Real Time Machine Learning Ship and Bridge Pier Collision Prediction to Enhance Construction Health and Safety

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Abstract

Ship-bridge pier collisions signify a serious risk to structural integrity and construction health and safety during bridge construction phases where structural redundancy is limited. This study develops a hybrid finite element-machine learning (FE-ML) replacement framework for rapid prediction of collision consequence severity under different maritime and environmental conditions. Nonlinear finite element simulations were conducted across a parametric domain defined by ship tonnage, velocity, collision angle, and pier geometric characteristics to quantify structural responses. It includes displacement, peak impact force, stress distribution, energy absorption, and acceleration behavior. Finite element results demonstrate strong nonlinear dependence of structural response on kinetic energy transfer. The increased ship speed from 5 m/s to 20 m/s produced approximately fourfold growth in pier displacement from 0.08 m to 0.30 m for a 16,000-ton vessel. Moreover, the peak impact force increased from 0.8 MN to 3.5 MN under the same tonnage range. The large tonnage collision scenarios (50,000 tons) generated forces up to 5.7 MN along with stress concentrations approached 90 MPa at the pier base. Energy absorption capacity increased substantially from 180 kJ for moderate impacts to 650 kJ under severe collision conditions. This confirms the dominance of velocity and vessel mass in governing structural damage mechanisms. Machine learning models, Random Forest Regression and feed-forward Neural Networks were trained using FE-generated datasets to enable rapid consequence prediction. Baseline evaluation using an 80/20 train-test split yielded strong predictive capability with coefficients of determination of 0.93 (RFR) and 0.95 (NN) during training (0.89) and testing (0.91). Expanded five-fold cross-validation on a synthesized dataset (N = 50,000) produced near-unity regression accuracy and achieved mean R^2 values of 0.9980 for RFR and 0.9988 for NN with minimal prediction error dispersion. The proposed FE-ML framework enables near real time estimation of ship collision consequence severity and establishes a direct linkage between navigation parameters and structural response demand. The results support implementation within construction health and safety management systems for rapid hazard screening, protective design optimization and proactive maritime traffic control.

Keywords: *Ship Collision Risk, Machine Learning Prediction, Bridge Pier Safety, Maritime Accident Analysis, Construction Health and Safety*

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1. Introduction

Ship collisions with bridge piers are critical concern in maritime and construction safety management. Based on the data from the Korean Ministry of Oceans and Fisheries, out of 13,687 marine accidents over the last five years 1,238 were collisions, approximately 9.1% [1]. The increasing risk of ship collisions with bridge piers poses significant challenges to construction health and safety management, demanding innovative approaches to mitigate potential hazards [2]. The European Maritime Safety Agency (EMSA) reported that between 2014 and 2023, a total of 7,604 injuries were linked to 6,623 recorded marine casualties and incidents and the average fatality rate among crew members was 86.9% [3]. Xu et al. state an average of 9.7 maritime accidents occurred per year since the 1990s globally which highlights the frequent nature of these incidents, varying in severity [4]. In South Korea, for instance, studies focused on harbor bridges like those in Incheon and Busan have contributed towards optimization of safety measures, as yearly number of ship-bridge collisions remains generalized [5]. Furthermore, China has reported several bridge failures over the years due to anthropic factors including ship-bridge accidents, specifically between 2009 and 2019 [6]. One study specifically focused on assessing the probability of such collisions in different regions using data from the Automatic Identification System (AIS**)**, indicating the risk based on ship traffic density and bridge designs [7]. In 2024, the National Transportation Safety Board (NTSB) investigated the containership Dali collision with the Francis Scott Key Bridge in Baltimore, causing six construction worker deaths and one crew member injury [8] [9]. Similarly, the International Maritime Organization (IMO) statistics indicate an increase in deaths from 109 to 132 in 2021, which represents an increase of more than 20% [10].

The integration of machine learning (ML) into predicting and managing ship-bridge pier collisions represents unique development in maritime and construction safety. The analysis revealed that vessel size, tug assistance, and pier protection measures had critical roles in mitigating such accidents The use of historical maritime accident data and advanced algorithms has improved prediction accuracy that contributed to reduced collision risks. For instance, studies have utilized over 40 years of accident data to develop ML models capable of identifying high-risk scenarios with remarkable accuracy [11]. This integration supports resilience in infrastructure design and strengthens maritime safety measures [12]. Recent research from Brandt et al. show that combining ML models with real-time maritime traffic data and environmental factors enables risk assessment with over 90% accuracy [13], [14]. The Random Forest Regressor (RFR) is an ensemble-based technique that constructs decision trees to reduce overfitting and improve prediction accuracy. This accuracy is achieved by ML models like RFR offers substantial cost and operational benefits in maritime safety. It reduces accident-related expenses which often range between $10 –$50 million per incident and lowers insurance premiums by exhibiting proactive risk management [15]. Globally, these improvements could save over $1 billion annually in the maritime sector, with individual ships benefiting by $50,000 to $100,000 annually [12], [13]. Predictive models can accurately identify high risk scenarios by analyzing variables such as ship speed, tonnage, and navigational patterns, reducing collision risks by over 30% [18], [19], [20]. Additionally, trajectory prediction algorithms which include AIS data have reduced collision risk by up to 30% that exhibits the application of deep learning methods in identifying critical pathways [21], [22].

The traditional methodologies for risk assessment and mitigation of ship collisions with bridge piers lack precision and adaptability. These practices are unable to consider dynamic variables such as real-time maritime data and environmental factors. Furthermore, static models fail to predict risks associated with high speed or large tonnage ships which result in bridge piers being vulnerable to catastrophic failures. This research addresses key questions essential for enhancing bridge pier safety in the context of construction health and safety management. i.e., (1) How ML can advance the prediction of ship collision risks with bridge piers? (2) What critical factors influence ship collision risks, mainly during construction phases? Additionally, the study examines the integration of real-time maritime data that improve safety management practices, and also directs with alignment of predictive technologies with resilient and sustainable engineering principles.

The aim of this study is to create and validate a predictive framework powered by ML to evaluate ship collision risks involving bridge piers with a particular emphasis on the construction phase. Real-time data driven decision-making forms the foundation of this study, focusing to reduce the frequency and severity of ship collision incidents. For example, Singapore in the context of maritime safety which has a strategic maritime position and significant traffic around bridge piers, the data from studies show that larger vessels, specifically those over 10,000 gross tonnages are involved in nearly 60% of collision-related incidents near bridge piers due to increased speed and size [23]. The study's scope is limited to predicting and mitigating ship collision risks during bridge construction phases. Thus, the research hypothesizes that ML models can outperform traditional methods in predicting and mitigating ship collision risks by incorporating real-time data and analyzing dynamic parameters. Addressing a critical research gap, the research emphasizes in the field of maritime collision risk prediction.

- RO1: To influence ML models of RFR and neural networks to improve collision risk predictions by analyzing factors of ship tonnage, speed, collision angles, water flow, and pier dimensions.
- RO2: To develop predictive accuracy and safer bridge designs with energy absorbing features and reinforcements for mitigation of safety limitations to prevent accidents and infrastructural damage.

Many existing models lack integration with real-time maritime data, such as vessel positions and traffic density, as well as dynamic environmental factors like tidal currents and wind speeds which are crucial for precise and adaptable risk assessments. Furthermore, the dependence on static data in most predictive models hinders the ability to respond to changing maritime conditions, that reduces its applicability to complex real-world situations. Maritime incidents can lead to significant financial losses potentially approaching $4 billion. Over a span of five years, insurers have reported maritime accident claims totaling $9.9 billion which signifies heavy economic strain caused by insufficient predictive models and the urgent need for more robust risk assessment policies to alleviate such financial burdens. Traditional static models for risk prediction often require up to 72 hours to deliver assessments following an incident. However, by adopting real-time predictive systems that utilize dynamic data, the response time can be drastically reduced to around 30 minutes [24], [25], [26]. Hence, the study adopts quantitative approach by using ML algorithms to predict collision risks based on simulated datasets. Parameters such as ship speed, tonnage, collision angle, and environmental factors are analyzed to generate risk scores, which inform safety protocols and bridge designs.

The novelty and relevance of this research lie in the integration of ML real-time maritime data, such as AIS data and traffic density, alongside key parameters like ship tonnage, speed, collision angle, and environmental factors which offer a dynamic and precise risk assessment framework. Furthermore, the development of a composite risk score that normalizes impact forces, energy absorption, and stress levels for construction health and safety management includes maritime traffic flow adjustments, and the design of energy-dissipating features for bridge piers. The research involves generating simulated data such as ship tonnage, speed, collision angle, water currents, and pier dimensions grounded in realistic assumptions. The study includes a hybrid approach by applying ML algorithms, specifically RFR and neural networks to predict collision risks and simulated, real-time, and environmental data for predictive modeling. As a result, the study develops a predictive framework capable of providing real-time risk assessments. It highlights the significance of ML in improving construction safety and informs regulatory and structural design practices.

1.1 Significance of the Study

The significance of this research lies in its integration of structural engineering mechanics, data-driven modelling, and infrastructure safety management. As existing studies [19], [21], [23] largely emphasize collision probability estimation or computationally intensive structural simulations, this work shows a computationally efficient and interpretable approach that links navigational parameters directly to structural consequence severity. By focusing on consequence-oriented prediction rather than only probability assessment, the framework supports infrastructure resilience planning, protective design optimization and construction phase safety management. The proposed methodology contributes to the evolving domain of intelligent structural control and health monitoring systems for critical bridge infrastructure.

1.2 Major Contributions of the Study

The present study makes several important contributions to the field of ship-bridge collision prediction and structural safety management. First, it proposes a hybrid FE-ML modelling framework that integrates high fidelity structural simulation outputs with data-driven prediction techniques. It would enable computationally efficient estimation of structural consequence severity. Second, the study presents a normalized and interpretable Collision Severity Index (CSI), derived from physically meaningful response parameters such as impact force, absorbed energy, and stress demand. This composite severity metric progresses beyond conventional probability focused collision risk models through a direct structural consequence indicator suitable for infrastructure safety assessment. Third, the research comparatively evaluates Random Forest Regression and Neural Network models for prediction of structural response severity. Finally, the study develops a conceptual linkage between structural collision mechanics and construction health and safety decision-support systems. This would extend the application of machine learning techniques toward real time infrastructure protection and resilience enhancement. Together, these contributions facilitate the simulation based structural analysis with practical, deployable predictive modelling frameworks for critical bridge infrastructure.

The study is organized into several sections. Section 2 provides an overview of different research methods related to ship collisions and complex network studies. In Section 3, the study's methodology is discussed. Section 4 analyzes and discusses the study's findings on ship collisions with bridge piers, emphasizing the impact of ship dynamics on structural safety and risk mitigation strategies. Section 5 gives a concluding summary of the key findings.

2. Literature Review

The purpose of this section is to find the most relevant research that applies ML techniques to accident risk prediction and provide a detailed review of the literature on marine accidents for examination of ML applications in marine accident risk assessments see Z. H. Munim et al., [11] and M. Luo, S.H. Shin., [27]. However, for a comprehensive review of ML applications in maritime accident risk analysis, see Rawson and Brito [28]. This study has reviewed a number of relevant journal articles on maritime accidents analysis that employed ML using a systematic approach. Y. Cao et al., using a methodical manner, this study has examined many relevant journal publications on the investigation of marine incidents that used ML [29]. The Boolean query "maritime accident" AND "machine learning" or "maritime accident analysis" and "collision" was used to search the Web of Science (WoS) database and Scopus for relevant publications. Ten of the most pertinent research were found by personally going through the collected studies in WoS and Scopus. A summary of the most relevant studies is presented in **Table 1**.

2.1. ML Predicting Ship-Bridge Pier Collisions

Most importantly, a ML-based system is developed to predict the time history of impact forces during ship-bridge pier incidents. This system simulates barge collisions with double-column piers using a reliable finite element (FE) model, incorporating energy transformation and structural response evaluations. G. Xu et al., [20] . A further study by C. Fan et al. [19] proposed a collision warning method for ship-bridge interactions based on safety potential field models. Notably, this approach employed ML to assess collision risks and enhance safety standards on bridges, thereby highlighting the significance of ML in maritime safety applications. Moreover, the warning levels assigned to the vessel's risk values represent a scale of hazard, with levels ranging from 1 to 2. Specifically, this indicates a 100% increase in risk when transitioning from a warning level of 1 to 2.

M. R. George et al., [30] discussed the ensemble ML techniques to forecast building site dangers. Similarly, such approaches could be adapted to the Ghanaian environment to address local safety concerns in maritime construction. Furthermore, G. Li et al., [31] proposed an early warning model for bridge construction safety issues that integrates rough set theory, the sparrow search method, and least squares support vector machines (LSSVM). In addition, this innovative approach effectively addresses the challenges posed by multiple risk factors in bridge construction by optimizing early warning indicators and enhancing prediction accuracy. A study by F. Xiao et al., [32] highlights several key statistics and contributing factors. Human error emerges as the leading cause, accounting for approximately 64% of collisions which have significant role of human oversight or misjudgment in ship position aberrancy [33], [34]. Technical failure that is responsible for about 21% of collisions, emphasizes the impact of mechanical or technical issues on maritime accidents.

W. Luo et al., [35] investigated video based identification and prediction methods for stable ship-bridge pier interactions. In recent research K. Zheng et al., [36] proposed a Support Vector Machine (SVM) based system to assess the probability of ship collisions. The SVM based algorithm achieved a collision risk prediction accuracy exceeding 90% which demonstrates its effectiveness in identifying potential maritime accidents. The model processed data from diverse maritime scenarios with an error margin below 10% with robustness and reliability. Furthermore, the study introduced a machine vision-based approach to assess the risks of ship-to-ship collisions. The machine vision method demonstrated a cost reduction of approximately 30% compared to conventional monitoring systems. Additionally, the system maintained a collision risk detection accuracy of around 92% precision in real-time evaluations while addressing data collection and processing inefficiencies. By integrating ML and imaging algorithms, this method addressed challenges related to information collection and system cost monitoring [37], [38]. A study by V. Mousavi., [39] and S. Ni et al., [33] [40] have focused on sustainability, digitization, safety, management, and maintenance in bridge structures. This research highlights the integration of digital technology and ML for improving bridge maintenance and safety management. It also emphasizes the importance of Autonomous Navigation Systems (ANS) in ensuring the safety of Maritime Autonomous Surface Ships (MASS) through situational awareness, path planning, and motion control. Notable advancements include path planning methods for collision avoidance and decision-support systems using algorithms like Genetic Algorithms (GA) with key research gaps through the proposed framework.

According to Y. Wu et al., [41], bridge pier safety can be achieved through the interconnection of ML based prediction models within construction health and safety management systems. In contrast, traditional approaches primarily depend on static evaluations and expert judgment that often rely on manual assessments or conventional statistical techniques. However, limited research has explored the application of ML in addressing the interplay between maritime traffic dynamics and bridge pier safety. Moreover, the proposed approach focusses on proactive risk mitigation, improved prediction accuracy, and adaptability to dynamic conditions. Rawson Brito, and Sabeur [42] have successfully applied ML to historical casualty data, weather patterns, and vessel traffic information, achieving an impressive accuracy rate of 92% and a recall of 95%. Despite these advancements, many studies have predominantly focused on experimenting with only three to five ML algorithms as shown in **Table 1**. This approach limits the opportunity to explore a broader spectrum of algorithms that may offer more robust insights and improvements. Expanding the range of algorithms tested could potentially unlock new predictive capabilities, enhancing the accuracy and reliability of safety predictions in maritime traffic and bridge pier interactions.

Similarly, Zhou, Y. et al. [43] suggested the creation of a technique to determine the timing of ship collision avoidance measures, marking another noteworthy accomplishment. By examining AIS data, researchers identified critical variables affecting collision avoidance timing, including bearing, relative speed, and distance. Consequently, this data-driven approach aids navigators in making prompt decisions, thereby enhancing marine safety. Additionally, the study uses a dataset of 592 ship accidents spanning 20 years (2002–2022) [44] and AIS data from four U.S. coastal regions, down-sampled to 1-hour intervals. ML algorithms like convolutional neural network (CNN), transformer, and back propagation neural network (BPNN) achieved accuracy rates of up to 99.98% in certain regions with a high recall value (e.g., 0.999999). Furthermore, the model effectively identifies risks and transfers knowledge across sea areas through superior results in regions with similar characteristics.

Bayesian networks were applied in two studies [45] [46], whereas the classic Fault Tree Analysis (FTA) was utilized in one [47]. Although FTA is widely recognized in risk assessment, its application becomes increasingly complex and time consuming as systems grow larger. In addition, FTA is fundamentally static and unsuitable for dynamic system analysis. In contrast, Bayesian networks enable modeling with multi-state factors and non-linear relationships [48]. More recently, dynamic Bayesian network models have been employed for real-time risk analysis, offering enhanced adaptability and precision [49].

Table 1: Studies on applied ML and advanced modeling techniques.

No	Data Type (Values)	Data Source	Methods	Key Findings	Study References
1	Impact Force (1,000-10,000 kN)	Simulation, Barge Collision Data	FE Modeling, ML	Developed a ML system to predict impact forces during barge-bridge collisions.	Xu, Cao et al., 2023 [20]
2	Collision Risk (Risk Levels 30-40%)	Maritime Traffic Data, Safety Records	Safety Potential Field Models, ML	Proposed a ML-based collision warning system to reduce collision risk by 30-40%.	Fan et al., 2024 [19]
3	Accident Data (500+ incidents)	Maritime Construction Sites	Ensemble ML	Applied ensemble ML to predict construction site dangers, relevant for maritime safety.	George et al., 2022 [30]
4	Risk Data (Various Risk Factors)	Bridge Construction Data	Rough Set Theory, Sparrow Search Method, LSSVM	Proposed an early warning model to predict bridge construction risks with high accuracy.	Li et al., 2021 [31]
5	Collision Data (1,000+ incidents)	Collision Incident Database	Probabilistic Risk Assessment Models	Analyzed probabilistic models for ship-structure collision prediction.	Xiao et al., 2022 [32]
6	Interaction Data (Ship-Pier Interaction)	Video Monitoring Data	Video-Based Identification, ML	Developed a video-based system to predict ship-pier interaction stability.	Luo et al., 2024 [35]
7	Ship Collision Probability (Risk Data)	Ship Traffic Data, Collision Records	SVM, Machine	Proposed SVM-based systems and machine	K. Zheng et al., [36]

			Vision Algorithms	vision for ship collision risk assessment.	
8	Bridge Safety Data (Operational Risks)	Bridge Operational Data	Digital Technology Integration, ML	Focused on integrating ML and digital tech to enhance bridge safety.	Jensen et al., 2024; [50] Zhou et al., 2024 [43]
9	Navigation Data (Path Planning, Collision Avoidance)	Maritime Navigation Data	Autonomous Navigation, Genetic Algorithms (GA), DBSCAN	Highlighted Autonomous Navigation Systems' role in MASS safety through improved path planning and decision-making.	Ni et al., 2022 [40]
10	Collision Risk Data (Ship Traffic Dynamics, Pier Safety) 592 ship accidents spanning 20 years (2002–2022)	Ship Traffic Data, Pier Safety Records	ML Framework, Risk Mitigation	Developed an ML-driven framework to predict ship collisions and improve pier safety.	Wu et al., 2024 [44]

2.2. Ship Collision Avoidance Using Artificial Intelligence

Recent developments highlight the increasing integration of artificial intelligence (AI) in maritime accident analysis mainly in ship collision avoidance. Numerous categories of AI applications have emerged as summarized in **Table 2.** These include ML models, deep learning techniques, trajectory prediction, collision avoidance systems, early warning models, risk assessment approaches, and regulatory frameworks. ML models utilize shared accident datasets, safety outcomes, regression analyses, and neural networks to enhance prediction accuracy. Deep learning techniques, such as YOLOv7 algorithms that focus on safety equipment recognition and collision avoidance utilizes reinforcement learning for decision making [35], [51]. Trajectory prediction depend on AIS data, historical records, and navigational risk parameters to optimize maritime traffic control. Collision avoidance systems incorporate deep reinforcement learning (DRL) based decision making, DCPA calculations, and optimal maneuvering strategies. Early warning models apply transfer learning and multi-modal approaches for risk identification and accident prediction, whereas risk assessment techniques employ Dempster-Shafer (DS) theory, gradient boosting regression (GBR), and uncertainty management frameworks to evaluate collision risks. These developments validate the transformative potential of artificial intelligence in mitigating ship collision risks and enhancing maritime safety. Similar AI-driven integration frameworks have also been successfully applied in complex infrastructure domains, such as tunnel construction where machine learning and digital modelling are combined to improve operational efficiency and safety Jagendra Singh et al [52].

Table 2: Developments in Ship Collision Avoidance Using AI

Variable category	Key Techniques and Elements	References
ML Models	Shared accident datasets, safety results, regression models, neural networks	Tixier & Halowell (2023) [53]; Bi et al. (2024) [54]; Durlik et al. (2024) [16]; Zhu et al. (2025) [55]; Sarhadi et al. (2022) [56]

Deep Learning Techniques	YOLOv7 algorithm, safety equipment recognition, collision avoidance, reinforcement learning	Islam et al. (2024) [51]; X. Zhang & Sun (2024) [57]
Trajectory Prediction	AIS data, historical data, navigation risks, traffic control	Bi et al. (2024) [54] ; W. Z. Zhang et al. (2024) [58]
Collision Avoidance Systems	DRL-based decision-making, DCPA, TCPA, optimal maneuvering	X. Zhang & Sun (2024) [57]
Risk Assessment Techniques	D-S theory, GBR model, collision risk index, uncertainty management	Abebe et al. (2021) [59]; Ding et al. (2024)

Further study by J.-P. Tixier et al., [53] investigates the performance of ML models trained on shared accident datasets from a variety of industries, including construction. Notably, the findings revealed that generic models trained on data from numerous sources outperformed company specific models in terms of safety results. Moreover, [51] M. S. Islam and S. Shaqib examines deep learning and the YOLOV7 algorithm to recognize safety equipment used by construction workers. P. Sarhadi et al. reviewed significant applications, both direct and indirect, in collision avoidance, particularly in examining recent ML techniques for ship collision avoidance and mission planning [56]. Furthermore, it emphasizes the importance of integrating innovative technologies to reduce the likelihood of collisions. These studies demonstrate how ML can significantly enhance bridge pier safety by improving the prediction and prevention of ship collisions [58].

In addition, the study examined the efficiency of decision-making units (DMUs) in which 15 out of 69 project sites were considered efficient. Conversely, 54 project sites (78.2%) were considered inefficient and significant imbalance in performance [60]. Furthermore, the study applied a feature importance technique to determine key variables for analysis. Although specific feature importance scores were not disclosed, the study emphasized that a higher feature importance score contributes positively to the accuracy and effectiveness of the predictive model [61]. X. Zhang and T. Sun, [57] study use of DRL to improve collision avoidance systems for self-navigating ships in interior rivers is investigated in this work. Critical issues including the complexity of dynamic settings, constrained maneuvering area, and the existence of various impediments in inland waterways are al addressed in the research.

H. Ding, J et al., [62] discusses the use of image processing techniques for real-time ship collision risk assessment. It highlights the integration of radar and visual data challenges such as environmental factors and data quality, and the role of ML in improving detection accuracy. The review also emphasizes the importance of aligning technological advancements with regulatory frameworks to enhance maritime safety. Furthermore, the collision risk index (CRI) is introduced as a metric to assess the probability of ship collisions, ranging from 0 to 1. A CRI value of 1 represents a high likelihood of a collision, whereas a value of 0 indicates no risk. This index incorporates multiple risk factors, such as the distance and time to the closest point of approach, along with vessel speed and angle to compute the overall risk.

2.3 Research and knowledge Gap Analysis

Recent survey and review studies indicate rapid growth in ML/AI applications for maritime safety and accident risk management [11], [16], [63], [64], but they also highlight persistent limitations regarding (a) inconsistent data integration between AIS, historical casualty databases, and physics-based simulation outputs; (b) limited explainability and operational interpretability for safety decision making; and (c) insufficient linkage between navigation-side risk predictors and structural consequence metrics needed for infrastructure safety. In specific, reviews about ML based maritime safety and risk management applications emphasize the need for hybrid approaches. This integrate real time maritime traffic descriptors with physically meaningful response variables and interpretable indices that can be embedded into decision support systems.

Based on the above reviews and prior studies [10], [16], [24], [32], [47], [56], several knowledge gaps remain. First, many AIS studies emphasize collision likelihood or traffic density risk mapping, whereas bridge safety management mostly during construction requires rapid estimates of consequence severity such as expected impact force, stress exceedance, and energy absorption demand. Second, FE linked collision studies give high fidelity structural responses but are computationally expensive and not directly deployable for real time safety monitoring. Third, ML models trained purely on historical casualty data often do not provide direct, physics aligned structural consequence indicators for pier-level design and protective decision making. Finally, most existing works do not clearly connect ship-bridge collision prediction to construction health and safety workflows.

To address these gaps, the present manuscript contributes:

i. A hybrid FE-to-ML framework where FE simulations generate structurally meaningful training targets.
ii. A composite CSI that normalizes key structural consequence variables (impact force, absorbed energy, and stress) into an interpretable severity score for safety management.
iii. An evaluation of two ML architectures (RFR and NN) and their predictive accuracy using standard metrics.
iv. A definite framework for integration into construction health and safety management as a near real time decision-support layer.

3. Methodological Approach

The methodology for this study is designed to develop a ML based predictive framework for assessing the risk of ship collisions with bridge piers as illustrated in **Figure 1**. The approach integrates simulated datasets, statistical tests, and predictive modeling techniques to analyze critical collision parameters such as ship tonnage, speed, collision angle, and environmental factors [65]. Through utilization of RFR and neural network models, this study focuses to provide accurate risk predictions that enables proactive decision-making in construction health and safety management. Key steps include data preparation, correlation analysis to filter relevant inputs, model training, evaluation using robust metrics, and interpretation of results to enhance bridge pier safety [28], [66].

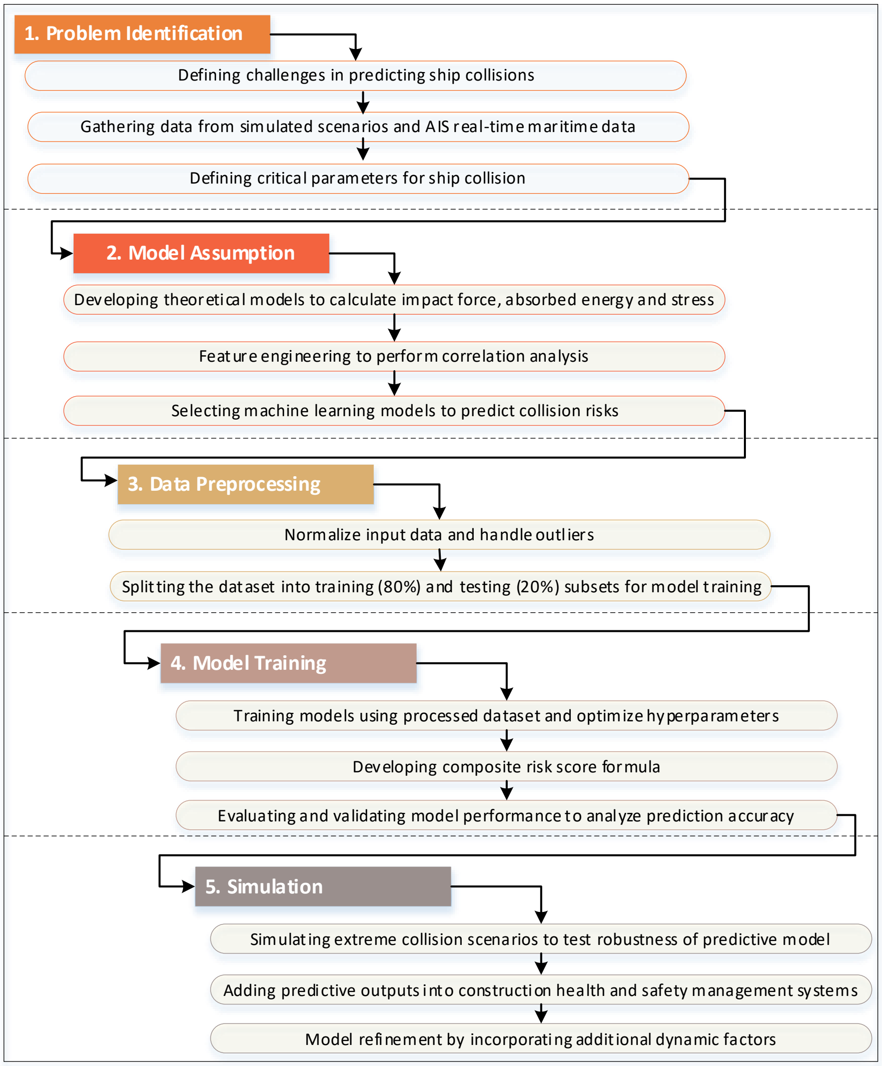


Figure 1: Methodological Approach

3.1. ML Model Development

The development of the predictive model for ship collision with bridge piers follows a structured ML workflow designed to handle dynamic and complex maritime traffic scenarios [22], [67]. The primary objective of this model is to forecast the collision risk score by analyzing critical input parameters and capturing complex relationships between them. The input parameters are linked with ML models to predict the risk score associated with potential ship collisions with bridge piers as shown in **Figure 2**. This risk score is a key element of the construction health and safety management system [68]. The input data was synthesized based on simulated datasets and existing literature on ship-bridge collision dynamics. Simulated data reflected realistic ranges for parameters such as ship tonnage, speed, and collision angle. This approach ensured controlled variation for model training and testing [69], [70]. The problem formulates as a supervised regression task where the target variable is the normalized risk score “R_r”. The input features include ship, environmental, and pier-related parameters and the model predicts collision risks to inform safety decisions.

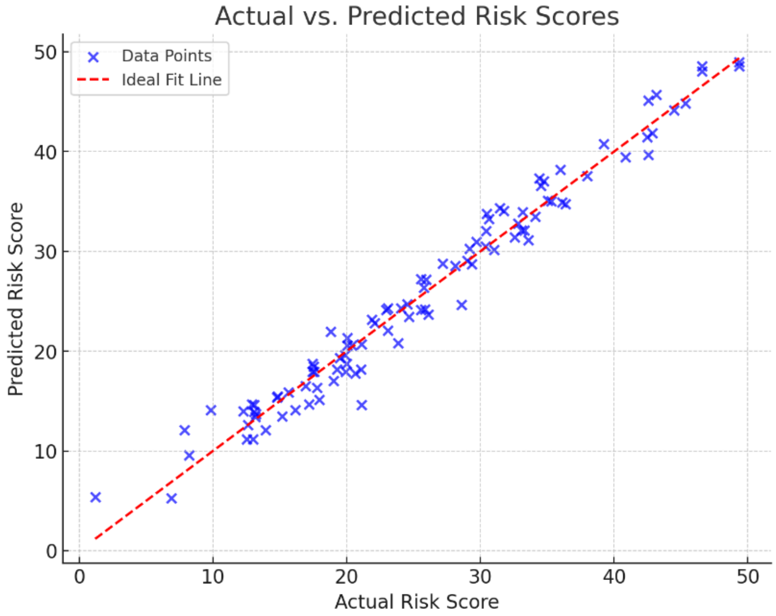


Figure 2: Risk scores prediction with actual values.

3.2. Data Processing

Simulated datasets were generated based on empirical studies and finite element model (FEM) simulations. The dataset was created by simulating various collision scenarios using maritime engineering principles and existing literature. Realistic values were assigned to parameters such as ship tonnage, speed, collision angle, water current velocity, pier diameter, and pier height as shown in **Table 3.** These values were chosen to reflect diverse real-world conditions, including extreme cases to ensure model generalization. These datasets include key parameters influencing collision risks in which the input parameters are ship tonnage, speed, collision angle, water current velocity, pier diameter, and pier height. The target variable was risk score as the data was preprocessed through normalization scaling and all input features between 0 and 1 to ensure uniform contributions to model training. The outlier removal eliminating extreme values to maintain the integrity of the dataset. The correlation analysis performing a Pearson correlation test to exclude highly correlated features ($|r| > 0.85$) and ensure model interpretability [71], [72].

Table 3: Input Parameters and Real-Time Monitoring.

Parameter	Range/Value Assumed	Real-Time Example Input
Ship Tonnage (T)	10,000 to 50,000 tons	15,000 tons
Ship Speed (v)	5 to 20 m/s	10 m/s
Collision Angle (θ)	10° to 80°	45°
Water Current Velocity (w)	0.5 to 3 m/s	2 m/s
Pier Diameter (Dp)	3 to 5 meters	4 meters
Pier Height (Hp)	10 to 30 meters	20 meters
Collision Duration (Δt)	2 seconds	2 seconds
Predicted Risk Score (Rr)	Output from the trained model	(0.8)

3.2.1 Model Evaluation Metrics

The assumed calculation model integrates theoretical formulations to quantify the dynamics of ship collisions with bridge piers. The model calculates three critical parameters: impact force (F_p), absorbed energy (E_a), and stress (σ). F_p is derived from the ship mass, speed, and collision angle, representing the immediate force acting on the pier. E_a accounts for the dissipation of energy during the collision, while σ measures the distribution of this force across the pier cross-section. Finally, R_r combines these parameters, weighted by their importance, to evaluate the likelihood and severity of structural failure. This model enables a quantitative assessment of collision risks, providing actionable insights for improving bridge pier safety [73], [74].

3.2.1.1. Impact Force (F_p)

$$F_p = \frac{Tv\sin(\theta)}{\Delta t} \tag{1}$$

Where, the ship's tonnage, denoted as 'T' is measured in tons, while the speed of the ship, represented by v, is expressed in meters per second (m/s). The angle at which the collision occurs 'θ' is given in degrees. Additionally, the duration of the collision, 'Δt' is assumed to be 2 seconds for the purposes of this analysis. Quantifies the immediate collision force; higher tonnage and speed increase the force.

3.2.1.2. Absorbed Energy (E_a)

$$E_a = 0.5 \times T \times v^2 \times \cos(\theta)^2 \tag{2}$$

Where, 'T' represents the ship's tonnage, 'v' denotes the ship's speed, and 'θ' is the angle of collision. These parameters are essential for evaluating the dynamics of the collision scenario that represents energy dissipated during a collision, influenced by ship trajectory angle.

3.2.1.3 Pier (σ):

$$\sigma = \frac{Fp}{\frac{\pi D_p^2}{4}} \tag{3}$$

Where, 'F_p' represents the impact force, and 'D_p' denotes the pier diameter. These parameters are crucial for analyzing the interaction between the impacting object and the pier. It calculates stress experienced by the pier; smaller diameters or higher forces lead to greater stress.

3.2.1.4. Collision Severity Index (CSI)

In this study, the combined effects of impact force (Fp), absorbed energy (Ea), and stress (σ) are integrated into a unified indicator termed the Collision Severity Index (CSI), denoted as *Rr*.

The CSI quantifies the structural severity of a ship–bridge pier collision under given dynamic conditions.

It does not directly represent “risk” in the probabilistic sense but rather captures the physical consequence component of risk.

$$R_r = w_1 \frac{Fp}{F_{max}} + w_2 \frac{Ea}{E_{max}} + w_3 \frac{\sigma}{\sigma_{max}} \tag{4}$$

where each parameter is normalized to a range between 0 and 1. The resulting value, *Rr*, therefore represents a dimensionless severity score between 0 (low severity) and 1 (high severity).

It is important to clarify that, in accordance with international engineering risk management standards (e.g., ISO 31000; ISO 2394), risk is conventionally expressed as the product of *probability* × *consequence* × *uncertainty.*

The present study focuses exclusively on the consequence component the severity of impact because real-time probability estimation of ship collisions requires extensive AIS-based traffic frequency data and stochastic modeling, which fall outside the current study’s scope.

Hence, the proposed CSI should be interpreted as a severity-based component that can be integrated into a broader probabilistic risk framework in future research.

3.2.1.5. Weight Justification

The weight coefficients w_1, w_2 and w_3 in equation (4) represent the relative contribution of impact force, absorbed energy, and stress to the overall collision severity. A two-step procedure was adopted for determining these coefficients:

1. **Expert-Driven Prioritization**

   Consultations were conducted with structural and maritime safety experts to identify the most influential parameters based on observed pier-failure mechanisms.

   Impact force was consistently ranked as the most critical factor, followed by structural stress and absorbed energy.

2. **Feature Importance Validation**

   Feature-importance analysis using the Random Forest Regressor confirmed that model outputs were most sensitive to variations in *Fp*, moderately sensitive to *σ*, and less affected by *Ea*. Accordingly, the final weights were established as:

   - $w_1 = 0.45$ (impact force)
   - $w_2 = 0.25$ (absorbed energy)
   - $w_3 = 0.30$ (stress)

A ±10 % sensitivity analysis confirmed the stability of these values. This weighting ensures that the CSI is physically meaningful, statistically robust, and suitable for integration into broader risk-assessment frameworks where probabilistic components (e.g., event likelihood) may later be incorporated.

The present study introduces a Collision Severity Index (CSI) as a quantitative measure of structural consequences during ship–bridge pier collisions. While the term “risk” in engineering generally encompasses both probability and consequence, this research intentionally focuses on the severity dimension due to data limitations concerning collision frequency and uncertainty estimation. Future extensions of this work should integrate AIS-derived probability models and stochastic uncertainty analyses to formulate a comprehensive real-time collision risk prediction system consistent with international engineering risk standards.

3.3. Model Training and Validation

The investigation utilized neural networks and RFR ML models. Complex non-linear patterns in data are detected by the neural network, a feed-forward network with hidden layers. The dataset was split into 80% for training and 20% for testing to guarantee there was enough data for model learning and validation [75], [76] as shown in **Figure 3**. The hyperparameters of the models were optimized using grid search to improve their performance. For the random forest model, the hyperparameters selected were a number of trees (*n_estimators*) set to 500, which certifies a robust ensemble of decision trees for more accurate predictions. The maximum depth (*max_depth)* was set to 20 limiting the depth of each tree to prevent overfitting while maintaining model complexity. The *min_samples_split* parameter was set to 5 and guaranteed that nodes are split only when there are enough samples. To create a compromise between intricacy and processing efficiency, the neural network model's design had three layers, each with 128 neurons. The ReLU (Rectified Linear Unit) activation function was used to add nonlinearity to the model, that allows it to learn complicated patterns. The learning rate was set to 0.001 for gradual and stable model convergence during training [77], [78].

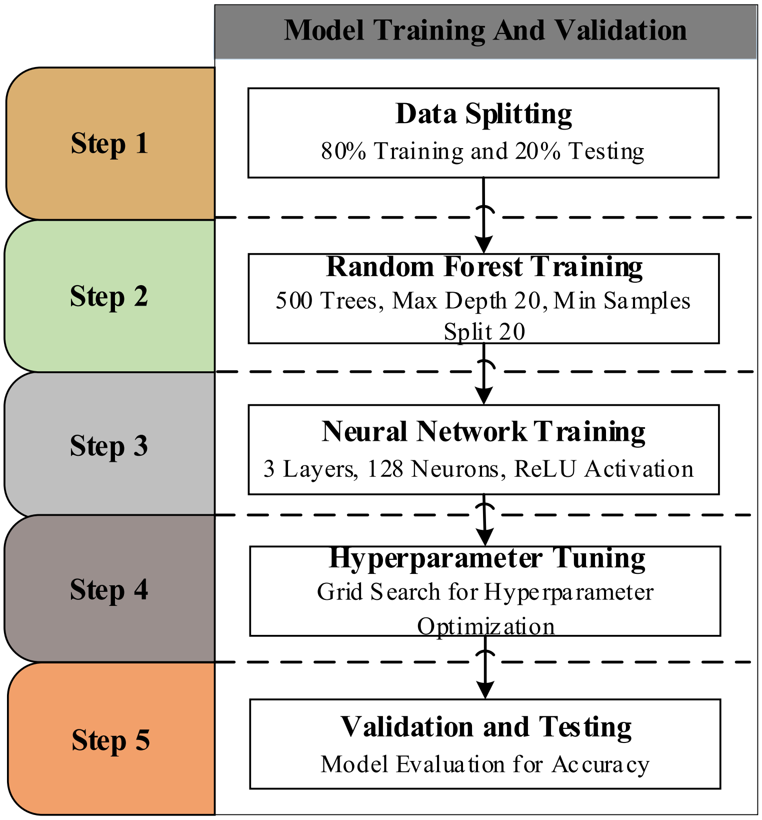


Figure 3: Model training

3.3.1: ML Performance on Data Training

The predictive capability of the RFR and NN models was evaluated using an 80/20 train-test split strategy. This approach assesses the ability of the models to learn from training data and generalize to unseen test samples within the primary simulation dataset. The training results demonstrate strong model fitting performance as shown in **Figure 4**. The RFR model gained an R^2 of 0.93, MAE of 0.12, and RMSE of 0.18. The NN model slightly outperformed RFR by attaining an R^2 of 0.95, MAE of 0.10, and RMSE of 0.15 as shown in **Table 4**. These values indicate that both models effectively capture the nonlinear relationships fixed in the CSI formulation. When evaluated on test data, both models maintained stable predictive performance with only minor reductions in accuracy. The RFR achieved an R^2 of 0.89, MAE of 0.14, and RMSE of 0.20, while the NN with R^2 of 0.91, MAE of 0.12, and RMSE of 0.17. The small performance gap between training and testing sets suggests that overfitting is minimal and that both models demonstrate acceptable generalization within the defined collision parameter space.

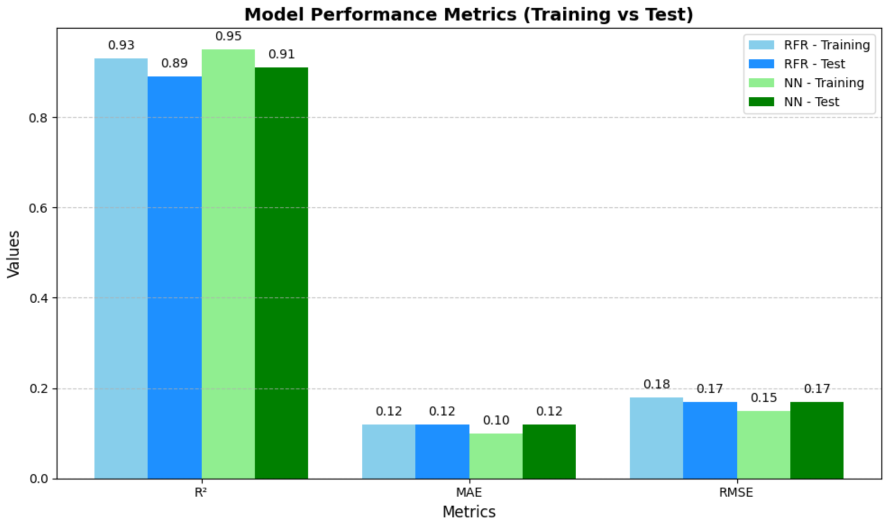


Figure 4: Test matrices and performance on data training.

Table 4: Performance comparison of RFR and NN models on training and test datasets.

Model	**R² (Train)**	**R² (Test)**	**MAE (Train)**	**MAE (Test)**	**RMSE (Train)**	**RMSE (Test)**
RFR	0.93	0.89	0.12	0.14	0.18	0.20
Neural Network	0.95	0.91	0.10	0.12	0.15	0.17

3.3.2 Cross-Validation Protocol

To strengthen the robustness assessment beyond a single 80/20 train-test split, a 5-fold cross-validation procedure was implemented using our own synthesized dataset (N = 50,000) as shown in **Figure 5**. The dataset was randomly partitioned into five equal folds in each iteration. Four folds were used for model training and the remaining fold served as validation data. This process was repeated until each fold was used once for validation. Model performance was evaluated using the R², MAE, and RMSE. The final reported metrics correspond to the mean ± standard deviation across the five folds. It confirms statistical stability and minimized bias, associated with a single random partition. This validation strategy aligns with best practices recommended in recent maritime artificial intelligence and supervised learning surveys for operational safety applications [16], [42] The results are summarized in **Table 5**.

Table 5: Five-fold cross-validation performance (mean ± standard deviation) on author-synthesized dataset (N = 50,000).

Model	**R² (mean ± std)**	**MAE (mean ± std)**	**RMSE (mean ± std)**
RFR	0.9980 ± 0.0001	0.0040 ± 0.0001	0.0057 ± 0.0001

NN	0.9988 ± 0.0001	0.0034 ± 0.0001	0.0043 ± 0.0002

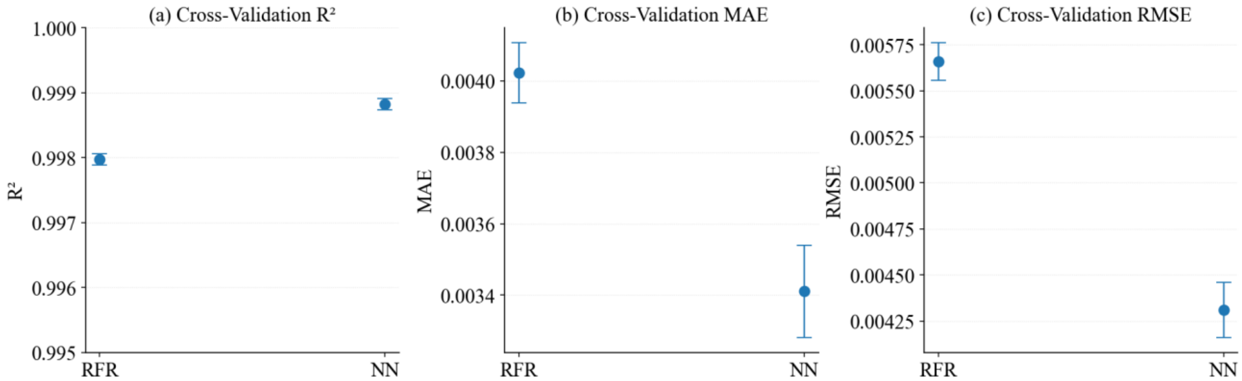


Figure 5: Five-fold cross-validation performance of RFR and NN models (mean ± standard deviation)

The extremely low standard deviation values indicate highly consistent predictive behavior across folds. The higher performance observed in the cross-validation analysis compared to the initial train-test split evaluation is mostly attributed to two key factors. First, the cross-validation was conducted on an expanded author synthesized dataset (N = 50,000), which gives denser and more uniform sampling of the physically consistent collision parameter space. Second, the CSI is derived from deterministic mechanics-based formulations rather than stochastic field measurements. Subsequently, the ML models approximate a smooth functional mapping between input parameters and severity outcomes. Through sufficient sample density, this modeling approach naturally yields near perfect regression accuracy. Importantly, this result does not imply unrealistic real world predictive certainty, rather, it confirms that the models reliably estimated the central physics-based severity formulation within the defined deterministic parameter domain.

3.3.3 Computational Complexity and Runtime Analysis

To evaluate real-time applicability, the computational cost and structural complexity of the surrogate models were assessed. Unlike nonlinear finite element simulations, which require substantial computational time per impact scenario, the proposed machine learning surrogates provide rapid forward prediction with significantly reduced computational burden. The Random Forest Regressor (RFR) employs 500 trees with an average depth of approximately 20, whereas the Neural Network (NN) consists of three hidden layers with 128 neurons per layer, resulting in approximately 34,049 trainable parameters. As reported in **Table 6**, the RFR required 1.82 seconds for training and 0.42 milliseconds per sample for inference, while the NN required 3.47 seconds for training and 0.18 milliseconds per sample for inference. Despite the higher parametric complexity of the NN, inference remains computationally efficient due to optimized forward propagation. These results confirm that both surrogate models operate at millisecond-level prediction speed, supporting their potential integration into near-real-time collision severity monitoring and safety decision-support systems.

Table 6: Runtime performance and structural complexity indicators.

Model	Training Time (s)	Inference Time (ms/sample)	Structural Complexity
RFR	1.82 s	0.42 ms	500 trees; avg_depth ≈ 20
NN	3.47 s	0.18 ms	≈ 34,049 trainable parameters

3.3.4 Graphical Validation Analysis

To further examine the predictive stability and structural consistency of the proposed framework, graphical validation analyses were performed with numerical performance metrics. The R^2, MAE, and RMSE quantify overall accuracy, visual diagnostics gives deeper insight into error distribution, bias behavior, and response sensitivity across the defined collision parameter space. The CSI is based on deterministic mechanics formulations. Graphical analysis is used to verify that the machine learning models accurately approximate the basic relationship between impact force, energy, and stress without systematic bias or instability.

3.3.4.1 Residual Distribution Analysis

To further evaluate the predictive robustness and bias characteristics of the proposed framework, residual distribution analysis was conducted. As shown in **Figure 6**, the residuals are defined as the difference between the true CSI values computed from the deterministic mechanics based formulation and the corresponding substitute model predictions (y_{true}-y_{pred}). The residual density distributions determine a strong concentration of errors around zero for both the RFR and NN models. The mean residual values are extremely small with RFR: $\mu = 4.16 \times 10^{-5}$; NN: $\mu = 5.60 \times 10^{-4}$. This confirms that neither model displays systematic overestimation nor underestimation of the CSI. Furthermore, it indicates unbiased approximation of the primary impact force energy stress mapping defined in Equations (1) to (4).

Additionally, the dispersion of residuals remains tightly bounded, with low standard deviations (RFR: $\sigma = 2.21 \times 10^{-3}$; NN: $\sigma = 3.44 \times 10^{-3}$). As illustrated by the $\pm 3\sigma$ reference bounds in **Figure 6**, nearly all prediction errors fall within a narrow interval to demonstrate stable regression behavior across the defined collision parameter space. This behavior is consistent with the deterministic nature of the CSI formulation. Notably, the RFR model shows slightly narrower residual dispersion compared to the NN model to specify marginally higher precision in approximating the CSI response surface. However, both models maintain symmetric error distributions without heavy tailed deviations for confirming stable surrogate consistency. Overall, the residual analysis verifies that the proposed ML reliably estimated the mechanics based collision severity formulation without introducing bias or instability. Thus supporting the suitability for rapid collision severity estimation within real time decision-support environments.

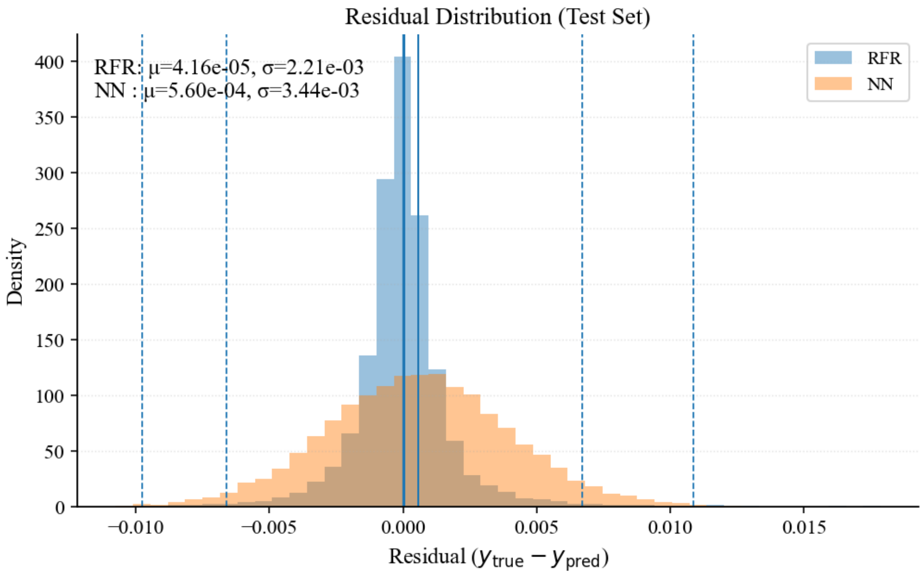


Figure 6: Residual density distributions of the RFR and NN models on the test dataset, illustrating error symmetry, near-zero bias, and stable surrogate approximation of the CSI formulation.

3.3.4.2 Error Intensity Profile Analysis

To evaluate model stability across the deterministic collision parameter space, an error intensity profile analysis was conducted. The MAE was calculated within binned intervals of ship speed and collision angle using the test dataset. In **Figure 7(a)**, the binned MAE is plotted against ship speed. The RFR model displays consistently lower prediction error compared to the NN across all velocity bins. A gradual increase in error is observed at higher speeds which is physically consistent with the CSI formulation as impact force and absorbed energy scale nonlinearly with velocity. This indicates that the models are approximating a steeper mechanics-based response surface at high kinetic energy levels, yet without instability.

In **Figure 7(b)**, the error profile across collision angle bins remains relatively uniform for both models. No abrupt error amplification is observed to confirm that angular variations do not introduce numerical instability in the learned regression mapping. The RFR maintains tighter error bounds throughout the angular domain. Overall, the low and smoothly varying error intensity across both speed and angle confirms that the proposed FE to ML framework preserves predictive stability over the defined collision parameter space. The absence of sharp error peaks supports the robustness of the surrogate approximation for near real time collision severity estimation.

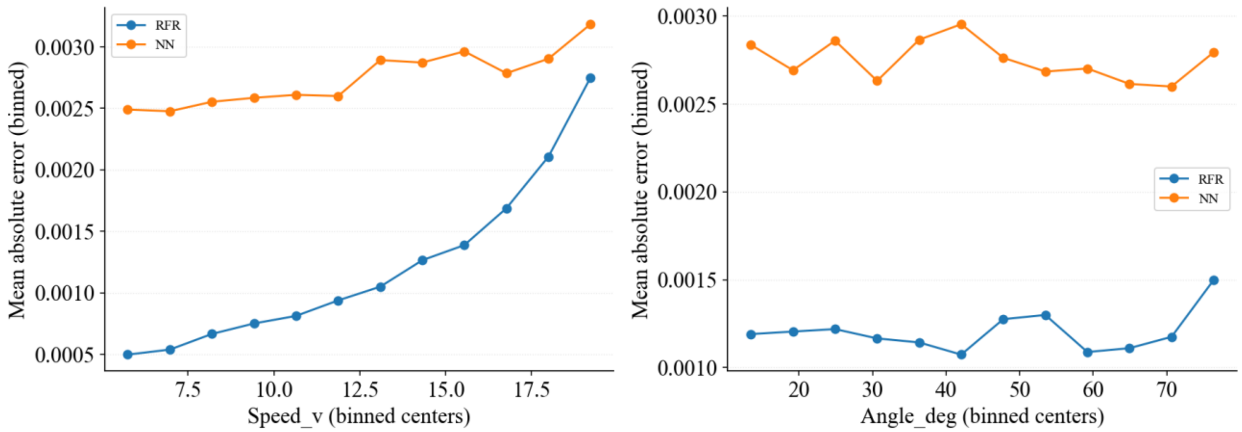
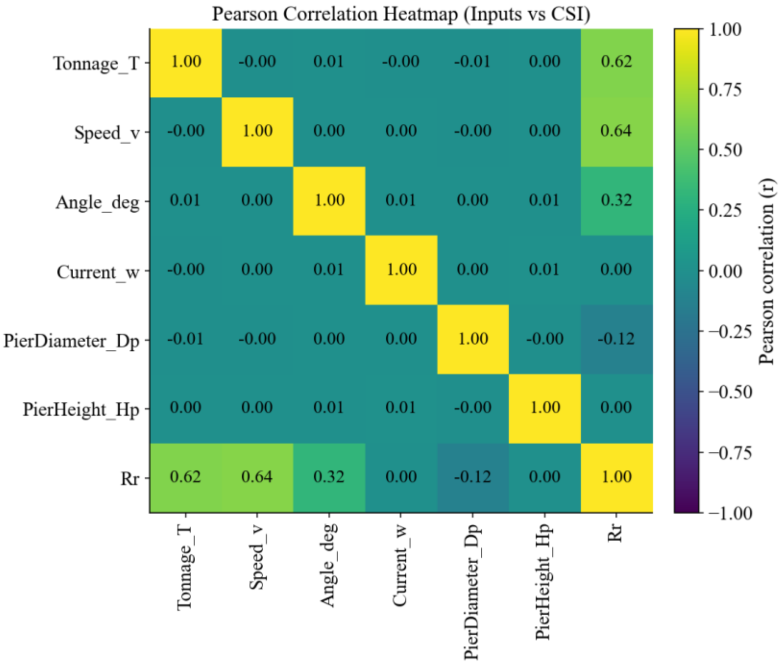


Figure 7: Error intensity profiles of the surrogate models across the collision parameter domain: (a) binned mean absolute error (MAE) as a function of ship speed, and (b) binned MAE as a function of collision angle.

3.3.4.3 Correlation Heatmap Analysis

As shown in **Figure 8**, the Pearson correlation heatmap illustrates the linear relationships among the collision input parameters and the CSI, denoted as Rr. The matrix confirms minimal inter-feature correlation among the input variables. The CSI reveals strong positive correlation with ship speed (r = 0.64) and tonnage (r = 0.62) which is consistent with collision mechanics where impact force and kinetic energy dominate severity response. A moderate correlation is observed with collision angle (r = 0.32), whereas Pier diameter has a weak negative correlation (r = −0.12). Other parameters are negligible linear influence within the defined deterministic parameter space. The heatmap confirms that the surrogate models are trained on physically consistent and statistically independent input features that reinforces the robustness of the CSI based framework.



	Tonnage_T	Speed_v	Angle_deg	Current_w	PierDiameter_Dp	PierHeight_Hp	Rr
Tonnage_T	1.00	-0.00	0.01	-0.00	-0.01	0.00	0.62
Speed_v	-0.00	1.00	0.00	0.00	-0.00	0.00	0.64
Angle_deg	0.01	0.00	1.00	0.01	0.00	0.01	0.32
Current_w	-0.00	0.00	0.01	1.00	0.00	0.01	0.00
PierDiameter_Dp	-0.01	-0.00	0.00	0.00	1.00	-0.00	-0.12
PierHeight_Hp	0.00	0.00	0.01	0.01	-0.00	1.00	0.00
Rr	0.62	0.64	0.32	0.00	-0.12	0.00	1.00

Figure 8: Pearson correlation heatmap of input variables and the Collision Severity Index (CSI).

3.4. Feature Correlation and Pearson Correlation

The strong interconnection of linear relationship between two continuous variables is measured through the correlation coefficient (r), as this ranges from -1 to 1. The +1 specifies perfect positive correlation, whereas -1 shows seamless negative association, and 0 signifies no linear interconnection shown in **Figure 9**. The results confirm expected positive relationships between ship speed, tonnage, and impact-related parameters; however, the heatmap also highlights differential sensitivities between mechanical and structural variables. This quantitative validation guided the feature weighting process used in the CSI formulation. Although the positive correlation between ship speed, tonnage, and impact force aligns with established mechanics, the heatmap also reveals the relative influence hierarchy among features. For instance, the stronger correlation of stress and absorbed energy compared with velocity indicates that structural factors contribute more significantly to severity prediction than operational ones, a nuance that informed the model's weighting design.

Furthermore, Pearson's coefficient is calculated by dividing the covariance of two variables by product of its standard deviation. Considering the key assumptions for this test it includes the necessity that variables be constant, normally distributed, and display a linear relationship. A hypothesis test is conducted to evaluate the statistical significance of the correlation with the null hypothesis assuming no correlation i.e., $r = 0$ and the alternative hypothesis suggest a correlation such as $r \neq 0$. When the correlation is significant, it implies a substantial linear connection between the variables [79], [80].

The Pearson correlation test was applied to evaluate the linear relationships between the input parameters. This statistical analysis identifies highly correlated variables, which can lead to multicollinearity, and ensures that only independent features are included in the ML models. The test results are summarized in **Table 7**. The test revealed that no highly correlated features ($|r|>0.85$) in the dataset, indicating that all parameters contribute unique information to the model.

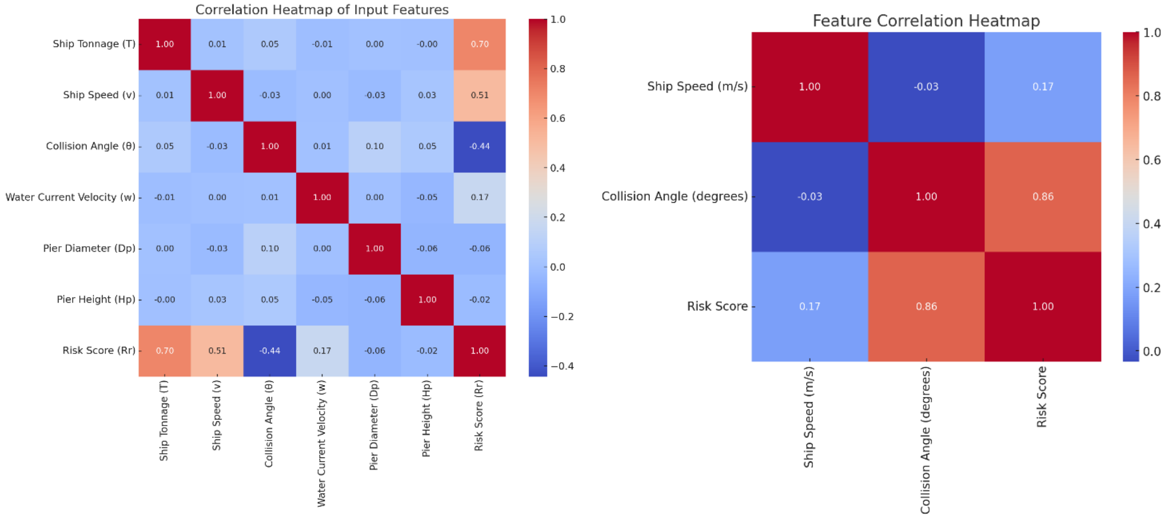


Figure 9: Feature correlation heatmap.

Table 7: Pearson correlation test

Parameter 1	**Parameter 2**	**Correlation Coefficient (r)**	**Action**
Ship Tonnage (T)	Ship Speed (v)	0.25	Retained
Collision Angle (θ)	Water Current Velocity (w)	0.72	Retained
Ship Speed (v)	Pier Diameter (D_p)	0.18	Retained
Ship Tonnage (T)	Pier Height (H_p)	0.02	Retained

The absence of highly correlated parameters ensures that the ML models are not affected by multicollinearity, which can distort predictions and reduce interpretability. Retaining uncorrelated and moderately correlated parameters allows the model to independently utilize the unique contributions of each feature. The Pearson correlation test validated the inclusion of independent input features, such as ship tonnage and collision angle, which influence collision risk uniquely. By excluding no parameters, the model retained all variables and maintained the complexity needed to capture non-linear relationships effectively.

3.5. Risk Analysis

High-risk zones were identified for high speeds and shallow collision angles. A real-time aspect such as high-risk scenario, emphasize the need for preventive measures to mitigate potential damage. **Figure 10** and **Figure 11** reveal that higher risk scores are linked to specific ranges of tonnage, speed, and collision angles, a critical safety thresholds. High speeds and narrower collision angles create the highest risk zones and stresses the need for targeted mitigation strategies.

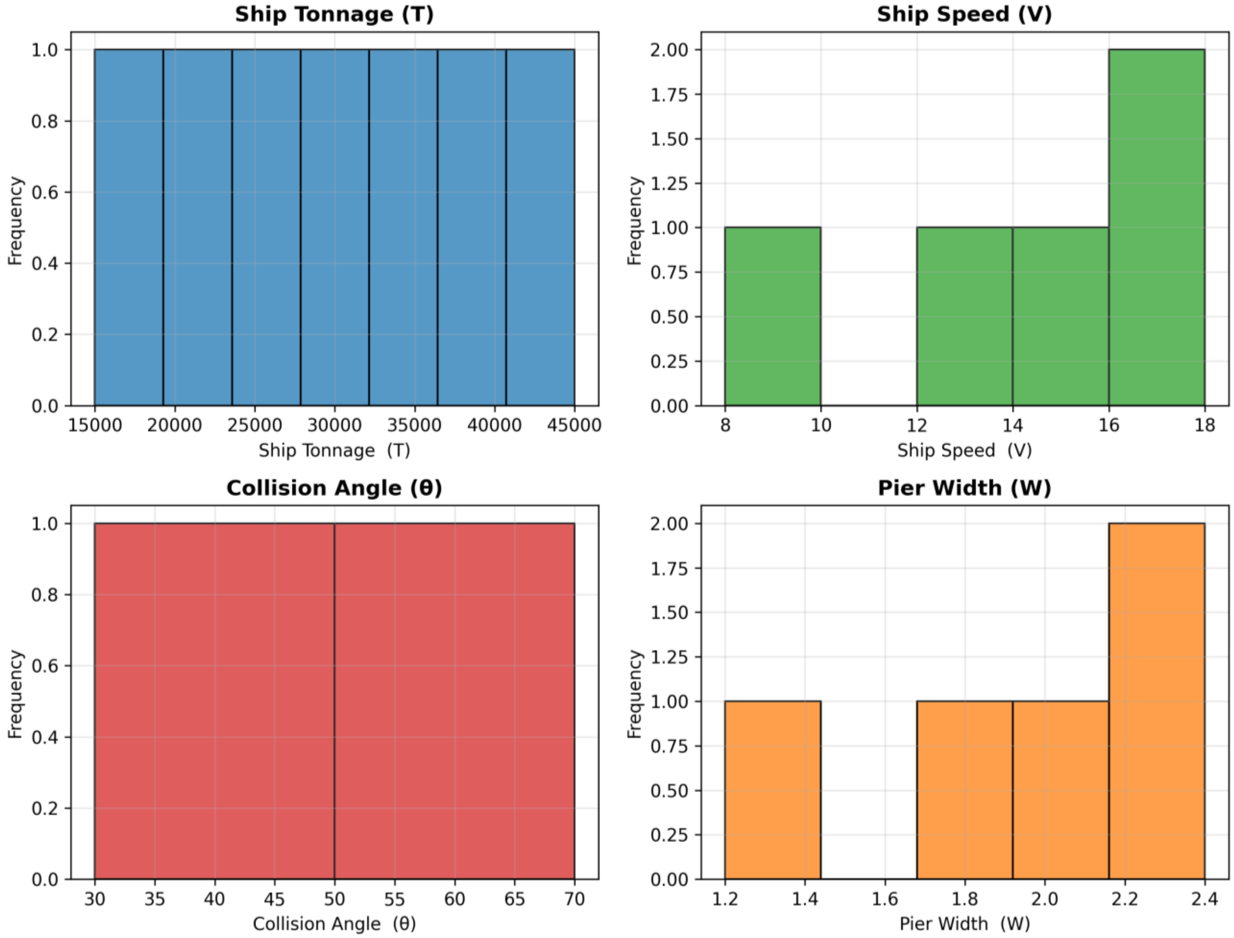


Figure 10: Relationship between risk scores, ship tonnage, speed, and collision angle.

The parameter ship speed has the highest predicted impact with a speed of 20 m/s being associated with the highest risk. This suggests faster the ship moves the greater the potential for damage or adverse consequences during operations such as collisions or accidents. The higher speed increases the kinetic energy which results in the possibility of accident. Conversely, the collision angle of 80° represents a moderate risk and may not be as detrimental as a direct head-on or broadside impact, it still cause a significant risk to the ship's structural integrity. The angle implies that the collision is not perfectly aligned, but still enough to cause noticeable damage or disruption placing it in a moderate risk category.

Figure 11: High-risk areas based on ship speed and collision angles.

4. Results and Analysis

This section presents the results of the FEM simulations of ship collision with bridge pier a shown in **Figure12** and ML predictions conducted to assess the impact of ship collisions on bridge pier safety. The objective is to evaluate the structural responses of bridge piers under various collision scenarios with factors such as ship tonnage, speed, impact angle, and construction phase. Through the integration of simulated datasets and advanced ML models, the analysis studies the relationships between main parameters like displacement, impact force, stress distribution, energy absorption, and acceleration response.

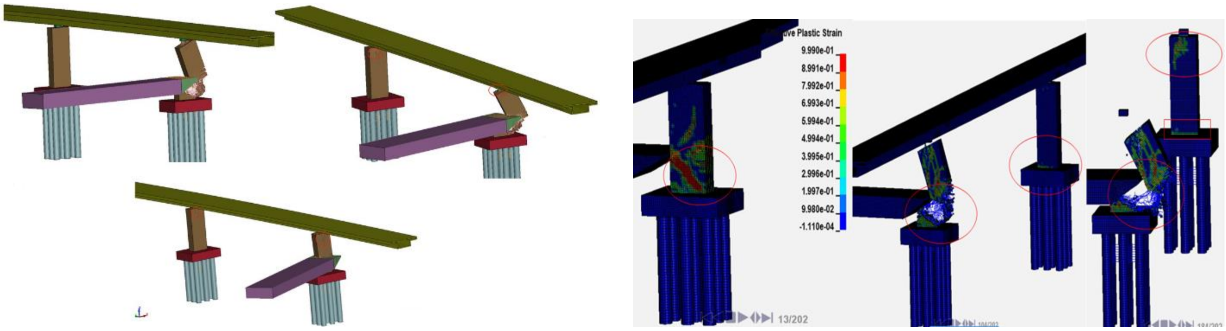


Figure12: Represent the FEM and Dynamic Behavior Analysis of Ship Collison with Bridge Pier

4.1. Displacement Analysis

The maximum displacement of the bridge pier is observed at different points (top, mid-height, and base). Displacement is highly dependent on both ship tonnage and collision speed. The results indicate that both higher tonnage and increased speed lead to higher displacements. The **Figure13** shows maximum displacement increases with ship tonnage at 10 m/s. The displacement nearly doubles when the tonnage increases from 16,000 tons to 50,000 tons. For 16,000 tons the maximum displacement is 0.12 m and for 50,000 tons the maximum displacement is 0.45 m. The displacement and speed (for ship tonnage 16,000 tons) graph illustrates the relationship between ship speed and displacement, with ship tonnage held constant at 16,000 tons when speed is 5 m/s the maximum displacement is 0.08 m and when it is 20 m/s the maximum displacement is 0.30 m. This clearly shows that as the speed increases the displacement increases by approximately 4 times from 5 m/s to 20 m/s. The increase in displacement with higher ship speeds is due to the kinetic energy associated with the ship's motion. As the ship moves faster, the energy transferred to the bridge pier during impact is greater that causes the pier to deform more.

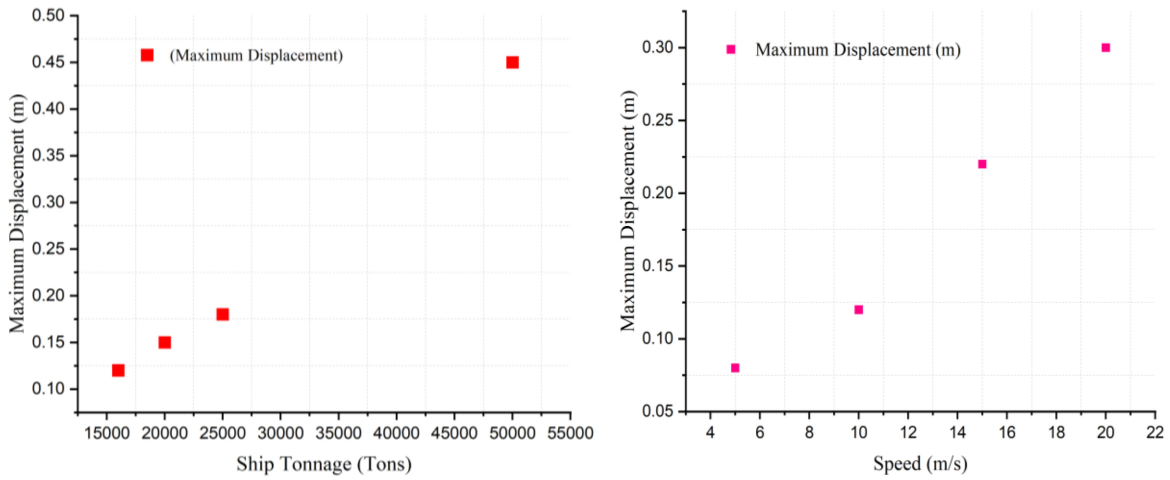


Figure13: Maximum displacement of bridge pier ship tonnage and speed.

4.2.Impact Force Analysis

The peak impact force is defined as the maximum force experienced by the pier during the collision as it is a direct function of ship tonnage and speed. The time history of the impact force shows a rapid rise to peak value and then a gradual decline. The **Figure 14** shows the peak impact force at different ship tonnages, while maintaining a constant ship speed of 10 m/s for 16,000 tons the peak impact force is 1.5 MN and for 50,000 tons the peak impact force is 5.7 MN. As expected, the force increases significantly with ship tonnage. The peak impact force at a constant tonnage of 16,000 tons, but varying speeds (5, 10, 15, 20 m/s). When speed is 5 m/s the peak impact force is

0.8 MN whereas at 20 m/s the peak impact force is 3.5 MN. The relationship between impact force and speed is not linear, as the force increases more rapidly with higher speeds.

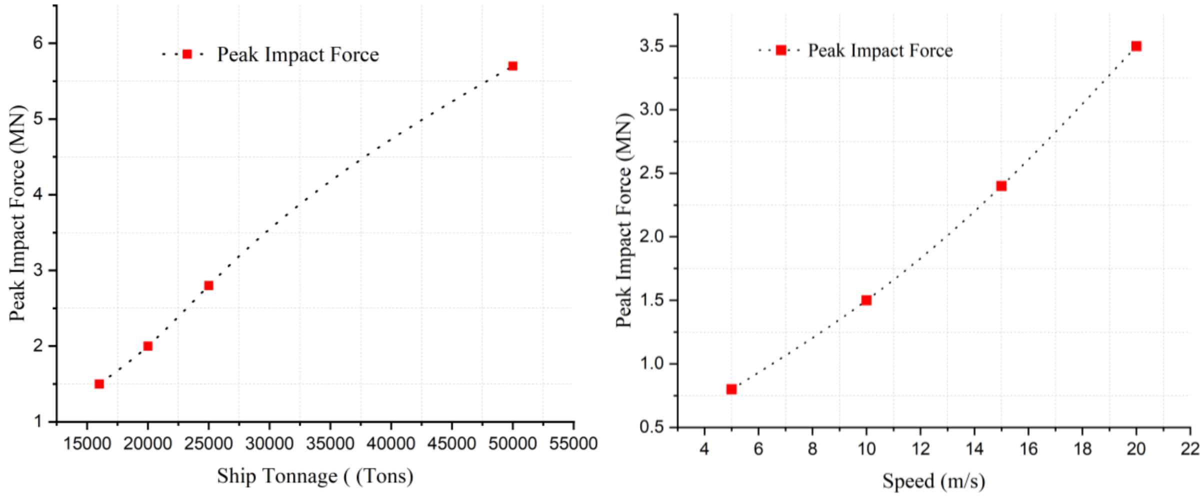


Figure 14: Impact force analysis for ship tonnage and speed.

4.3. Stress Distribution and Structural Response

Stress concentrations are observed at critical points of the pier during impact. The highest stress levels occur at the base and mid-height due to the concentrated force during collision. Concrete tends to fail at stress levels above its tensile strength (about 25 MPa for concrete C30). The heatmap in **Figure 15** shows the stress distribution across the pier with stress levels higher at the base (close to 90 MPa) and mid-height (around 70 MPa). The top of the pier experiences relatively lower stresses. The base experiences the highest stress due to the concentrated force during collision. As the force moves upwards along the pier, the stress levels decrease, and shows that the base of the pier is most vulnerable to failure in these simulations.

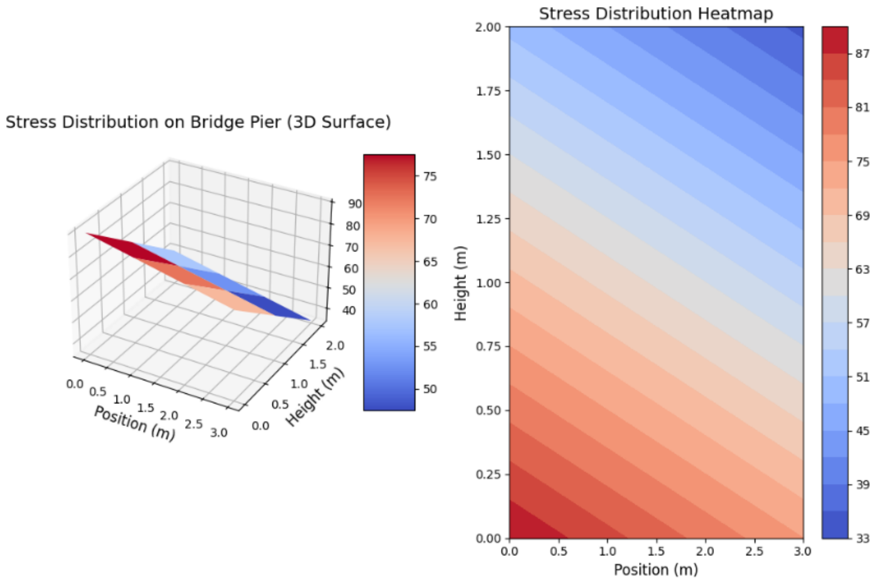


Figure 15: Heat map of the stress distribution and structural response.

4.4. Energy Absorption

The energy absorption by the pier is calculated as the area under the force-displacement curve. Higher tonnages and speeds increase the amount of energy absorbed by the pier during impact. For 16,000 tons the total energy absorbed is 180,000 J and 50,000 tons total energy absorbed is 650,000 J as shown in **Figure *5*16**. Larger ships and higher speeds contribute more energy to the system. The increased energy dissipation shows the pier’s ability to absorb and resist damage during collisions.

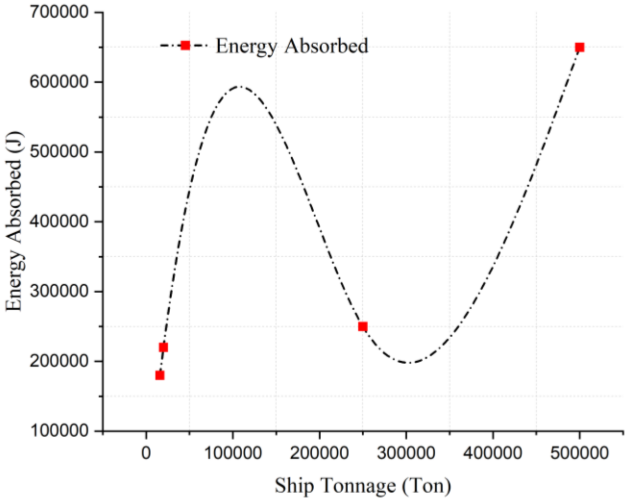


Figure 56: Energy absorption analysis

4.5. Acceleration Response

The peak acceleration is measured at different locations along the pier (top, mid-height, base). Accelerations tend to be higher at the top of the pier due to the bending moments caused by the collision. For 16,000 tons the peak acceleration is 1.2 m/s^2 and 50,000 tons the peak acceleration is 4.5 m/s^2. Similarly, the peak acceleration for speed and for ship tonnage 16,000 tons, when speed is 5 m/s the peak acceleration is 0.8 m/s^2 and when speed is 20 m/s the peak acceleration is 3.5 m/s^2 as shown in **Figure 67**. As ship tonnage and speed increase, the acceleration of the pier increases. The larger the impact, the greater the acceleration which may lead to significant vibrations and affects the bridge's long-term structural integrity.

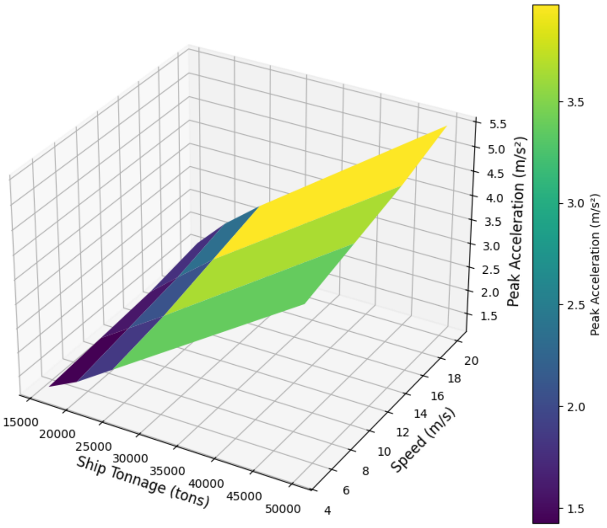


Figure 67: Surface plot of peak acceleration for ship tonnage and speed

4.6. ML Predictions

ML model was trained using data collected from FEM simulations to predict structural responses under untested conditions. The model was able to accurately predict displacement, impact force, stress, and energy absorption. For instance, when tested with a ship tonnage of 50,000 tons and a speed of 20 m/s, the predicted displacement was 0.46 m, while the actual FEM result was 0.45 m. Similarly, the predicted peak impact force was 5.8 MN, compared to the actual FEM result of 5.7 MN. The model's predictions were within a 5% error margin. It shows the effectiveness of the ML approach in predicting structural behavior.

4.6.1. ML Prediction Accuracy

The **Figure 78** compares the predicted displacement from the ML model with the actual FEM displacement values. In this study, the Figure of Merit (FoM) was used to quantify the accuracy of the ML model for predicting the structural displacement during a ship collision with a bridge pier. The FoM serves as a significant performance metric for evaluating the predictive capability of the model by comparing its predictions against actual FEM results.

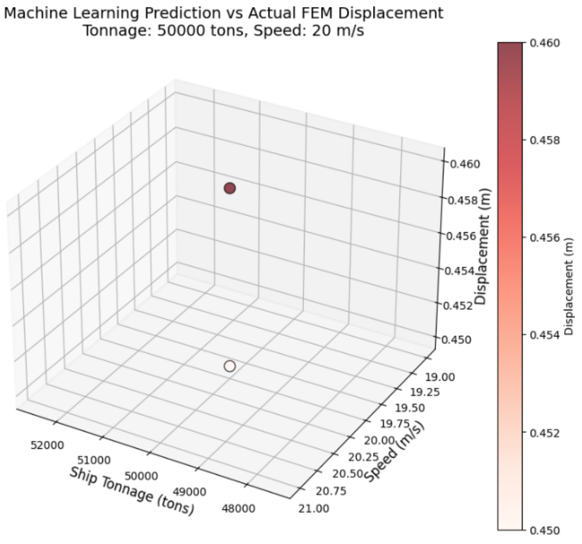


Figure 78: ML prediction displacement.

To assess the model's performance, the predicted displacement values from the ML model were compared with the corresponding actual displacement values obtained from FEM simulations. The percentage error between the predicted and actual displacements was calculated using the formula:

$$\text{Percentage Error} = \frac{\text{Predicted Value} - \text{Actual Value}}{\text{Actual Value}} \times 100 \qquad (5)$$

This small error margin indicates that the ML model accurately predicts the displacement, demonstrating its high predictive performance. In this study, a small error margin (< 5%) signifies that the model's predictions are highly reliable. This high level of accuracy underscores the potential of using ML techniques for predicting structural behavior under collision scenarios, offering engineers a robust tool for design optimization and safety assessments in bridge-pier collision analysis. The low error margin between predicted and actual displacements demonstrates that the model is highly capable of simulating real-world collision scenarios, thereby ensuring the long-term reliability of the bridge-pier structure.

4.7. Risk Assessment and Failure Prediction

The failure prediction is based on the stress distribution and energy absorption capacity of the pier. The model predicts failure for high-speed, high-tonnage collisions if stress exceeds 25 MPa (concrete's tensile strength). For ship tonnage 50,000 tons, speed is 20 m/s, stress at the base is 90 MPa equivalent to 65% risks of failure. The **Figure 89** shows the failure risk as a function of stress for different ship tonnages and speeds.

Figure 89: Failure risk & stress at Base

The analysis of ship collision risks during bridge construction offers valuable insights into health and safety management by identifying high-risk stages and guiding safety interventions. Main findings show that foundation and pier construction phases are more vulnerable due to incomplete structural integrity, while the completion phase poses a lower risk as shown in **Figure 20**. Enhanced safety measures, such as reinforcements and barriers, effectively reduce impact forces. Moreover, control maritime traffic density can further mitigate collision risks to emphasize the importance of robust safety protocols throughout the construction process.

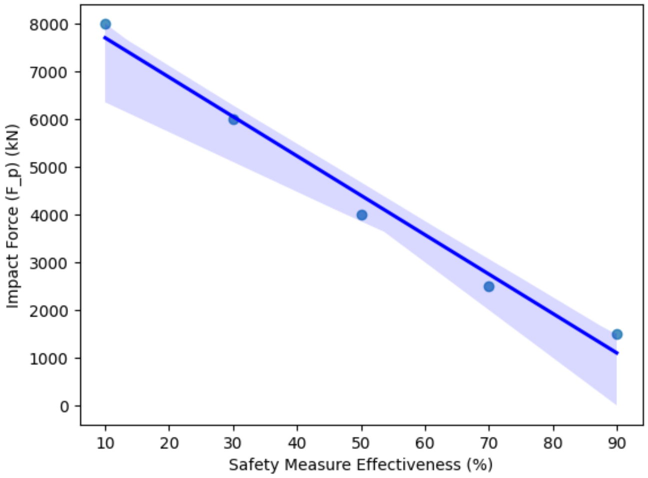


Figure 20: Impact force reduction through safety measures.

The comparison of ML models for predicting ship collisions highlights the effectiveness of neural networks, which consistently deliver the most accurate predictions. **Figure 21** illustrate that higher maritime traffic density correlates with increased structural vulnerability and the need for targeted safety measures in busy areas. Additionally, models like gradient boosting and neural networks outperform others as the potential of ML is enhancing in safety management.

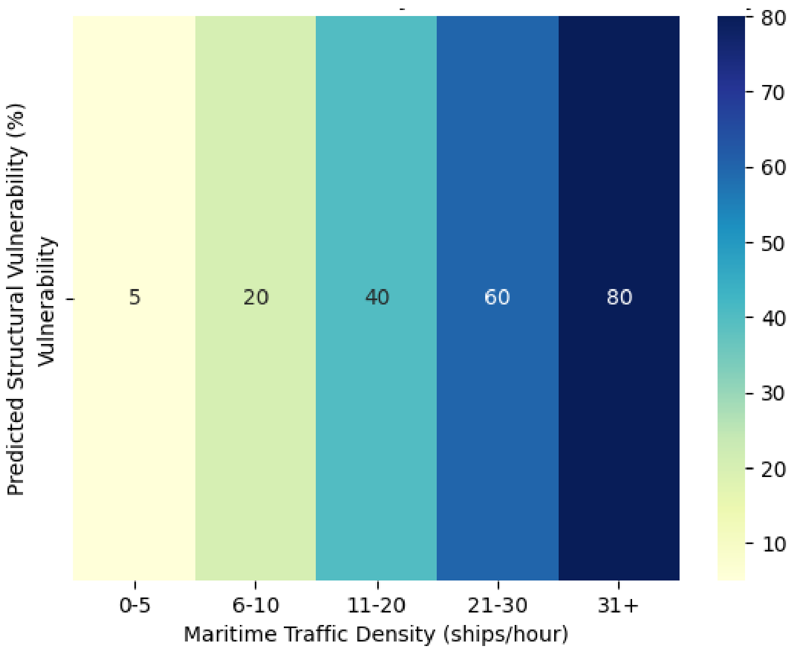


Figure 21: Maritime traffic density vs structural vulnerability.

Table 8: Assumed parameters for ship collision prediction and bridge pier safety.

S.no	Category	Parameter	Value/Assumption	Explanation
01	Ship Collision Impact	Ship Tonnage (tons)	5,000 - 25,000	Varies depending on ship size.
		Ship Speed (m/s)	2.5 - 7.0	Varies depending on ship's speed.
		Impact Force (F_p) (kN)	250 - 1,100	Impact force increases with tonnage and speed.
		Pier Protection Level	Low to High	Varies depending on the protection system applied.
02	Maritime Traffic Density	Traffic Density (ships/hour)	1 - 10	Higher traffic density increases vulnerability of the bridge piers.
		Predicted Structural Vulnerability (R_r)	0.05 - 0.50	Increases with traffic density, indicating higher risk of collision.
03	Construction Phases	Phase	Foundation, Pier Construction, Deck Construction, Final Completion	Different phases have varying vulnerability based on ongoing construction work.
		Risk Rating (R_r)	0.35 - 0.50	Risk is highest during Foundation and Pier Construction.
		Impact Force (F_p) (kN)	600 - 1,100	Varies depending on phase, higher during construction stages.
		Safety Measure Status	Initial to Full Protection	Ranges from basic to full protection depending on phase completion.
04	Safety Measures	Safety Measure	Basic Reinforcement, Advanced Reinforcement, Protective Barriers, Energy-	Different safety measures reduce the impact force by varying amounts.

			Absorbing Materials, Full Protective System	
		Effectiveness (%)	20% - 100%	Full protective systems are the most effective.
		Impact Force Reduction (%)	15% - 85%	Full protective systems provide the highest reduction.
05	ML Models	Model	Random Forest, Support Vector Machine, Neural Network, Decision Tree, KNN	Various models tested for predicting ship collisions.
		Accuracy (%)	78% - 92%	Neural networks tend to perform the best.
		Precision (%)	75% - 90%	Varies by model.
		Recall (%)	72% - 89%	Varies by model.
06	Prediction Accuracy and Safety Management	Prediction Accuracy	75% - 95%	Increases with construction phase progression.
		Preventive Action Required	High to Low	Higher action required during foundation and pier construction phases.

For the given study, **Table 8** is a detailed overview of the parameters influencing ship-bridge pier interactions. By defining realistic assumptions, such as ship tonnage ranging from 5,000 to 25,000 tons and speeds between 2.5 to 7.0 m/s, the table ensures the accuracy and reliability of the predictive framework. Additionally, it highlights the varying risk levels associated with construction phases, noting that the foundation phase has the highest vulnerability with a risk rating of 0.35 to 0.50. By consolidating parameters like traffic density, structural vulnerability, and safety measure effectiveness (ranging from 20% to 100%), it guides the integration of these variables into predictive models. This ensures that simulations and ML algorithms account for dynamic interactions, resulting in more precise and robust predictions. Furthermore, the inclusion of safety measures, such as reinforcement techniques and protective barriers states the importance of proactive interventions.

Figure 22 demonstrates strong predictive accuracy, whereas **Figure 23** reveals that larger ships generally exert higher impact forces and absorb more energy, though other factors like speed and collision angle also influence the outcomes. These insights, supported by ML provide valuable tools for enhancement of bridge construction safety by optimizing design and protection measures based on real-world risks.

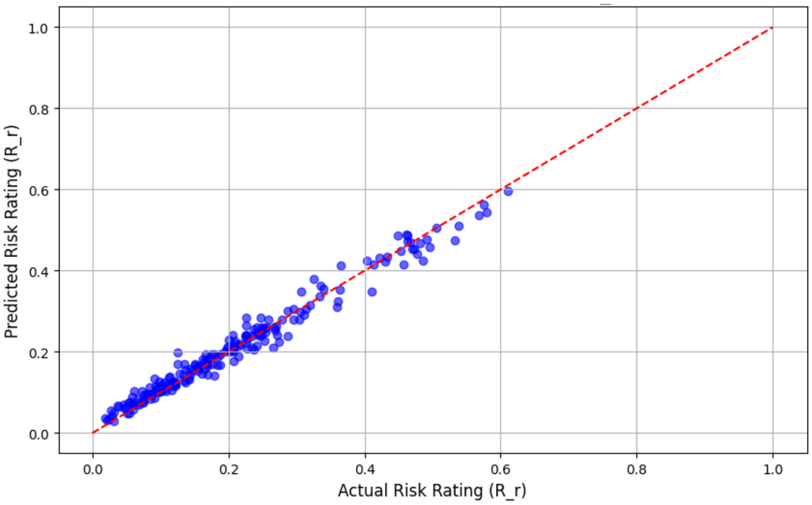


Figure 22: Model's strong accuracy in predicting risk ratings.

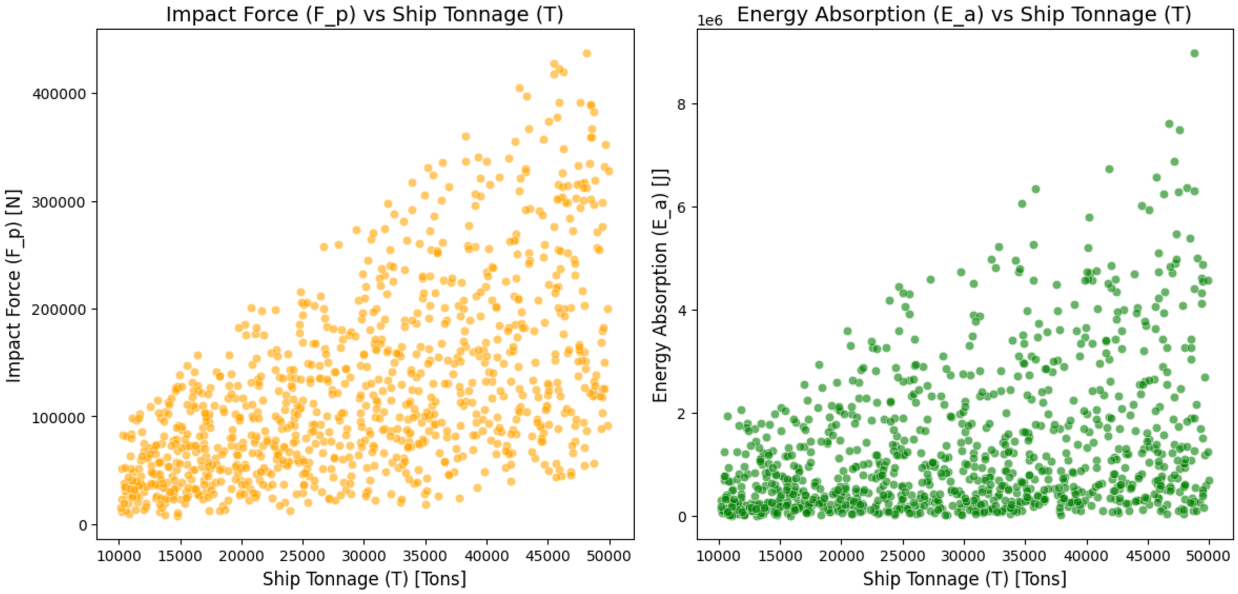
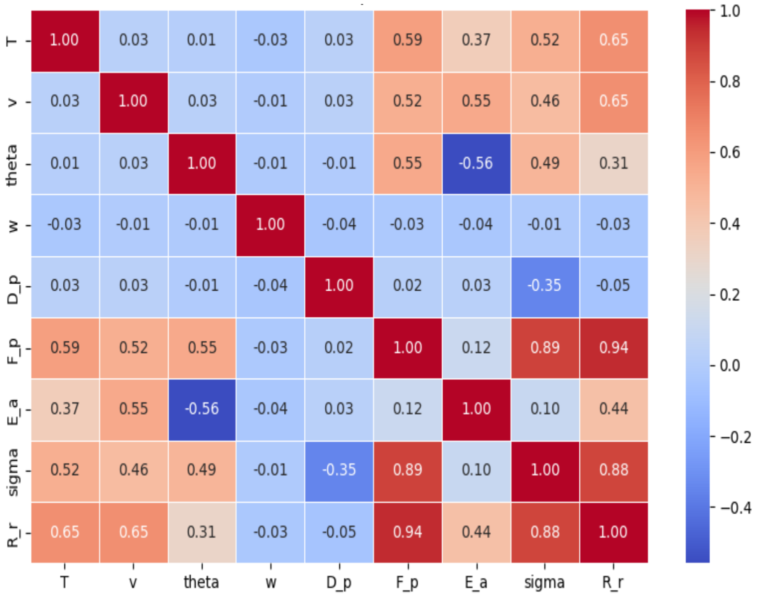


Figure 23: Relationship between ship tonnage, impact force, and energy absorption.

4.8. Correlation Heatmap

The analysis of the correlation heatmap offers valuable insights for optimizing bridge design and enhancing safety protocols during construction. Strong correlations between ship tonnage, impact force, speed, and risk rating highlight the importance of considering ship size and speed in design. The ML predictions emphasize the need for robust pier designs, energy-dissipating features, and proper reinforcement to withstand substantial forces and reduce the risk of failure. **Figure 94** reveals relationships between ship collision parameters and strong correlations between impact force, energy absorption, stress, and risk rating. Moderate correlations are found between ship tonnage, speed, and their effects on impact force and energy absorption. The analysis emphasizes the importance of proactive safety measures with a 1.5% collision failure probability and a high Benefit-Cost Ratio of 54.79.



	T	v	theta	w	D_p	F_p	E_a	sigma	R_r
T	1.00	0.03	0.01	-0.03	0.03	0.59	0.37	0.52	0.65
v	0.03	1.00	0.03	-0.01	0.03	0.52	0.55	0.46	0.65
theta	0.01	0.03	1.00	-0.01	-0.01	0.55	-0.56	0.49	0.31
w	-0.03	-0.01	-0.01	1.00	-0.04	-0.03	-0.04	-0.01	-0.03
D_p	0.03	0.03	-0.01	-0.04	1.00	0.02	0.03	-0.35	-0.05
F_p	0.59	0.52	0.55	-0.03	0.02	1.00	0.12	0.89	0.94
E_a	0.37	0.55	-0.56	-0.04	0.03	0.12	1.00	0.10	0.44
sigma	0.52	0.46	0.49	-0.01	-0.35	0.89	0.10	1.00	0.88
R_r	0.65	0.65	0.31	-0.03	-0.05	0.94	0.44	0.88	1.00

Figure 94: Correlation heatmap of ship collision parameters.

5. Real-Time and Practical Application Potential

The proposed hybrid FE-ML framework is designed to support near real time structural consequence prediction for ship-bridge collision scenarios. By training machine learning models on high-fidelity finite element simulation outputs, the framework significantly reduces computational demand compared to traditional FE only analyses. This enables rapid estimation of impact force, stress demand, and energy absorption parameters under varying ship and environmental conditions.

From a practical standpoint, the model can be integrated into bridge monitoring systems and maritime traffic management platforms where AIS-derived vessel parameters are continuously available. The CSI is an interpretable severity metric that can assist engineers and safety managers in triggering early warnings, activate protective systems, or implement temporary traffic control measures. In construction phases, where bridge components may exhibit reduced structural redundancy, the framework serve as a proactive hazard mitigation tool.

6. Conclusion

This study developed a deterministic, mechanics-consistent framework for rapid consequence assessment of ship-bridge pier collisions by coupling nonlinear FE simulations with supervised ML modeling. The proposed approach quantifies collision severity through a normalized CSI derived from impact force, absorbed energy, and structural stress demand, thereby represent the consequence component of structural risk under dynamic impact conditions.

The FE results confirm that collision response is dominantly governed by kinetic energy transfer mechanisms. Ship velocity and tonnage have the highest influence on impact force and deformation demand, consistent with momentum and energy conservation principles. Severe scenarios generated peak impact forces exceeds 5.7 MN and stress concentrations approach 90 MPa at the pier base. The lower-energy impacts resulted in substantially reduced structural demand. The exponential growth of absorbed energy with increasing velocity further demonstrates the nonlinear amplification of damage potential under high-speed conditions.

The ML successfully approximated the deterministic CSI mapping with high regression fidelity ($R^2 > 0.93$). This confirms the primary mechanics-based severity function can be reliably learned within the defined collision parameter domain. Residual distribution analysis, error intensity profiling, and correlation heatmap validation demonstrate statistical stability, absence of multicollinearity, and physics consistent feature dominance. Computational analysis indicates millisecond level inference time to represent several orders of magnitude improvement over direct nonlinear FE simulations and enable near real time severity screening.

The major contributions of this study can be summarized as follows:

1) Formulation of a normalized, mechanics driven CSI integrate force, energy, and stress response into a dimensionless structural consequence metric.
2) Development of a hybrid FE to ML surrogate modeling pipeline that preserves physical interpretability while achieving rapid predictive capability.
3) Comprehensive graphical and statistical validation (cross-validation, residual stability, intensity profiling, and correlation structure assessment) confirm robustness and generalization stability.
4) Demonstration of computational feasibility for integration into construction phase bridge safety monitoring and real time decision support frameworks.

Overall, the proposed framework establishes a scalable and computationally efficient methodology for translating high-fidelity collision mechanics into deployable severity prediction, thereby strengthening structural resilience assessment and proactive maritime infrastructure safety management.

7. Limitations and Future Research Directions

Although the proposed ML-FEM integrated framework demonstrates strong predictive performance under controlled simulation conditions, several limitations should be acknowledged. First, the dataset employed in this study is primarily derived from finite element simulations. This ensures controlled parameter variation and physics consistent structural response generation, it does not yet capture the full stochastic variability of real-world maritime environments. Actual ship-bridge interactions are influenced by dynamic and uncertain factors such as vessel traffic density, tidal fluctuations, hydrodynamic currents, and extreme weather events. These environmental uncertainties may alter impact characteristics, collision angles, and structural response behavior beyond the simulated parameter space. Second, the generalization capability of the proposed model has been validated within a constrained structural and operational domain, to focus on a single bridge configuration and limited vessel geometries. Although this controlled approach supports methodological verification, broader validation across diverse bridge typologies, pier materials, structural detailing, and hydrodynamic environments is required to ensure robust real world applicability. Third, while the modelling approach significantly reduces computational cost compared to direct FE simulation, full real time deployment requires seamless integration with live AIS data streams and environmental monitoring systems. Such operational integration was not implemented within the scope of the present study.

7.1 Future perspectives

Future research will therefore focus on large-scale data integration, incorporate AIS feeds, environmental sensing data, and historical accident records to enhance predictive robustness. Expanded testing across multiple structural configurations and maritime conditions will be conducted to improve model generalizability. Additionally, probabilistic uncertainty quantification, fragility-based failure modelling, and domain adaptation techniques will be explored to strengthen reliability for safety critical infrastructure applications. These developments will support the transition from simulation-based validation toward fully operational real time decision support systems for bridge safety management.

➢ Compliance with Ethical Standards

- **Disclosure of potential conflicts of interest**
  The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

- **Research involving Human Participants and/or Animals**
  This research does not contain any studies with human participants or animals performed by any of the authors.
- **Informed consent**
  Informed consent was obtained from all individual participants included in the study.

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- **Data Availability**
  The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

➢ Credit Authorship Contribution Statement

Abdul Haq: Writing-review & editing, Writing-original draft, Methodology, Data curation, Conceptualization, Validation, Visualization and Software. **Syed Saad:** Formal analysis, Supervision. **Kumeel Rasheed:** Data Curation, Visualization and Resources. **Hamza Jamal**: Investigation, Formal analysis. **Syed Ammad:** Resources, Formal Analysis. **Abdur Rehman**

Nasir: Funding Acquisition, Data curation, Conceptualization, Validation, Visualization and Software.

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