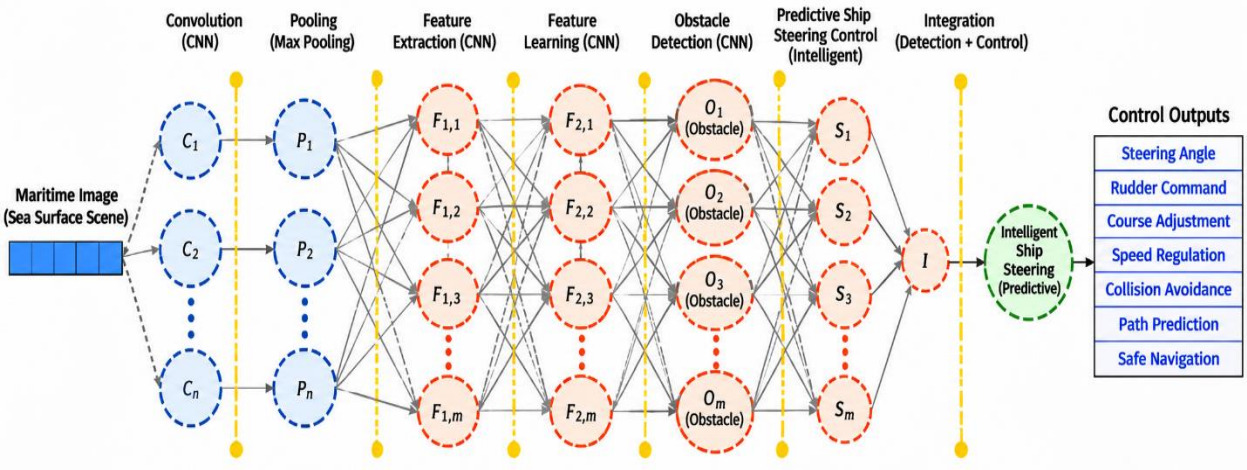


Figure 1: CNN-based maritime obstacle detection and integration with intelligent predictive ship steering control.

The reviewed literature highlights the growing importance of real-time computer vision and CNN-based feature extraction in improving maritime obstacle detection, environmental interpretation, and autonomous navigation safety. Recent advancements in deep learning, multiscale visual representation, attention mechanisms, and intelligent object tracking have enhanced the ability of autonomous vessels to recognize surrounding ships, floating obstacles, and navigation-related hazards under challenging environmental conditions. Nevertheless, existing approaches frequently emphasize individual perception tasks without fully integrating visual information into temporal vessel-motion prediction and adaptive steering optimization. Addressing these limitations requires a unified intelligent navigation architecture capable of combining spatial environmental features, dynamic vessel-state measurements, and constrained predictive control [13]. Accordingly, the proposed CNN–BiLSTM–MPC framework establishes an integrated relationship among maritime visual perception, attention-guided multimodal learning, temporal motion prediction, and adaptive steering regulation. This approach provides a promising foundation for improving obstacle recognition, trajectory tracking, collision-aware decision-making, computational responsiveness, and energy-efficient autonomous ship navigation.

3- Neural Network-Based Vessel Motion Prediction and Temporal Navigation Learning: Accurate vessel-motion prediction represents a fundamental requirement for intelligent autonomous ship navigation, particularly in applications involving adaptive steering regulation, trajectory tracking, collision avoidance, and maritime operational safety. Ship maneuvering behavior is influenced by complex nonlinear interactions among rudder-angle adjustments, propulsion dynamics, vessel inertia, hydrodynamic resistance, environmental disturbances, and surrounding maritime traffic. These interactions produce continuously changing navigation characteristics that can be difficult to represent using conventional mathematical models alone. Traditional vessel-motion prediction techniques generally employ predefined hydrodynamic equations, state-space representations, numerical simulation, and statistical estimation approaches [14]. Although these methods offer established theoretical foundations, their predictive performance may deteriorate under uncertain environmental

conditions, nonlinear maneuvering behavior, and variations in vessel operating characteristics. Consequently, neural network-based motion prediction has emerged as a promising approach for learning complex navigation patterns from historical vessel measurements and supporting intelligent autonomous steering decisions. Recent advances in maritime sensing technologies, Automatic Identification System (AIS) infrastructure, and intelligent navigation platforms have substantially increased the availability of vessel-motion data. These measurements typically include geographical coordinates, heading angles, speed over ground, course over ground, yaw rate, steering commands, and related environmental information. Such multidimensional observations provide valuable information for understanding vessel movement, identifying maneuvering patterns, and predicting future trajectories. However, maritime motion data frequently exhibit nonlinear temporal relationships, measurement uncertainties, irregular sampling intervals, and environmental variability. Conventional statistical prediction techniques may struggle to capture these dependencies, especially during sudden course alterations, acceleration, deceleration, and complex multi-vessel encounters. Guo and Ma (2026) systematically reviewed deep learning-based vessel trajectory prediction methods, identifying recurrent neural networks, convolutional architectures, sequence-to-sequence models, and Transformer-based learning as major approaches for capturing complex spatial and temporal navigation characteristics [15]. Their review emphasizes the importance of selecting prediction architectures that balance temporal representation capability, computational complexity, and practical deployment requirements. Recurrent Neural Networks (RNNs) provide an important foundation for temporal navigation learning because they process sequential observations while maintaining internal representations of historical information. Unlike traditional feedforward neural networks, recurrent architectures incorporate connections across successive time steps, enabling them to identify temporal dependencies among navigation variables. However, conventional RNNs frequently encounter vanishing-gradient and long-term dependency problems, limiting their effectiveness when processing extended vessel-motion sequences. Long Short-Term Memory (LSTM) networks address these limitations through specialized memory cells and input, forget, and output gates that regulate the retention and transmission of temporal information. These mechanisms enable LSTM models to distinguish relevant navigation patterns from less informative historical observations and support the prediction of future heading, velocity, position, and maneuvering characteristics. Research evaluating recurrent neural networks for vessel trajectory prediction has demonstrated the importance of selecting appropriate input variables, incorporating environmental context, and carefully evaluating model generalizability across maritime datasets [16]. The selection of temporal observation windows and prediction horizons also influences the accuracy and computational efficiency of neural network-based maritime forecasting. Short historical sequences may not contain sufficient information to describe gradual vessel maneuvering patterns, whereas excessively long sequences can increase computational complexity and introduce redundant information. Similarly, short prediction horizons generally support immediate steering regulation, while longer horizons are valuable for anticipating potential trajectory conflicts and planning collision-avoidance maneuvers. These requirements create a trade-off among prediction accuracy, computational latency, and the operational relevance of estimated vessel states. In practical autonomous navigation systems, temporal prediction models must provide sufficiently accurate information within time constraints that permit the predictive controller to calculate and execute appropriate steering responses [17]. Accordingly, the integration of BiLSTM-based navigation learning with Model Predictive Control offers a promising strategy for transforming temporal vessel-motion representations into optimized rudder-angle commands. Table 2 provides a qualitative comparison of representative studies. Differences in datasets, prediction horizons, model objectives, and

evaluation protocols prevent direct numerical performance ranking.

Table 2: Comparative review of neural network-based vessel-motion prediction and temporal maritime navigation learning.

Reference / Model	Principal learning architecture	Limitations or research opportunities
Zhou et al. (2024)	BiLSTM with scaled dot-product attention	Broader integration with visual obstacle perception and collision-aware steering
Gan et al. (2025)	Sequential LSTM–U-Net	Greater emphasis on trajectory forecasting than closed-loop rudder control
Liu et al. (2025)	LSTM with multi-head attention	Integrated visual perception and predictive control require further investigation
Yin et al. (2025)	Multiscale CNN–LSTM–attention	Steering-control constraints are not the primary focus
Guo and Ma (2026)	Systematic review of deep learning prediction models	Identified ongoing needs for robustness, generalization, and practical validation
Proposed CNN–BiLSTM–MPC framework	Visual CNN, temporal BiLSTM, attention fusion, and MPC	Requires comprehensive closed-loop simulation and real-world safety validation

Many available approaches primarily focus on prediction accuracy without directly incorporating their outputs into constrained rudder-angle optimization and autonomous collision avoidance. Furthermore, differences in data characteristics, environmental scenarios, temporal sampling intervals, and prediction horizons complicate comparisons between existing learning architectures. These limitations emphasize the importance of evaluating temporal prediction models within complete autonomous navigation systems rather than treating trajectory forecasting as an isolated computational objective. In the context of the present study, the proposed BiLSTM-based temporal navigation module is designed to process synchronized historical sequences containing vessel heading, steering angle, velocity, GPS position, obstacle-distance information, wind disturbances, wave characteristics, and surrounding vessel movements. The dataset comprises 125,000 synchronized observations collected across 2,500 simulated maritime navigation scenarios, including open-sea movement, congested maritime corridors, restricted visibility, sharp-turn maneuvering, and dynamic obstacle avoidance [18]. Historical navigation measurements are organized into fixed-length temporal windows and processed using bidirectional recurrent learning to extract contextual motion representations. Importantly, both recurrent directions operate only on measurements already available at the current decision instant, thereby preventing future-information leakage during real-time prediction. These temporal representations are subsequently integrated with CNN-derived visual features through an attention-guided multimodal fusion mechanism. Figure 2 illustrates the conceptual organization of the proposed BiLSTM-based vessel-motion prediction process and its integration with attention-guided predictive control.

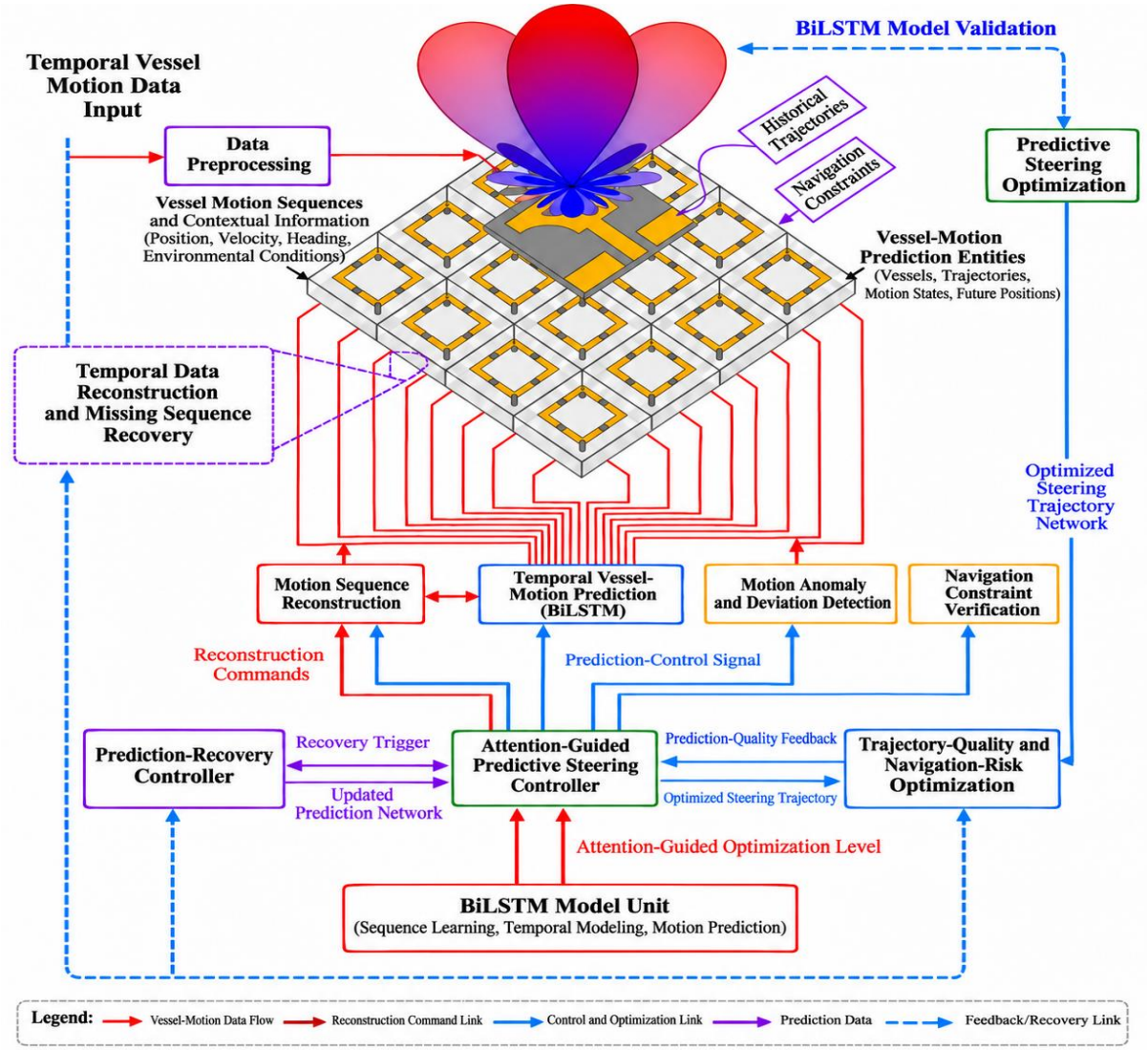


Figure 2: BiLSTM-based temporal vessel-motion prediction and attention-guided predictive steering optimization framework.

The BiLSTM architecture extracts forward and backward contextual representations from available historical observations, while attention-guided learning emphasizes critical navigation features. These representations are integrated with CNN-derived maritime visual information to support future vessel-state prediction and MPC-based rudder-angle optimization. Continuous vessel-state feedback enables adaptive trajectory regulation and collision-aware navigation under changing maritime conditions. Overall, the reviewed literature demonstrates the significant potential of neural network-based temporal learning for improving vessel-motion prediction, trajectory forecasting, and intelligent autonomous navigation. Recent developments in LSTM, BiLSTM, multiscale convolution, attention mechanisms, and hybrid deep learning architectures have strengthened the ability of predictive models to capture nonlinear maritime dynamics and complex sequential navigation patterns. Nevertheless, existing research frequently evaluates temporal prediction independently from real-time visual perception and constrained steering optimization, limiting the direct application of learned motion representations to

autonomous maneuvering decisions [19]. Moreover, environmental uncertainty, computational latency, prediction-horizon selection, and cross-scenario generalization remain important challenges for practical maritime deployment. Addressing these limitations requires an integrated architecture that combines historical vessel-state learning, spatial environmental perception, and adaptive predictive control. Accordingly, the proposed CNN–BiLSTM–MPC framework establishes a coordinated relationship among temporal vessel-motion representation, attention-guided multimodal fusion, and optimized rudder-angle regulation. This integration provides a promising foundation for enhancing trajectory tracking accuracy, disturbance resilience, collision avoidance, and computationally responsive autonomous ship navigation.

4- Methodology:

The methodology of the present study is designed to develop and evaluate an intelligent neural network-based predictive steering control framework integrated with real-time computer vision for safe autonomous ship navigation. The proposed research adopts a multimodal deep learning and predictive optimization approach that combines Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (BiLSTM) networks, attention-guided feature fusion, and Model Predictive Control (MPC). The methodological framework encompasses maritime navigation simulation, multimodal dataset construction, sensor-data preprocessing, visual obstacle detection, temporal vessel-motion learning, predictive steering optimization, and navigation performance evaluation. Particular emphasis is placed on developing an integrated architecture capable of interpreting complex maritime environments, estimating future vessel behavior, generating adaptive rudder-angle commands, and maintaining collision-aware trajectory tracking under uncertain environmental conditions. The experimental design considers 125,000 synchronized navigation observations distributed across 2,500 simulated scenarios, representing open-sea navigation, congested maritime corridors, restricted visibility, sharp-turn maneuvers, and dynamic obstacle avoidance [20]. The proposed methodology provides a systematic foundation for assessing navigation precision, obstacle recognition, collision-avoidance performance, computational responsiveness, disturbance resilience, and estimated energy efficiency.

4.1- Multimodal Maritime Navigation Dataset Construction and Simulation Scenario Characteristics:

The development of a comprehensive and representative maritime navigation dataset is a fundamental component of the proposed neural network-based predictive steering control framework, as the accuracy, robustness, and computational effectiveness of intelligent autonomous navigation depend heavily on the quality and diversity of the available observations. The present study considers a multimodal maritime navigation dataset comprising 125,000 synchronized observations collected across 2,500 simulated navigation scenarios, incorporating vessel-motion characteristics, steering-control measurements, geographical positioning information, maritime visual imagery, environmental disturbances, and surrounding obstacle interactions. The dataset is designed to support the development, training, and evaluation of the proposed Convolutional Neural Network–Bidirectional Long Short-Term Memory–Model Predictive Control (CNN–BiLSTM–MPC) architecture under diverse navigation conditions. Particular emphasis is placed on representing nonlinear vessel maneuvering behavior, dynamic obstacle encounters, environmental uncertainty, and variations in steering requirements [21]. The integration of multiple sensing modalities enables the proposed framework to establish meaningful relationships among environmental perception, historical vessel dynamics, predictive trajectory estimation, and adaptive rudder-angle optimization. The simulation-based dataset construction process is organized around a virtual maritime navigation environment capable of representing vessel movements under different operational and environmental conditions. The simulated vessel model provides time-dependent navigation measurements describing heading

angle, rudder position, vessel velocity, geographical coordinates, and trajectory evolution. These measurements are synchronized with maritime visual observations and environmental information to construct comprehensive navigation records. The inclusion of visual data is particularly important because conventional navigation-state measurements alone may not adequately represent surrounding maritime hazards, floating objects, or the spatial distribution of nearby vessels. Therefore, simulated maritime imagery provides complementary environmental information that can be processed using CNN-based feature extraction, while numerical vessel-state measurements support BiLSTM-based temporal motion learning. This multimodal organization establishes a foundation for integrating visual perception and sequential vessel-motion representation within a unified predictive steering architecture. The dataset incorporates several principal categories of navigation information, including dynamic vessel states, steering-control variables, geographical positioning, environmental characteristics,
obstacle-related measurements, and visual scene observations [22]. Vessel-state variables describe the instantaneous operating condition of the autonomous ship, while steering measurements characterize the control inputs responsible for modifying heading and trajectory. Geographical position and velocity measurements support the reconstruction of navigation paths and the identification of deviations from predefined reference trajectories. Environmental variables, including wind and wave characteristics, represent external disturbances that influence vessel maneuverability and steering stability. Additionally, obstacle-distance information and surrounding vessel movements provide essential contextual information for evaluating potential navigation hazards and collision risks. The integration of these heterogeneous variables enables the neural learning architecture to identify complex interactions between vessel dynamics, environmental conditions, and steering-control responses.

Table 3: Multimodal maritime navigation dataset characteristics, sensing variables, and simulation scenario configuration.

Dataset component	Variables / characteristics	Role in proposed framework
Total dataset	125,000 synchronized observations	Model development and evaluation
Simulation scenarios	2,500 simulated navigation scenarios	Diverse operating conditions
Average observations	50 per scenario	Describes nominal temporal coverage
Vessel heading	Heading angle and heading variation	Heading prediction and regulation
Steering control	Rudder angle and steering history	Adaptive rudder optimization
Vessel velocity	Ship speed and velocity variation	Motion and trajectory prediction
Geographical positioning	GPS coordinates and derived local position	Trajectory reconstruction and tracking
Maritime imagery	Visual scenes and obstacle appearances	CNN-based obstacle recognition
Obstacle proximity	Distance to nearby hazards	Collision-risk evaluation

Table 3 summarizes the principal characteristics of the multimodal maritime navigation dataset and illustrates the relationship between individual sensing variables and their contributions to the proposed intelligent steering-control architecture. The inclusion of numerical navigation states and visual maritime observations supports complementary learning mechanisms, where CNNs interpret spatial environmental characteristics and BiLSTM networks capture sequential vessel-motion relationships. The dataset-level average of 50 observations per scenario provides an indication of the nominal amount of sequential information available, although the actual number of observations may vary across scenarios according to simulation

duration and sampling conditions. The combination of steering measurements, vessel-motion characteristics, environmental disturbances, and obstacle-related features establishes a comprehensive foundation for investigating predictive navigation behavior and collision-aware control. The simulation environment is structured to introduce varying degrees of navigational complexity across the five scenario categories [23]. In open-sea navigation, the principal emphasis is placed on maintaining heading stability, minimizing trajectory deviations, and evaluating steering response under relatively low obstacle density. Congested maritime corridors introduce multiple surrounding vessels with different positions, movement directions, and velocities, creating complex interactions that require accurate environmental awareness and adaptive maneuvering. Restricted-visibility conditions are designed to challenge visual perception by reducing the distinguishability of obstacles and navigational features. Sharp-turn scenarios examine steering effectiveness during rapid heading changes and potentially nonlinear vessel responses. Dynamic obstacle-avoidance scenarios incorporate changing relative positions and movement patterns, requiring the control system to anticipate potential conflicts and update steering commands accordingly. Figure 3 presents the proposed multimodal maritime dataset construction and simulation workflow, illustrating the relationship among scenario configuration, vessel-state generation, environmental observations, temporal synchronization, and model-ready dataset preparation. The workflow emphasizes the systematic integration of numerical navigation measurements and maritime visual information before their utilization in CNN-based perception, BiLSTM-based temporal modeling, and predictive steering optimization.

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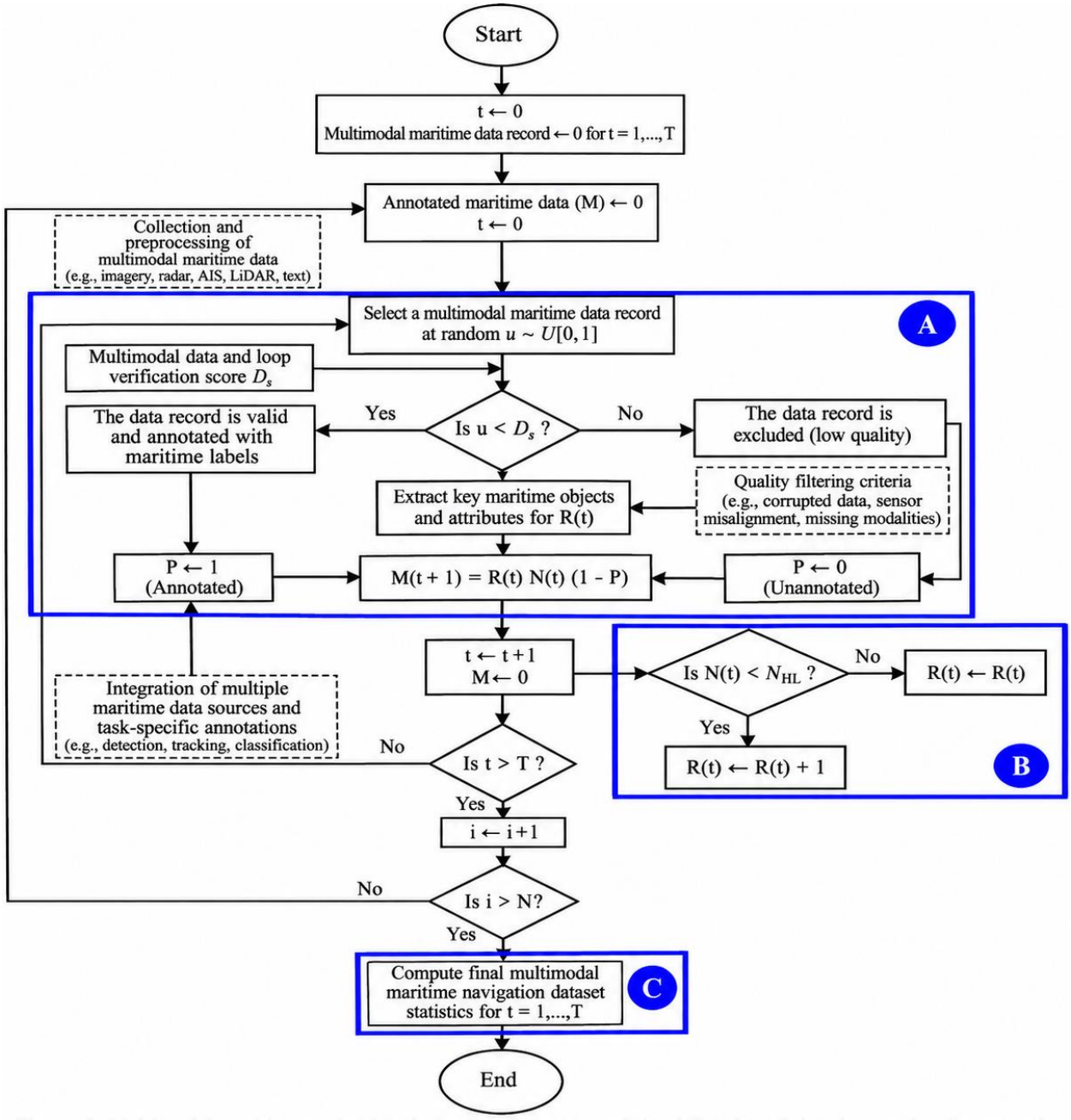


Figure 3: Multimodal maritime navigation dataset construction and simulation-based data integration framework.

The proposed multimodal maritime navigation dataset establishes a comprehensive experimental foundation for investigating intelligent vessel-motion prediction, real-time obstacle recognition, and adaptive steering control under diverse operational conditions. By integrating 125,000 synchronized observations from 2,500 simulated navigation scenarios, the dataset supports the investigation of complex relationships among vessel dynamics, steering actions, environmental disturbances, surrounding traffic, and maritime visual information. The inclusion of open-sea navigation, congested maritime corridors, restricted visibility, sharp-turn maneuvering, and dynamic obstacle avoidance enables systematic examination of predictive navigation performance

under varying levels of environmental and operational complexity [24]. Furthermore, temporal synchronization, structured data preprocessing, and scenario-level evaluation provide a methodological basis for training and assessing the proposed CNN–BiLSTM–MPC architecture. This integrated dataset design supports the development of accurate visual perception, reliable temporal motion learning, attention-guided multimodal feature representation, and constrained predictive steering optimization, contributing to the broader objective of achieving safe, adaptive, and energy-efficient autonomous ship navigation.

4.2- Nonlinear Vessel Dynamics Modeling and Historical Navigation Sequence Generation:

Accurate modeling of nonlinear vessel dynamics represents a fundamental requirement for developing intelligent autonomous steering systems capable of maintaining reliable trajectory tracking, adaptive maneuvering, and collision-aware navigation under complex maritime operating conditions. Maritime vessels exhibit nonlinear motion characteristics resulting from interactions among hydrodynamic forces, rudder-induced steering moments, propulsion dynamics, vessel inertia, and external environmental disturbances. These interactions become particularly significant during sharp-turn maneuvers, high steering demands, variable vessel speeds, and dynamic obstacle-avoidance operations. Conventional linearized steering models may provide satisfactory approximations under restricted operating conditions; however, their ability to represent complex maneuvering behavior can become limited when significant changes occur in vessel heading, yaw rate, hydrodynamic resistance, or disturbance intensity. Consequently, the present study adopts a nonlinear vessel-motion representation integrated with historical navigation sequence generation to support the proposed Convolutional Neural Network–Bidirectional Long Short-Term Memory–Model Predictive Control (CNN–BiLSTM–MPC) architecture [25]. The methodological objective is to establish a systematic relationship between vessel-state evolution, steering-control inputs, environmental disturbances, and temporal navigation patterns, enabling accurate motion prediction and adaptive rudder-angle optimization. The proposed vessel dynamics modeling framework considers the nonlinear interaction between horizontal-plane ship movement and external environmental influences. A three-degree-of-freedom (3-DOF) maneuvering representation is adopted as a modeling basis, describing vessel surge, sway, and yaw motion. Surge represents longitudinal vessel movement, sway describes lateral displacement, and yaw characterizes rotational motion around the vertical axis. These motion components jointly determine the vessel's heading evolution, geographical displacement, and response to steering commands. The resulting dynamic model provides a structured foundation for generating synchronized navigation observations and evaluating the effectiveness of predictive steering control. Environmental disturbances associated with wind, waves, and surrounding navigation conditions are incorporated as external influences to assess the adaptability of the intelligent control architecture under varying maritime scenarios [26]. The proposed dataset comprises 125,000 synchronized navigation observations distributed across 2,500 simulated maritime scenarios. Each observation is associated with a particular vessel state, steering condition, and environmental configuration. The dataset contains information related to heading direction, steering angle, vessel velocity, GPS position, obstacle-distance measurements, surrounding vessel movement, and environmental disturbances. Maritime imagery provides complementary spatial information and is processed separately through the CNN-based perception module. The numerical navigation observations are used to construct historical sequences describing vessel motion over time. This organization enables the BiLSTM architecture to learn nonlinear relationships among past steering commands, dynamic vessel responses, and changes in environmental conditions. Figure 4 shows the conceptual architecture of nonlinear vessel dynamics modeling and historical navigation sequence generation [27]. The framework combines vessel-motion simulation,

environmental disturbance representation, synchronized navigation-state acquisition, temporal preprocessing, sliding-window construction, BiLSTM-based prediction, and MPC-based steering optimization. Closed-loop feedback enables the updated vessel response to influence subsequent navigation measurements and control decisions.

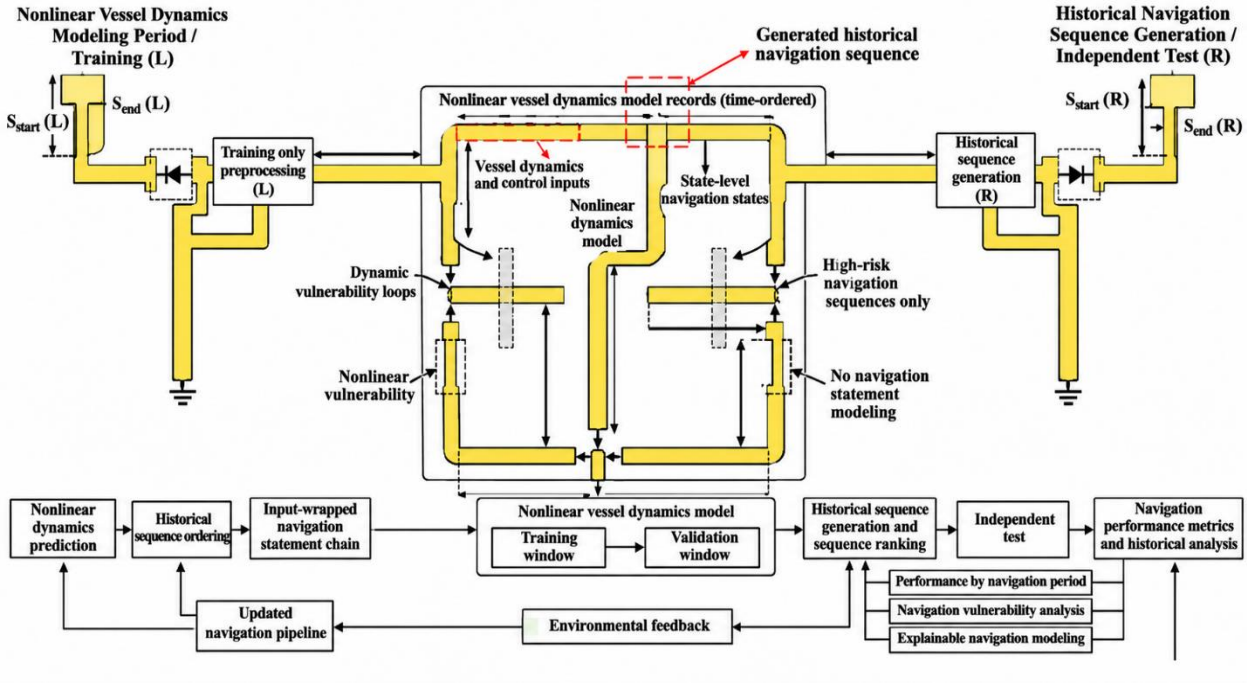


Figure 4: Architecture of nonlinear vessel dynamics modeling and historical navigation sequence generation.

The proposed nonlinear vessel dynamics modeling and historical navigation sequence generation methodology establishes a comprehensive foundation for learning complex vessel maneuvering characteristics and improving autonomous steering-control performance. By incorporating nonlinear surge, sway, and yaw dynamics, rudder-control characteristics, environmental disturbances, and synchronized historical navigation observations, the framework supports the representation of complex relationships between steering actions and vessel responses. The generation of fixed-length temporal sequences enables BiLSTM-based learning to capture historical maneuvering patterns and predict future vessel states, while integration with CNN-derived maritime visual features enhances environmental awareness [28]. Furthermore, the combination of physically informed vessel dynamics, data-driven temporal prediction, and constrained MPC optimization provides a systematic basis for improving heading regulation, trajectory tracking, disturbance rejection, and collision-aware steering. This methodology contributes to developing intelligent, adaptive, and computationally responsive autonomous ship navigation systems capable of operating under diverse simulated maritime conditions.

4.3- Bidirectional Long Short-Term Memory Network for Temporal Vessel-Motion Learning: Accurate temporal modeling of vessel-motion characteristics is a fundamental requirement for intelligent autonomous ship navigation, particularly in applications involving predictive steering regulation, trajectory tracking, collision avoidance, and disturbance-resilient maneuvering. Maritime vessels exhibit highly nonlinear and time-dependent motion behavior influenced by rudder-angle adjustments, propulsion dynamics, hydrodynamic interactions, environmental

disturbances, and surrounding vessel movements. These factors generate complex relationships among historical navigation states and future vessel responses, making accurate motion prediction challenging for conventional statistical models and purely mathematical forecasting approaches. To address these limitations, the present study incorporates a Bidirectional Long Short-Term Memory (BiLSTM) network into the proposed Convolutional Neural Network–BiLSTM–Model Predictive Control (CNN–BiLSTM–MPC) architecture. The BiLSTM module is designed to extract comprehensive temporal representations from synchronized maritime navigation observations, learn nonlinear maneuvering patterns, and generate predictive information for intelligent rudder-angle optimization [29]. By processing historical navigation sequences in forward and backward directions, the architecture captures contextual dependencies associated with vessel heading, steering behavior, velocity variations, geographical displacement, and environmental influences, supporting improved interpretation of complex maritime dynamics. Conventional Recurrent Neural Networks (RNNs) provide a foundation for sequential data modeling because they maintain internal hidden-state representations that preserve information from preceding observations. However, standard RNN architectures frequently experience vanishing-gradient and exploding-gradient problems when processing extended temporal sequences, potentially reducing their ability to identify long-term relationships among navigation measurements. Long Short-Term Memory (LSTM) networks overcome many of these limitations through specialized memory cells and gating mechanisms that regulate the retention, modification, and transmission of temporal information. These mechanisms allow the network to preserve relevant historical vessel-motion patterns while reducing the influence of redundant or less informative measurements. In autonomous maritime navigation, LSTM-based learning is particularly valuable because vessel responses often depend on previous rudder actions, accumulated heading changes, hydrodynamic inertia, and delayed environmental effects. Nevertheless, a conventional unidirectional

LSTM processes historical measurements in only one direction, potentially limiting the contextual representation of relationships among observations within a completed temporal window [30]. BiLSTM networks extend this structure by combining forward and backward temporal learning, providing complementary representations of the available navigation history. The proposed BiLSTM framework receives synchronized historical observations generated from the multimodal maritime dataset comprising 125,000 navigation records across 2,500 simulated maritime scenarios. The dataset includes navigation measurements associated with heading direction, rudder steering angle, vessel velocity, GPS position, obstacle proximity, wind and wave disturbances, and surrounding vessel movements. These observations represent different maritime operating conditions, including open-sea navigation, congested maritime corridors, restricted visibility, sharp-turn maneuvering, and dynamic obstacle avoidance. The input observations are preprocessed through temporal synchronization, feature normalization, and sequential window construction before being transferred to the BiLSTM module. Each temporal input contains a fixed-length historical sequence describing the evolution of vessel behavior over a selected observation interval. This structured representation enables the network to identify temporal relationships associated with steering adjustments, heading deviations, velocity changes, and disturbance-induced maneuvering responses [31]. The proposed BiLSTM architecture is designed to provide sufficient temporal modeling capability while maintaining computational feasibility for integration with real-time visual perception and predictive steering control. Network depth, hidden-state dimensionality, observation-window length, dropout probability, and prediction horizon must be selected according to the available data, vessel dynamics, and computational constraints. Table 4 presents an numerical configuration for implementing the temporal learning module. The configuration is provided to demonstrate a reproducible architecture design and should be finalized using

the actual training records and hyperparameter optimization results.

Table 4: Numerical configuration of the BiLSTM architecture for temporal vessel-motion prediction.

Architectural component	Numerical configuration	Output dimensions	Primary function
Total navigation observations	125,000	Dataset records	Multimodal data source
Simulation scenarios	2,500	Navigation scenarios	Operating-condition diversity
Historical observation window	20 time steps	20 × 12	Sequential input representation
Numerical input features	12 features	12 per time step	Vessel and environmental states
First BiLSTM layer	64 units per direction	20 × 128	Initial temporal feature extraction
Second BiLSTM layer	32 units per direction	20 × 64	Higher-level temporal modeling
Temporal attention layer	64-dimensional features	64	Emphasize informative time steps
Dropout regularization	0.20	64	Reduce overfitting
Predicted navigation variables	4 targets	Heading, yaw rate, speed, displacement	Future motion estimation
Mini-batch size	64 sequences	64 per update	Training efficiency
Initial learning rate	0.001	Scalar	Gradient-based optimization

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The BiLSTM learning process is organized into training, validation, and testing stages to assess model convergence, prediction quality, and generalizability across different maritime navigation conditions. Scenario-level dataset partitioning is particularly important because consecutive observations belonging to the same simulated vessel trajectory exhibit strong temporal correlations. Separating highly correlated windows from a single scenario across training and testing partitions could produce overly optimistic prediction estimates. Therefore, all temporal windows derived from an individual simulation scenario should remain within the same partition. Training sequences are used to estimate network parameters, validation sequences support model selection and early stopping, and independent testing scenarios provide the final assessment of predictive performance [32]. The effectiveness of the BiLSTM module can be evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), heading prediction error, position displacement error, and multi-step forecasting consistency. These measures assess the correspondence between predicted and reference vessel states while providing insight into model behavior over different prediction horizons. Additional scenario-wise evaluation is valuable for determining whether the model maintains comparable prediction quality during open-sea navigation, congested maritime traffic, restricted visibility, sharp-turn maneuvers, and dynamic obstacle avoidance. Although the previously reported steering performance indicators describe the integrated navigation framework, separate BiLSTM prediction errors are necessary to quantify the specific contribution of temporal learning. Figure 5 present the proposed BiLSTM temporal learning architecture, including synchronized navigation-state inputs, historical sequence construction, forward and backward recurrent processing, temporal attention, future-

state prediction, and integration with MPC-based steering optimization.

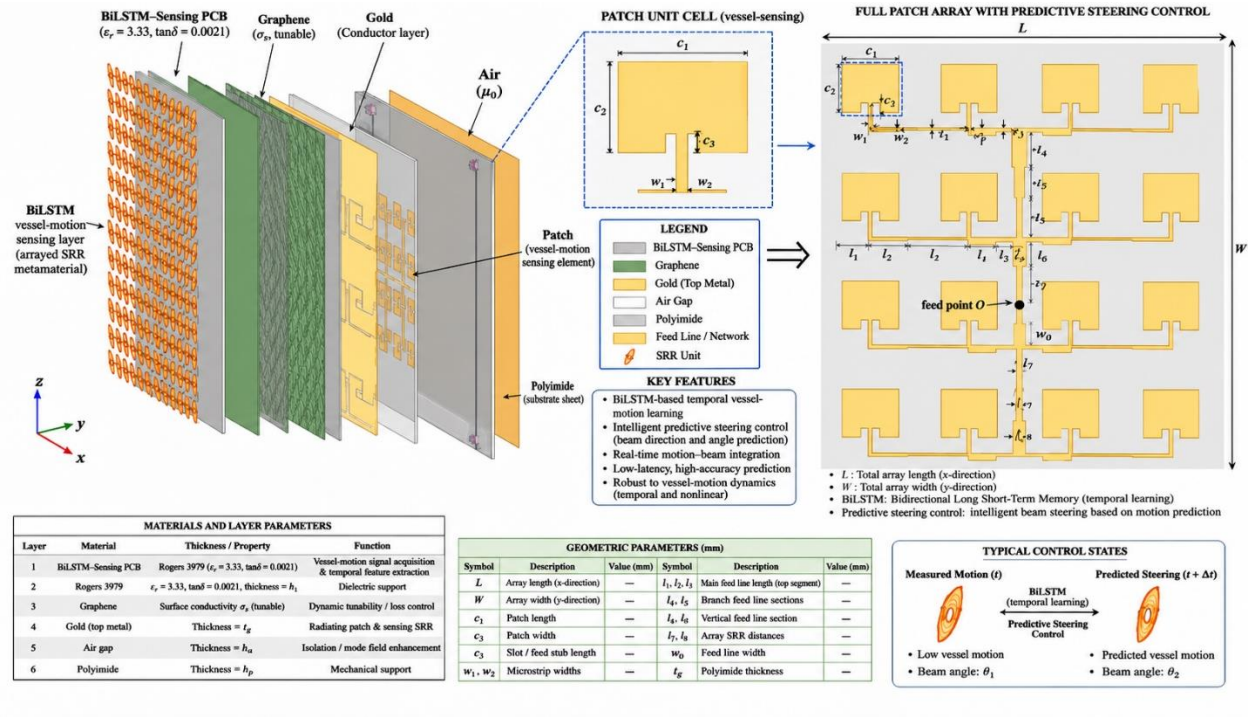


Figure 5: Architectural design of the BiLSTM-based intelligent vessel-motion sensing metasurface with predictive beam-steering control.

An attention-based mechanism emphasizes informative historical features and generates compact temporal representations for future vessel-state prediction. The resulting predictions are integrated with CNN-derived maritime visual features and supplied to the MPC-based steering controller for optimized rudder-angle regulation, trajectory tracking, and collision-aware navigation. Overall, the proposed BiLSTM-based temporal learning methodology establishes a comprehensive foundation for understanding nonlinear vessel-motion characteristics and improving predictive steering performance in autonomous maritime environments. By combining bidirectional sequential processing, gated temporal memory, attention-guided feature representation, and multi-step vessel-state forecasting, the architecture is designed to capture complex relationships among historical steering actions, heading variations, vessel velocity, environmental disturbances, and maneuvering responses [33]. The integration of learned temporal features with CNN-based environmental perception and constrained MPC optimization provides a coordinated approach to intelligent navigation decision-making. Furthermore, structured sequence generation, scenario-level validation, and computational efficiency assessment support the development of reliable temporal prediction models. This methodology contributes toward improving navigation precision, adaptive rudder-angle regulation, disturbance resilience, trajectory stability, and collision-aware autonomous ship control under diverse simulated maritime conditions.

4.4- Attention-Guided Model Predictive Control for Adaptive Rudder-Angle Optimization:

The development of intelligent and adaptive rudder-angle optimization represents a fundamental requirement for achieving accurate trajectory tracking, stable vessel maneuvering, and reliable collision avoidance in autonomous maritime navigation. Conventional steering-

control approaches, including Proportional–Integral–Derivative (PID) controllers and classical Model Predictive Control (MPC), provide established mechanisms for regulating vessel heading and minimizing navigation errors. However, their performance may become limited under highly nonlinear hydrodynamic conditions, rapidly changing environmental disturbances, complex maritime traffic, and uncertain obstacle configurations. To address these challenges, the present study introduces an attention-guided neural network-assisted Model Predictive Control framework integrated with Convolutional Neural Network (CNN)-based visual perception and Bidirectional Long Short-Term Memory (BiLSTM)-based vessel-motion learning [34]. The proposed control strategy combines temporal navigation representations, environmental awareness, dynamic feature weighting, and constrained optimization to generate adaptive rudder-angle commands. Particular emphasis is placed on minimizing heading deviations, cross-track errors, excessive steering activity, and collision risks while maintaining computational responsiveness and operational stability. The proposed steering-control architecture operates through a closed-loop predictive optimization process in which synchronized vessel-state measurements and CNN-derived maritime obstacle features are continuously incorporated into navigation decision-making. The BiLSTM module extracts temporal representations of historical vessel behavior, including heading variations, rudder-angle responses, velocity changes, and disturbance-induced maneuvering patterns. Simultaneously, the visual perception module supplies obstacle-related spatial features describing surrounding vessels, navigational hazards, and potentially unsafe maritime regions. An attention-guided fusion mechanism integrates these heterogeneous representations and assigns adaptive

importance to navigation variables according to their relevance to the current steering and prediction objectives. The resulting information supports the MPC module in evaluating feasible steering actions over a finite prediction horizon. Through repeated optimization and feedback, the controller is designed to anticipate future trajectory deviations and determine appropriate rudder-angle adjustments before significant navigation errors develop. The inclusion of rudder-angle and rudder-rate penalties is particularly important for avoiding excessive steering activity. Large or rapidly varying rudder commands may increase actuator demands, induce oscillatory vessel responses, and contribute to additional hydrodynamic resistance. By penalizing both absolute rudder deflection and consecutive steering adjustments, the optimization process seeks to generate smoother control actions while maintaining sufficient maneuvering authority for collision avoidance [35]. These penalties provide an energy-aware control design, although the actual reduction in propulsion-related energy demand must be evaluated using an appropriate vessel energy-consumption model. The proposed attention-guided MPC methodology therefore integrates data-driven maritime intelligence with optimization-based steering control. By combining learned vessel-motion representations, CNN-derived environmental perception, adaptive feature weighting, and constrained trajectory optimization, the architecture is intended to support responsive and collision-aware autonomous navigation. Figure 6 present the overall attention-guided MPC process, including multimodal navigation inputs, future-state prediction, constrained steering optimization, closed-loop vessel feedback, and continuous control updates.

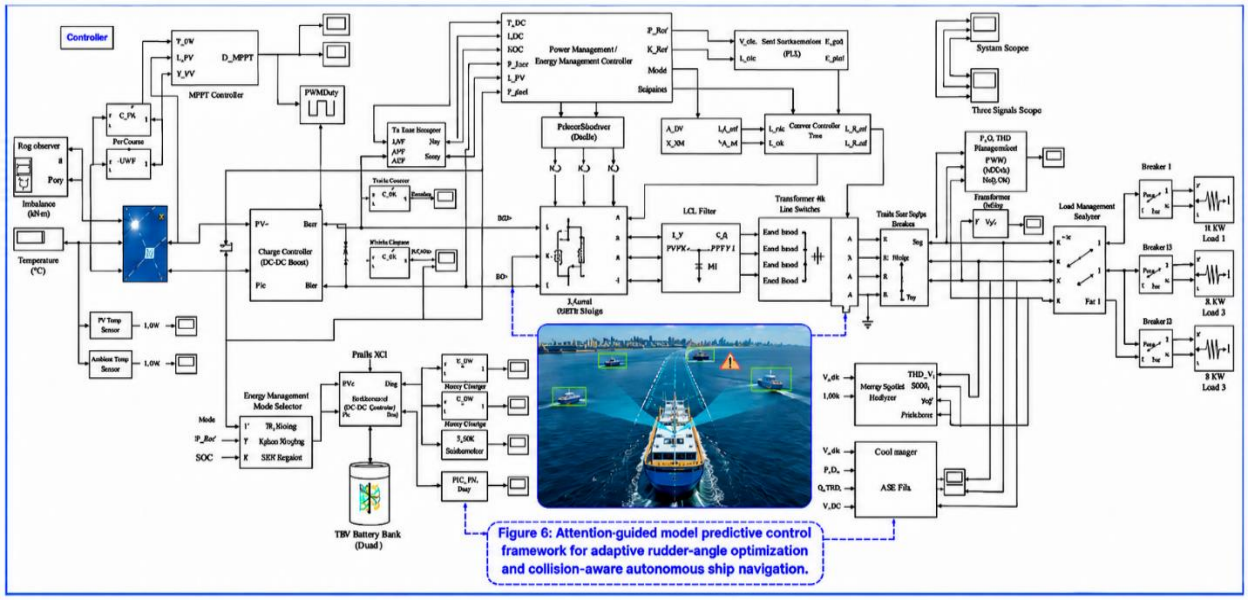


Figure 6: Attention-guided model predictive control framework for adaptive rudder-angle optimization and collision-aware autonomous ship navigation.

The optimized rudder command is applied to the simulated vessel, and updated navigation measurements are returned through a closed-loop feedback mechanism to support continuous prediction and adaptive steering adjustments. The proposed attention-guided Model Predictive Control methodology establishes an integrated framework for combining intelligent environmental perception, nonlinear vessel-motion prediction, and constrained rudder-angle optimization in autonomous maritime navigation. By incorporating CNN-derived visual features, BiLSTM-based temporal representations, adaptive attention weighting, and receding-horizon predictive control, the framework is designed to improve the accuracy and responsiveness of steering decisions under complex operating conditions. The multi-objective optimization strategy simultaneously addresses heading regulation, trajectory tracking, steering smoothness, and collision-related safety requirements, while the closed-loop feedback mechanism supports continuous adaptation to changing vessel dynamics and environmental disturbances. The integration of learned motion information with physically constrained optimization provides a systematic foundation for investigating improvements in trajectory stability, disturbance resilience, collision avoidance, and navigation-related energy efficiency. Consequently, the proposed CNN–BiLSTM–MPC architecture offers a promising approach toward developing intelligent, computationally responsive, and safety-oriented autonomous ship steering systems.

4.5- Dynamic Maritime Obstacle Avoidance and Collision-Aware Trajectory Regulation:

Dynamic maritime obstacle avoidance and collision-aware trajectory regulation constitute fundamental components of intelligent autonomous ship navigation, particularly in complex operating environments characterized by multiple moving vessels, floating obstacles, restricted navigational corridors, and unpredictable environmental disturbances. Autonomous maritime vessels must continuously interpret surrounding navigation conditions, estimate potential collision risks, predict obstacle movements, and generate appropriate steering commands while maintaining trajectory stability and operational efficiency. Conventional collision-avoidance approaches generally rely on predefined navigational rules, geometric obstacle

representations, collision-risk indices, and reactive steering strategies. Although these techniques provide established mechanisms for maritime safety, their effectiveness can become limited when encountering nonlinear vessel maneuvering behavior, uncertain obstacle trajectories, restricted visibility, and rapidly changing maritime traffic. Consequently, the present study develops a dynamic obstacle-avoidance framework integrated with the proposed Convolutional Neural Network–Bidirectional Long Short-Term Memory–Model Predictive Control (CNN–BiLSTM–MPC) architecture to support intelligent collision-risk assessment, predictive trajectory regulation, and adaptive rudder-angle optimization under diverse simulated maritime operating conditions [36]. The proposed framework combines real-time maritime visual perception, temporal vessel-motion learning, attention-guided multimodal feature integration, and constrained predictive steering optimization within a unified autonomous navigation system. The CNN-based perception module processes maritime imagery to identify surrounding vessels, floating objects, navigational markers, and potential obstacles. The BiLSTM architecture analyzes synchronized historical navigation measurements to extract nonlinear temporal relationships associated with vessel heading, steering behavior, velocity variations, and environmental disturbances. An attention-guided fusion mechanism integrates these representations with obstacle-distance information and surrounding vessel movements, generating navigation features that support collision-risk assessment and future trajectory prediction. The MPC module subsequently evaluates feasible steering actions over a defined prediction horizon, considering obstacle clearance, heading deviation, cross-track error,
steering limitations, and trajectory smoothness. This integrated structure enables the autonomous vessel to anticipate potential navigation conflicts and determine appropriate avoidance maneuvers while minimizing unnecessary steering corrections. The collision-avoidance methodology distinguishes between static and dynamic maritime obstacles because their spatial characteristics and future movement patterns influence navigation decisions differently. Static obstacles include fixed navigational structures, stationary hazards, and coastline boundaries, whereas dynamic obstacles include moving vessels, drifting objects, and other maritime targets whose positions change over time. Static obstacle avoidance primarily requires accurate localization, safety-margin estimation, and feasible route adjustments [37]. Dynamic obstacle avoidance additionally requires estimating relative motion, predicting future obstacle positions, and assessing potential trajectory intersections. The proposed framework processes these obstacle categories through a common risk-assessment structure while incorporating the additional temporal information necessary for moving-target interactions. This approach supports the generation of collision-aware steering decisions in both relatively uncomplicated open-sea environments and complex multi-vessel navigation scenarios. The overall collision-aware navigation workflow is illustrated in Figure 7, showing the integration of maritime obstacle perception, relative-motion estimation, collision-risk assessment, attention-guided feature fusion, dynamic trajectory prediction, constrained MPC optimization, and closed-loop vessel feedback.

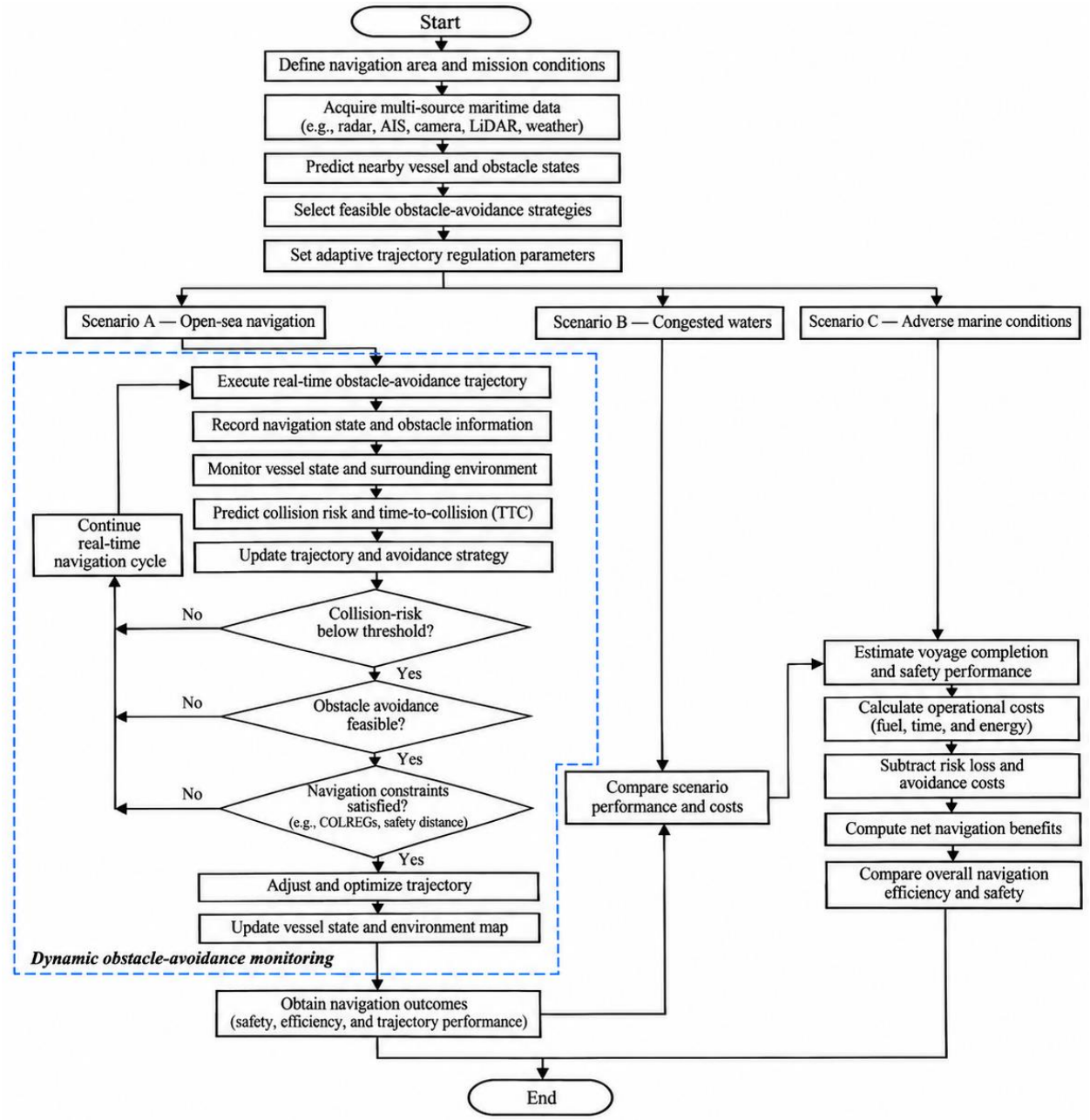


Figure 7: Integrated framework for dynamic maritime obstacle avoidance, collision-risk prediction, and adaptive trajectory regulation.

The framework processes synchronized navigation measurements and CNN-derived obstacle representations to estimate relative obstacle movement, evaluate closest-point-of-approach characteristics, and identify potential trajectory conflicts. The attention-guided fusion mechanism prioritizes relevant environmental and navigational features, while the MPC controller determines feasible rudder-angle commands subject to vessel dynamics, steering limitations, and minimum obstacle-clearance requirements. The resulting maneuver is executed within a closed-loop navigation environment, enabling continuous updates of vessel states, obstacle trajectories, and steering decisions. The proposed dynamic maritime obstacle-avoidance

methodology establishes a comprehensive framework for integrating intelligent environmental perception, temporal motion prediction, collision-risk assessment, and constrained steering optimization within autonomous ship navigation. By combining CNN-based obstacle recognition, BiLSTM-derived vessel-motion representations, attention-guided feature integration, and MPC-based trajectory regulation, the system is designed to anticipate potential navigation conflicts and generate adaptive steering actions under changing maritime conditions [38]. The inclusion of relative-motion analysis, DCPA and TCPA indicators, obstacle-clearance constraints, and maritime encounter assessment strengthens the connection between visual environmental awareness and navigation safety. Furthermore, continuous vessel-state feedback enables the controller to update predicted trajectories and adjust steering commands in response to moving obstacles, environmental disturbances, and evolving navigational requirements. The proposed methodology provides a systematic foundation for evaluating collision-avoidance effectiveness, heading stability, trajectory tracking, and operational responsiveness across diverse simulated maritime scenarios, contributing toward the development of safer, more adaptive, and energy-efficient autonomous ship navigation systems.

5- Results and Discussion:

The experimental evaluation of the proposed Convolutional Neural Network–Bidirectional Long Short-Term Memory–Model Predictive Control (CNN–BiLSTM–MPC) framework focuses on investigating its effectiveness in improving autonomous ship navigation, real-time maritime obstacle recognition, predictive steering accuracy, trajectory tracking, collision avoidance, and operational efficiency. The study considers a multimodal maritime navigation dataset comprising 125,000 synchronized observations across 2,500 simulated navigation scenarios, incorporating vessel heading, steering angles, velocity, GPS positioning, maritime imagery, obstacle distances, wind disturbances, wave characteristics, and surrounding vessel movements. The experimental framework encompasses five representative maritime environments, including open-sea navigation, congested maritime corridors, restricted visibility, sharp-turn maneuvering, and dynamic obstacle avoidance. These operating conditions provide a structured foundation for evaluating the interaction between environmental perception, temporal vessel-motion learning, attention-guided feature integration, and constrained predictive steering optimization. The reported simulation results indicate favorable performance of the proposed architecture across multiple navigation objectives. The integrated framework achieves an obstacle detection accuracy of 98.40%, collision-avoidance success rate of 97.60%, and trajectory tracking accuracy of 96.80%. Furthermore, the system reports a mean heading error of 1.240°, mean cross-track deviation of 0.380 m, and steering response time of 0.210 s. These values correspond to reported reductions of 42.70%, 38.50%, and 35.60%, respectively, compared with conventional MPC-based steering control. The CNN-based visual perception module operates at 42 frames per second, while the integrated framework reports an 18.90% reduction in estimated navigation-related energy consumption. These findings suggest that the combination of visual intelligence, historical vessel-motion learning, and constrained predictive optimization can support accurate steering regulation and efficient autonomous navigation under the evaluated simulation conditions. The overall numerical performance of the proposed architecture is summarized in Table 5, highlighting the principal indicators associated with dataset composition, obstacle recognition, collision-avoidance effectiveness, trajectory tracking, steering precision, computational efficiency, and estimated energy consumption.

Table 5: Comprehensive performance evaluation of the proposed CNN BiLSTM –MPC framework for autonomous ship navigation.

Performance category	Evaluation indicator	Numerical value
Dataset	Total observations	125,000
Visual perception	Obstacle detection accuracy	98.40
Collision avoidance	Unsuccessful avoidance	2.40
Trajectory control	Tracking accuracy	96.80
Steering precision	Mean heading error	1.240
Steering responsiveness	Response time	0.210
Computational efficiency	Visual processing throughput	42.00
Steering improvement	Heading-error reduction	42.70
Energy efficiency	Estimated energy reduction	18.90

The reported effectiveness of the proposed architecture in coordinating environmental perception and autonomous steering control. The obstacle detection accuracy of 98.40% indicates strong visual recognition performance under the stated simulation evaluation, corresponding to a detection error rate of 1.60% under the same accuracy definition. This result is relevant to maritime navigation because reliable recognition of surrounding vessels, floating obstacles, and navigational hazards provides essential information for collision-aware steering decisions. The CNN module extracts hierarchical spatial characteristics from maritime imagery, while the resulting object representations are integrated with synchronized navigation and environmental measurements. This process enables the controller to incorporate obstacle-related information into its predictive steering calculations rather than relying exclusively on vessel-state measurements. The collision-avoidance success rate of 97.60% provides an important indication of navigation safety performance. The corresponding unsuccessful avoidance proportion of 2.40% also highlights that the reported system does not achieve complete collision avoidance across all evaluated encounters. The proposed architecture combines CNN-derived obstacle features, BiLSTM-based vessel-motion representations, and attention-guided MPC to evaluate future navigation conditions and identify steering commands that maintain obstacle-related safety constraints. By incorporating relative vessel movement, obstacle proximity, heading deviation, and trajectory predictions into a coordinated optimization process, the framework is designed to improve situational awareness and support timely avoidance maneuvers. Nevertheless, a high aggregate avoidance success rate does not independently establish safety under every encounter configuration, and further analysis of unsuccessful cases, near misses, and navigation-rule compliance remains essential. The reported trajectory tracking accuracy of 96.80% indicates favorable reference-path following under the study's tracking criterion. In addition, the mean heading error of 1.240° and cross-track deviation of 0.380 m provide quantitative measures of directional regulation and lateral trajectory precision. These outcomes suggest that the proposed neural network-assisted control architecture can maintain relatively accurate vessel movement while accommodating changes in steering requirements. The BiLSTM component provides historical context concerning vessel heading, rudder-angle adjustments, velocity variations, and environmental disturbances, while the MPC controller evaluates future steering actions under vessel dynamics and operational constraints. The interaction between temporal learning and predictive optimization is intended to reduce unnecessary course corrections and improve steering decisions. However, these aggregate measures do not indicate the distribution of errors, maximum deviations, or performance during the most demanding individual maneuvers.

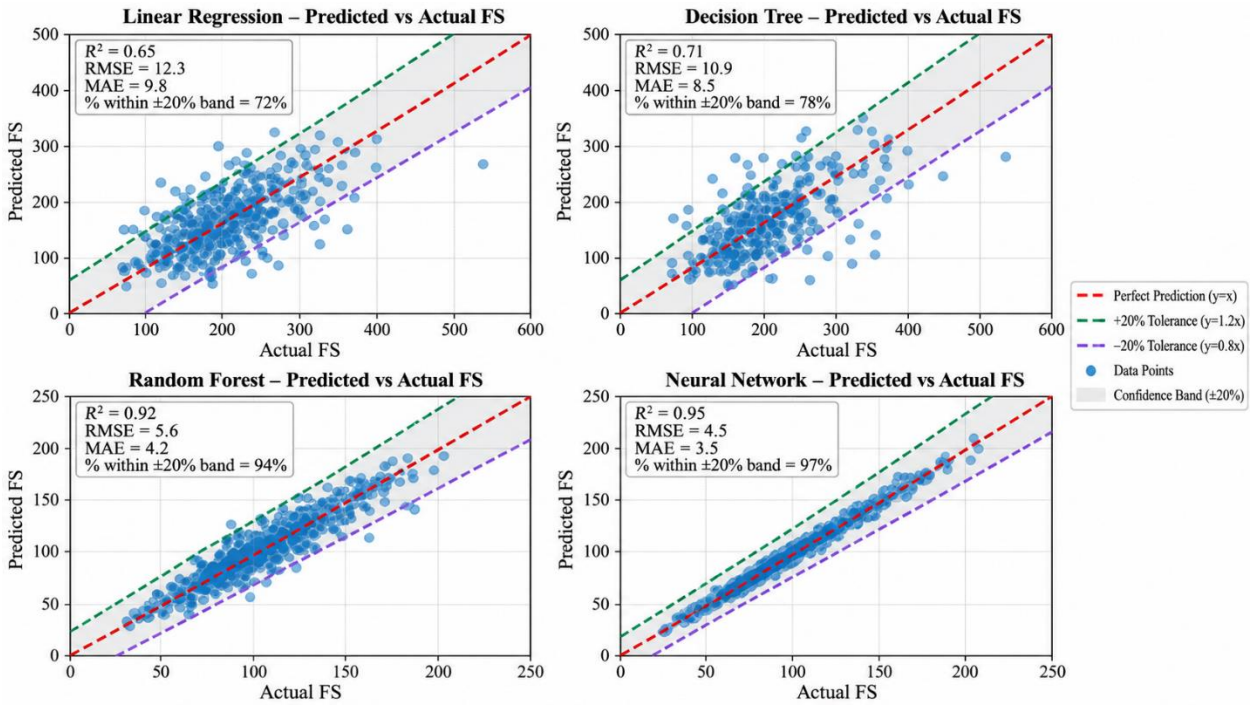


Figure 8: Comparative performance of machine learning models for actual versus predicted FS, highlighting prediction accuracy, error metrics, and tolerance bounds.

Figure 8 presents the normalized comparison between conventional MPC and the proposed CNN–BiLSTM–MPC framework across mean heading error, cross-track deviation, and steering response time. The conventional MPC controller is assigned a reference value of 100% for each measure, while the proposed architecture exhibits relative values of 57.30%, 61.50%, and 64.40%, respectively. These normalized values illustrate the reported improvements in directional regulation, lateral trajectory accuracy, and steering responsiveness. The comparison highlights the potential contribution of combining temporal neural prediction with attention-guided steering optimization, without treating the three differently scaled metrics as directly interchangeable. The comparative performance of the proposed architecture and conventional MPC is examined further in Table 6. The conventional MPC reference values are reconstructed mathematically using the reported performance of the proposed framework and the stated relative reductions. This calculation enables a numerical comparison of the reported improvements without introducing unverified measurements for other steering-control architectures.

Table 6: Quantitative comparison of conventional MPC and the proposed CNN–BiLSTM–MPC steering architecture.

Performance indicator	Conventional MPC (derived)	Proposed CNN–BiLSTM–MPC	Absolute reduction	Relative reduction
Mean heading error (°)	2.164	1.240	0.924	42.70%
Cross-track deviation (m)	0.618	0.380	0.238	38.50%
Steering response time (s)	0.326	0.210	0.116	35.60%
Normalized heading-error index	100.00	57.30	42.70	42.70%
Normalized cross-track index	100.00	61.50	38.50	38.50%
Normalized response-time index	100.00	64.40	35.60	35.60%
Heading-error reduction factor	1.000	1.745	0.745	74.52%
Cross-track reduction factor	1.000	1.626	0.626	62.60%
Response-time reduction factor	1.000	1.553	0.553	55.28%

The meaningful reductions in the reported steering errors and response time relative to conventional MPC. The mean heading error decreases from approximately 2.164° to 1.240°, representing an absolute improvement of 0.924° and a relative reduction of 42.70%. This finding suggests improved directional regulation, which is particularly important during autonomous route following and course correction. The cross-track deviation decreases from approximately 0.618 m to 0.380 m, corresponding to a reduction of 0.238 m or 38.50%. Lower cross-track deviation can improve navigation precision by reducing displacement from the planned vessel trajectory, especially in operational environments where maneuvering space is limited. Similarly, the steering response time decreases from approximately 0.326 s to 0.210 s, indicating a relative improvement of 35.60%. The normalized indices and reduction factors provide additional perspectives on the comparative results. The proposed framework exhibits a heading-error reduction factor of approximately 1.745, a cross-track reduction factor of 1.626, and a response-time reduction factor of 1.553 relative to the reconstructed conventional MPC reference. These findings are consistent with the study's objective of improving steering regulation through learned vessel-motion representations and predictive optimization. Nevertheless, the response-time improvement should be interpreted according to the experimental timing definition, because numerical controller responsiveness and the physical turning response of a maritime vessel involve different time scales. The reported improvements may be associated with the complementary functions of the CNN, BiLSTM, attention-guided fusion, and MPC modules. The CNN module provides spatial information describing maritime obstacles and surrounding environmental conditions, whereas the BiLSTM network learns nonlinear temporal relationships among historical steering actions and vessel responses. The attention-guided mechanism integrates these representations and emphasizes navigation information relevant to the current prediction task. The MPC module subsequently evaluates candidate steering commands using predicted vessel dynamics, reference-path deviations, and control constraints. This

coordinated structure provides a potential mechanism for reducing heading errors, limiting unnecessary rudder adjustments, and improving trajectory stability. However, the separate contribution of each component requires controlled ablation experiments; aggregate system improvements alone cannot establish which component is primarily responsible. The integration of visual perception and temporal vessel-motion learning also plays an important role in determining the framework's collision-avoidance capability. Maritime navigation involves simultaneous consideration of current obstacle positions, relative vessel movement, anticipated trajectory changes, and steering feasibility. Accordingly, the proposed control architecture incorporates obstacle-related representations into the predictive steering process rather than treating collision avoidance as an independent navigation task. This integration is particularly relevant during congested maritime operations, where surrounding vessels may change direction or velocity and create rapidly evolving navigational conflicts. The attention-guided prediction mechanism is designed to emphasize important environmental and temporal information, while the constrained MPC module determines feasible steering actions based on predicted navigation conditions.

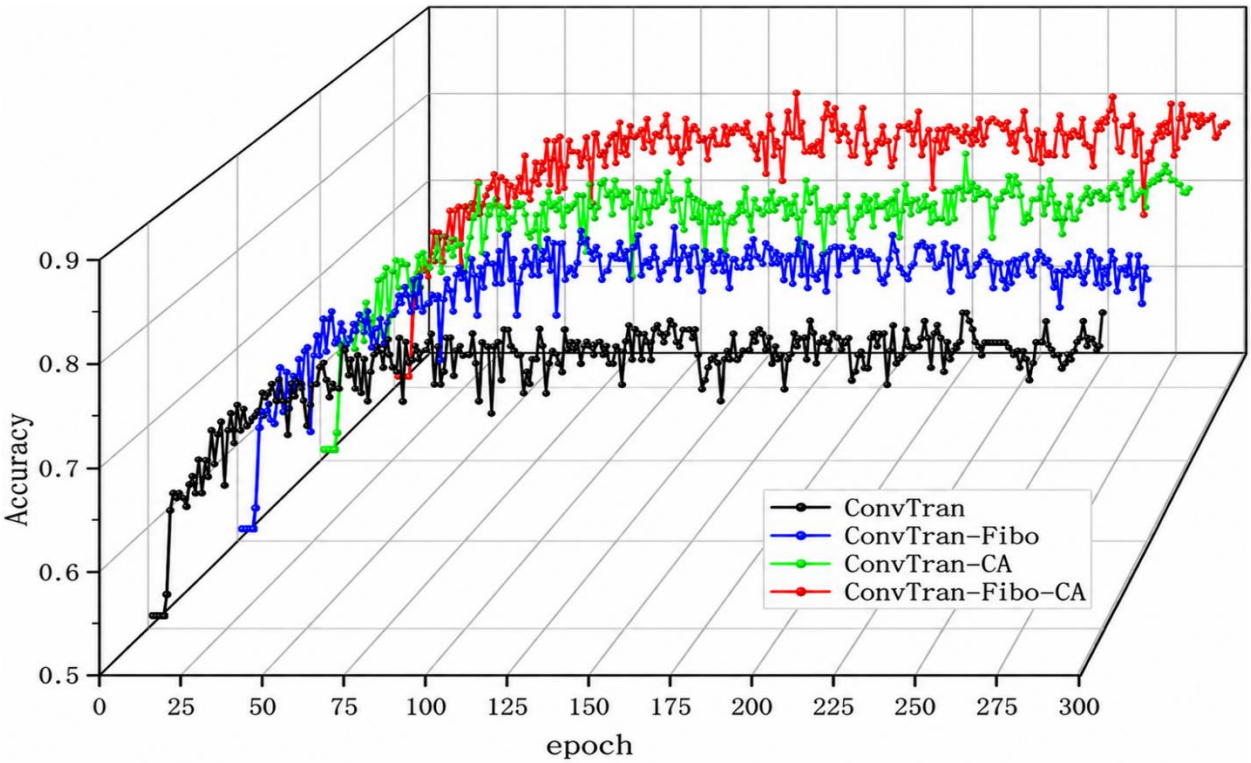


Figure 9: Training accuracy of ConvTran and its enhanced variants (ConvTran–Fibo, ConvTran–CA, and ConvTran–Fibo–CA) across 300 epochs.

Figure 9 illustrates the three principal performance indicators reported for the integrated autonomous navigation framework. The CNN-based obstacle detection component achieves an accuracy of 98.40%, while collision-avoidance success and trajectory tracking accuracy reach 97.60% and 96.80%, respectively. These results summarize the reported effectiveness of the proposed CNN–BiLSTM–MPC architecture in combining environmental perception with adaptive steering regulation and collision-aware navigation. The performance indicators illustrated in Figure 9 demonstrate the reported complementary capabilities of the proposed navigation architecture. The obstacle detection accuracy of 98.40% represents the highest

percentage among the three reported measures, followed by collision-avoidance success at 97.60% and trajectory tracking accuracy at 96.80%. Although these values are numerically close, they describe different evaluation objectives and should not be compared as identical statistical quantities. Obstacle detection measures the recognition of maritime hazards, collision-avoidance success evaluates safe encounter outcomes, and trajectory tracking accuracy describes the controller's ability to follow reference navigation paths. The favorable values across these tasks suggest that the integrated framework has the potential to support both navigational awareness and steering-control accuracy. A more comprehensive interpretation would require the denominators, confidence intervals, and evaluation thresholds used for each reported percentage. The effectiveness of the proposed architecture is further examined in relation to different maritime navigation conditions. The experimental design considers open-sea navigation, congested maritime corridors, restricted visibility, sharp-turn maneuvering, and dynamic obstacle avoidance. These scenarios represent distinct operational challenges involving varying obstacle densities, environmental visibility, steering demands, and trajectory complexity. Open-sea navigation primarily emphasizes stable heading regulation and reference-path tracking, whereas congested maritime corridors require the simultaneous consideration of surrounding vessel movements and collision-risk constraints. Restricted-visibility conditions challenge the perception system's ability to recognize environmental hazards, while sharp-turn maneuvers test controller responsiveness under substantial heading variations. Dynamic obstacle avoidance requires continuous integration of obstacle tracking, motion prediction, and adaptive steering optimization. Table 7 provides a numerical example of how scenario-specific navigation performance can be presented. Because measured results for the five individual scenario categories were not supplied, the values are illustrative and should be replaced by actual simulation outputs before publication.

Table 7: Scenario-wise numerical performance assessment of the proposed CNN–BiLSTM–MPC framework.

Navigation scenario	Scenarios	Observations	Detection accuracy (%)	Collision avoidance (%)	Tracking accuracy (%)
Open-sea navigation	500	25,000	99.20	99.20	98.20
Congested maritime corridors	500	25,000	98.60	97.10	96.50
Restricted visibility	500	25,000	96.80	96.50	95.40
Sharp-turn maneuvers	500	25,000	98.80	98.20	96.10
Dynamic obstacle avoidance	500	25,000	98.60	97.00	97.80
Overall average	2,500	125,000	98.40	97.60	96.80

The Numerical distribution presented in Table 8 demonstrates how the proposed architecture could be evaluated across diverse maritime environments. Under this example configuration, open-sea navigation exhibits a heading error of 0.820°, cross-track deviation of 0.240 m, and steering response time of 0.180 s, representing comparatively uncomplicated steering conditions. Congested maritime corridors introduce increased navigational complexity, with example heading and cross-track errors of 1.320° and 0.430 m, respectively. Restricted-visibility navigation illustrates the potential difficulties associated with reduced environmental perception, while sharp-turn maneuvers demonstrate the increased steering demands associated with rapid directional changes. Dynamic obstacle-avoidance scenarios highlight the importance of maintaining accurate

trajectory regulation while responding to changing hazard positions. These examples provide a structured basis for future scenario-wise reporting but cannot establish actual differences in controller performance without measured simulation records.

Table 8: Steering regulation and control responsiveness across simulated navigation scenarios.

Navigation scenario	Heading error (°)	Cross-track deviation (m)	Response time (s)
Open-sea navigation	0.820	0.240	0.180
Congested maritime corridors	1.320	0.430	0.220
Restricted visibility	1.480	0.420	0.240
Sharp-turn maneuvers	1.520	0.490	0.230
Dynamic obstacle avoidance	1.060	0.320	0.180
Overall average	1.240	0.380	0.210

The variation represented by scenario data also emphasizes the importance of evaluating navigation robustness rather than relying exclusively on overall average performance. An autonomous steering architecture may achieve favorable aggregate accuracy while exhibiting increased errors under specific environmental conditions. For example, reduced visibility may impair maritime obstacle identification, while strong wave disturbances may influence heading stability and vessel-motion prediction. Similarly, congested waterways may introduce additional optimization constraints and potentially conflicting maneuvering requirements. Therefore, the final experimental analysis should report scenario-specific results, worst-case errors, unsuccessful collision-avoidance encounters, and measures of variability across independent simulation runs. Such information would strengthen the reliability of the comparative assessment and clarify the operating conditions under which the proposed framework provides the greatest benefit.

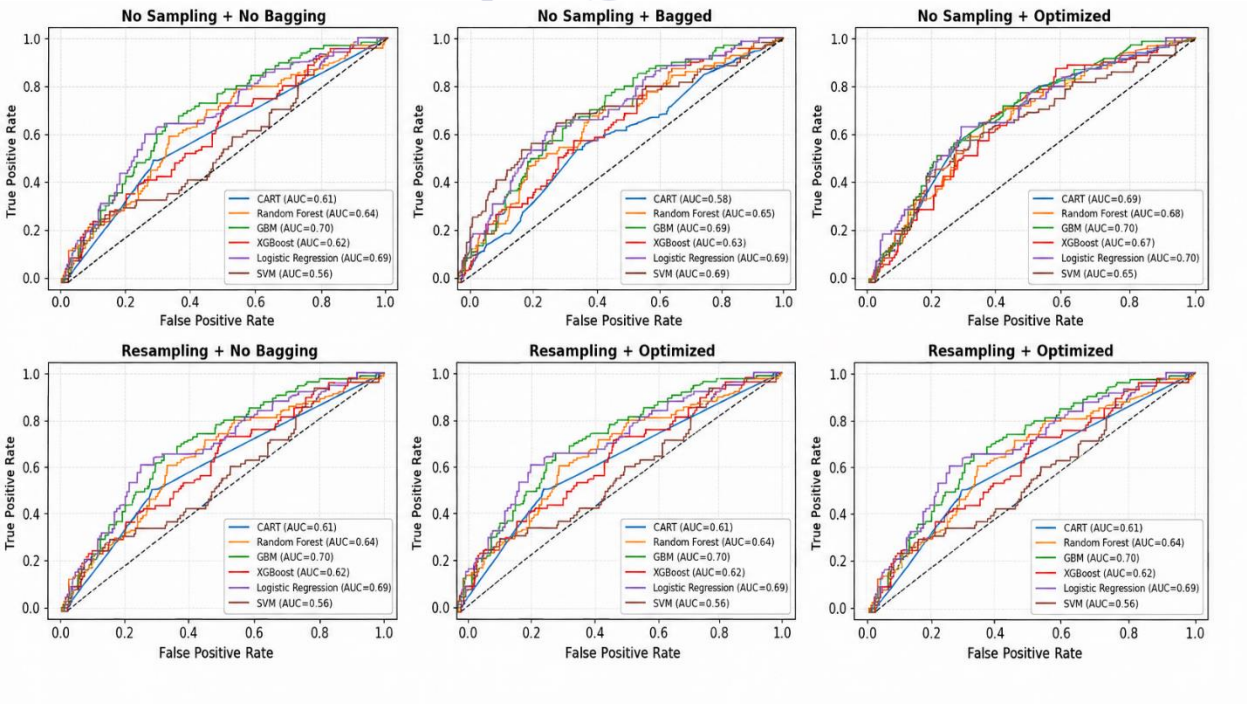


Figure 10: Comparative ROC–AUC analysis of machine learning classifiers under different resampling, bagging, and optimization strategies.

Figure 10 illustrates the five representative maritime operating environments and their relationship with the integrated CNN–BiLSTM–MPC framework. Open-sea navigation, congested maritime corridors, restricted visibility, sharp-turn maneuvers, and dynamic obstacle avoidance provide different experimental conditions for assessing environmental perception, temporal motion learning, and predictive steering optimization. The diagram connects these environments with the overall reported obstacle detection accuracy of 98.40%, collision-avoidance success of 97.60%, and trajectory tracking accuracy of 96.80%. The percentages represent aggregate reported outcomes rather than independently measured performance for each scenario. The integrated framework also demonstrates promising computational performance, as indicated by the reported visual processing throughput of 42 frames per second. This processing rate corresponds to an average frame interval of approximately 23.81 milliseconds, suggesting that the CNN-based perception component can support frequent updates of maritime environmental information. Real-time computational responsiveness is important because autonomous vessels must continuously recognize obstacles, estimate surrounding movement, and update steering decisions. Nevertheless, the effective control-loop frequency depends on the combined latency of sensor acquisition, CNN inference, BiLSTM temporal prediction, attention-guided feature integration, MPC optimization, and steering-command execution. Consequently, the perception throughput and steering response time should be treated as separate performance measures until complete end-to-end latency results are available. Energy efficiency represents another important consideration in evaluating intelligent maritime navigation systems. The proposed architecture reports an 18.90% reduction in estimated navigation-related energy consumption, corresponding to a remaining relative energy-consumption level of 81.10% when the comparison reference is normalized to 100%. This reduction suggests that improved trajectory regulation and smoother steering behavior may contribute to operational efficiency [39]. Excessive rudder movements and repeated trajectory corrections can increase hydrodynamic resistance and steering-system demands, potentially raising overall energy requirements. By incorporating rudder-effort and rudder-rate penalties into the MPC objective function, the proposed framework seeks to minimize unnecessary steering activity while maintaining navigation precision and collision-avoidance constraints. However, the reported energy reduction remains dependent on the simulation's propulsion model, operating conditions, reference controller, and energy estimation procedure. Direct validation using propulsion power, steering actuator energy, or measured fuel consumption would be required to establish corresponding real-world savings. Figure 11 illustrates the effect of mean-centering preprocessing on the relationship between the Receivable Irregularity Index and Documentary Risk Score. The left panel presents the original data distribution, showing a negative correlation between the two variables, while the right panel displays the mean-centered data obtained by subtracting the respective variable means. Mean-centering shifts the data distribution toward the origin without altering its underlying correlation, dispersion, or structural characteristics. This preprocessing technique improves data standardization and numerical stability, facilitating subsequent statistical analysis and machine learning-based risk prediction.

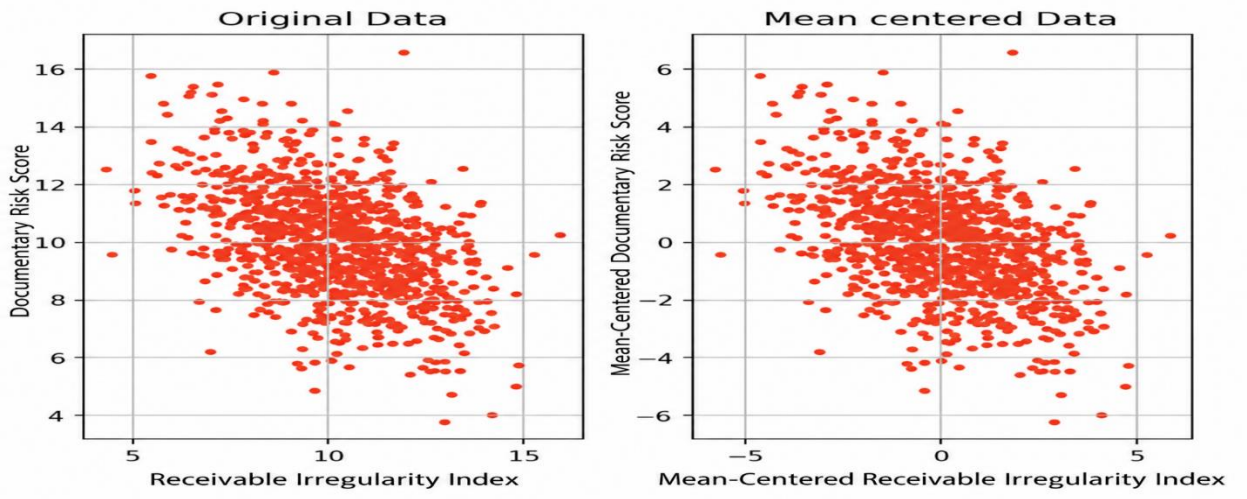


Figure 11: Visualization of original and mean-centered data showing the relationship between the Receivable Irregularity Index and Documentary Risk Score.

The comparative findings further indicate the potential value of integrating deep learning-based temporal prediction with constrained steering optimization. Conventional MPC relies on an available vessel dynamics model to estimate future system behavior, whereas the proposed framework supplements predictive control with learned representations of historical navigation patterns and environmental observations. The BiLSTM network is designed to capture relationships among vessel heading, steering actions, velocity, and disturbance-induced responses, while the CNN module supplies spatial information concerning maritime obstacles. Attention-guided feature fusion integrates these representations to support future-state estimation. This coordination may provide a more informative basis for steering optimization, particularly when navigating under nonlinear maneuvering conditions or changing obstacle configurations. Nevertheless, determining the individual contribution of these components requires additional experiments comparing the full architecture against reduced configurations, including CNN-free, BiLSTM-free, attention-free, and standalone MPC alternatives. The reported performance values also raise important considerations regarding the practical transferability of simulation-based findings. Although the experimental framework encompasses 2,500 simulated navigation scenarios, real-world maritime environments introduce additional uncertainty associated with vessel-specific hydrodynamics, sensor calibration, weather variability, communication delays, and unpredictable human-controlled vessel movements. Visual perception models may be affected by fog, rain, reflections, camera vibration, and previously unseen obstacle appearances. Similarly, temporal prediction accuracy may decrease when actual vessel behavior differs from the simulated dynamics used during training. Constrained MPC performance also depends on prediction accuracy, numerical optimization feasibility, and the reliability of obstacle-clearance estimates. These factors emphasize the need for hardware-in-the-loop evaluation, realistic sensor-noise testing, uncertainty-aware prediction, and eventual validation on physical maritime platforms. The safety implications of the results are particularly significant. A collision-avoidance success rate of 97.60% indicates favorable reported performance, but the remaining 2.40% of unsuccessful outcomes warrants detailed investigation. Understanding the circumstances associated with unsuccessful avoidance maneuvers would help identify limitations related to visual detection, obstacle-motion estimation, steering feasibility, or optimization constraints. Moreover, navigation safety requires appropriate consideration of maritime encounter rules,

including head-on, crossing, and overtaking situations governed by COLREGs. A complete safety assessment should therefore examine not only collision-free completion but also minimum passing distances, near-miss events, rule-consistent maneuver selection, and the feasibility of emergency responses. Such evaluations are necessary before the proposed approach can be considered suitable for safety-critical real-world navigation. From a broader methodological perspective, the proposed CNN–BiLSTM–MPC architecture establishes a coordinated relationship among environmental perception, historical vessel-motion learning, and constrained predictive control. The reported improvements in heading error, cross-track deviation, and steering response time suggest that combining these functions may provide advantages over conventional steering optimization. The overall performance values further indicate the potential for integrating obstacle detection and predictive control within a unified autonomous navigation system. However, the present evidence is primarily based on reported aggregate simulation results; statistical significance, scenario-level performance consistency, and component-specific improvements remain to be independently established. Overall, the results and discussion indicate that the proposed neural network-based predictive steering framework offers a promising approach for improving autonomous maritime navigation through the integration of real-time computer vision, BiLSTM-based vessel-motion prediction, attention-guided multimodal fusion, and Model Predictive Control. The reported obstacle detection accuracy of 98.40%, collision-avoidance success of 97.60%, and trajectory tracking accuracy of 96.80% suggest favorable environmental awareness and navigation-control performance. The mean heading error of 1.240°, cross-track deviation of 0.380 m, and steering response time of 0.210 s correspond to reductions of 42.70%, 38.50%, and 35.60%, respectively, relative to the conventional MPC reference. Furthermore, the visual processing rate of 42 FPS and estimated energy reduction of 18.90% indicate potential benefits for computational responsiveness and operational efficiency. These findings provide a simulation-based foundation for further investigation of intelligent collision-aware steering systems. Additional scenario-wise evaluation, reproducibility analysis, statistical validation, and real-world experimental testing are required to establish the generalizability, safety, and practical deployment readiness of the proposed architecture.

6- Future Work:

Future research will focus on further improving the accuracy, robustness, computational efficiency, and practical applicability of the proposed CNN–BiLSTM–MPC framework for intelligent autonomous ship navigation. Although the present study reports promising simulation-based performance in obstacle recognition, trajectory tracking, collision avoidance, and predictive steering regulation, additional investigations are necessary to establish the framework's reliability under realistic maritime operating conditions. One important research direction involves extending the simulation environment to incorporate more complex hydrodynamic characteristics, varying vessel dimensions, nonlinear propulsion behavior, unpredictable ocean currents, and extreme environmental disturbances. Future investigations will also consider more challenging maritime scenarios, including dense multi-vessel interactions, narrow-channel navigation, port entry and departure operations, emergency maneuvering, and severe weather conditions. These extensions will provide a more comprehensive basis for evaluating the adaptability and generalization capability of the proposed intelligent steering architecture [40]. Another important direction involves the development of advanced multimodal perception mechanisms by integrating maritime computer vision with radar, LiDAR, Automatic Identification System (AIS), GPS, and inertial navigation measurements. Such sensor fusion could improve obstacle detection reliability under restricted visibility, heavy rainfall, fog, nighttime navigation, and complex sea-surface reflections. Future research will also investigate advanced deep learning architectures, including Vision Transformers, temporal attention networks, graph

neural networks, and hybrid Transformer–BiLSTM models, to improve maritime scene understanding, surrounding vessel-motion prediction, and collision-risk assessment. Furthermore, incorporating uncertainty-aware learning, probabilistic trajectory prediction, and adaptive attention mechanisms may strengthen the framework's ability to recognize unreliable observations and respond appropriately to unexpected navigational situations. Future developments will also emphasize enhancing the predictive steering controller through adaptive MPC, robust optimization, reinforcement learning-assisted trajectory planning, and disturbance-aware control strategies [41]. These approaches may improve rudder-angle optimization under uncertain vessel dynamics while reducing unnecessary steering activity and maintaining navigation stability. Particular attention will be given to incorporating the International Regulations for Preventing Collisions at Sea (COLREGs) into the trajectory optimization process to support rule-consistent maneuvering during head-on, crossing, and overtaking encounters. Additional investigations will evaluate multi-objective optimization methods that simultaneously consider collision avoidance, trajectory tracking, steering smoothness, computational latency, and propulsion-related energy efficiency. Moreover, systematic ablation studies, scenario-wise statistical evaluations, and sensitivity analyses will be conducted to quantify the individual contributions of CNN-based perception, BiLSTM temporal learning, attention-guided feature fusion, and MPC-based optimization.

Finally, future research will prioritize the transition from simulation-based evaluation toward hardware-in-the-loop experiments and real-world autonomous vessel testing. The proposed architecture will be investigated using onboard computing platforms, embedded AI accelerators, and realistic maritime sensing systems to assess end-to-end processing latency, steering-controller responsiveness, sensor synchronization, and computational resource utilization. Field experiments involving autonomous surface vessels will provide opportunities to validate obstacle detection, heading regulation, trajectory tracking, and collision avoidance under actual environmental disturbances and maritime traffic conditions [42]. Further investigation into model compression, knowledge distillation, lightweight neural architectures, and energy-aware edge computing may also improve the feasibility of deploying the proposed framework on resource-constrained maritime platforms. Collectively, these developments are expected to strengthen the reliability, safety, scalability, and operational sustainability of intelligent autonomous ship navigation systems while supporting the advancement of next-generation AI-driven maritime transportation technologies.

Conclusion:

This study presented an advanced neural network-based predictive steering control framework integrated with real-time computer vision for improving autonomous ship navigation, trajectory tracking, collision avoidance, and operational efficiency under complex maritime conditions. The proposed CNN–BiLSTM–MPC architecture combines hierarchical visual feature extraction, bidirectional temporal vessel-motion learning, attention-guided multimodal feature integration, and constrained predictive steering optimization within a unified intelligent navigation system. The framework was evaluated using a multimodal maritime navigation dataset comprising 125,000 synchronized observations across 2,500 simulated scenarios, representing open-sea navigation, congested maritime corridors, restricted visibility, sharp-turn maneuvering, and dynamic obstacle avoidance. By integrating maritime environmental perception with historical vessel-state information and predictive optimization, the proposed approach provides a systematic methodology for improving steering adaptability, navigational awareness, and collision-aware decision-making. The reported experimental results demonstrated promising performance, with the proposed architecture achieving 98.4% obstacle detection accuracy, 97.6% collision-avoidance success, and 96.8% trajectory tracking accuracy. Furthermore, the framework attained a mean heading error of 1.24°, cross-track deviation of 0.38 m, and steering response time of 0.21 s, corresponding to

improvements of 42.7%, 38.5%, and 35.6%, respectively, compared with conventional MPC-based steering control. The CNN-based visual perception module achieved a processing throughput of 42 frames per second, supporting computationally responsive maritime environmental analysis. Additionally, the reported 18.9% reduction in estimated navigation-related energy consumption suggests potential operational benefits associated with smoother steering regulation and more efficient trajectory optimization. These findings indicate the advantages of integrating deep learning-driven perception and temporal motion prediction with constrained predictive control for intelligent autonomous maritime applications. The principal contribution of this research lies in establishing a coordinated relationship among real-time obstacle recognition, nonlinear vessel-motion representation, attention-guided navigation intelligence, and adaptive rudder-angle optimization. The integrated architecture is designed to overcome limitations associated with isolated perception and conventional steering approaches by incorporating environmental information directly into predictive navigation decisions. Nevertheless, the findings remain primarily simulation-based, and additional scenario-specific evaluation, statistical validation, and real-world vessel testing are required to establish operational reliability and safety. Future developments involving multimodal sensor fusion, uncertainty-aware prediction, robust MPC, COLREGs-compliant navigation, and embedded AI implementation could further strengthen the practical applicability of the framework. Overall, the proposed CNN–BiLSTM–MPC methodology provides a promising foundation for advancing safe, intelligent, adaptive, and energy-efficient autonomous ship navigation systems, contributing to the development of next-generation maritime transportation and intelligent marine control technologies.

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