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Priority Setting and Resource Allocation in Coastal Local Government Marine Regulatory Reform: Application of Machine Learning in Resource Optimization

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Abstract: This study investigates the prioritization and resource allocation strategies adopted by the coastal local governments of Qingdao, Dalian, and Xiamen in the context of marine regulatory reform aimed at enhancing regulatory efficiency. Data on relevant opinions, departmental requirements, and existing resource allocations were collected through a questionnaire survey. A backpropagation (BP) neural network was then applied to analyze the survey data, prioritize regulatory tasks, and propose resource allocation schemes. The findings demonstrate that integrating machine learning into marine regulation can significantly improve resource utilization efficiency, optimize task execution sequences, and enhance the scientific and refined nature of regulatory work. The BP neural network model exhibited strong predictive capabilities on the training set and demonstrated good generalization abilities on the test set. The performance of the BP neural network model varied slightly across different management levels. For the management level, the accuracy, precision, and recall rates were 85%, 88%, and 82%, respectively. For the supervisory level, these metrics were 81%, 83%, and 78%, respectively. At the employee level, the accuracy, precision, and recall rates were 79%, 81%, and 76%, respectively. These results indicate that the BP neural network model can provide differentiated resource allocation recommendations based on the needs of different management levels. Additionally, the model's performance was assessed based on the employees' years of experience. For employees with 0–5 years of experience, the accuracy, precision, and recall rates were 82%, 84%, and 79%, respectively. For those with 5–10 years of experience, the metrics were 83%, 86%, and 80%, respectively. For employees with over 10 years of experience, the accuracy, precision, and recall rates were 85%, 88%, and 82%, respectively. These data further confirm the applicability and effectiveness of the BP neural network model across different experience groups. Thus, the adoption of machine learning technologies for optimizing marine regulatory resources holds significant practical value, aiding in the enhancement of regulatory capacity and effectiveness within coastal local governments.

Keywords: coastal local government; marine regulatory reform; resource allocation; machine learning

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1. Introduction

1.1. Research Background and Significance

In the context of accelerated globalization and industrialization, governments worldwide are increasingly focusing on the development and utilization of marine resources. However, challenges such as marine ecological degradation, overexploitation of marine resources, and frequent violations have made marine regulatory tasks more complex. Coastal areas, being in close proximity to the sea, shoulder the primary responsibility for marine resource management. They also encounter more significant issues in marine environmental governance and regulation [1]. These challenges necessitate robust regulatory frameworks and innovative approaches to effectively manage and conserve marine ecosystems. Coastal regions must implement comprehensive strategies that integrate scientific research, policy development, and stakeholder engagement to address the multifaceted issues facing marine environments. Collaborative efforts among governments, industries, and communities are essential to ensure the sustainable utilization and protection of marine resources for future generations.

Coastal local governments presently encounter myriad challenges in marine regulation. Primarily, they confront a plethora of regulatory duties juxtaposed with limited resources, impeding comprehensive regulatory coverage. Secondly, the absence of clear priorities and focal points in regulatory endeavors leads to resource dispersion and inefficacy. Wang et al. [2] employed a legal analysis approach to examine the current international legal framework governing the development of alternative fuel vessels. From a critical perspective, they evaluated and predicted the consequences of legal policies regarding alternative marine fuels and their environmental risks, identifying existing shortcomings. Additionally, the research explored potential solutions and countermeasures to address the specific marine environmental risks posed by future alternative fuel vessels [2]. Furthermore, conventional regulatory frameworks rely heavily on manual expertise and static rules, hampering adaptation to the evolving and intricate marine milieu [3]. Coastal erosion is an increasingly severe global issue, not only causing the destruction of natural landscapes but also significantly impacting coastal communities and economic activities. Saengsupavanich [4] conducted a study in Chonburi Province, Thailand, investigating the coastal community's perspectives on the criteria used by the government to select coastal protection sites. Using the Analytical Hierarchy Process (AHP) to rank these criteria, the study found that the public viewed previous budget allocations as the most influential factor, whereas political directives were deemed the least influential in choosing erosion sites [4]. Furthermore, the overexploitation of fishery resources and illegal fishing practices pose severe threats to the balance of marine ecosystems. Effective fishery management measures are crucial for protecting marine biodiversity. Bulengela [5] explored local fishermen's perceptions and knowledge of fishing practices. Through interviews and group discussions with residents of three fishing villages along the Tanzanian Indian Ocean coast, the study discovered that these local fishermen possess valuable insights into the ocean and fishing practices, beyond merely engaging in fishing activities [5]. Mangroves, as a vital component of coastal ecosystems, provide habitats for numerous marine species and serve as natural barriers against storm surges and rising sea levels. However, they are facing habitat loss and degradation crises. Putra et al. [6] argued that the implementation of coastal management policies is crucial for promoting the sustainable economic, social, and environmental development of coastal areas [6]. This aligns with this study's exploration of how coastal local governments can enhance regulatory efficiency through priority setting and resource allocation in marine regulatory reforms. Effective policy formulation and implementation can better manage and protect marine resources while promoting the engagement and well-being of coastal communities. Given these challenges, the imperative to methodically prioritize regulatory tasks and allocate regulatory resources efficiently has emerged as a pressing concern for coastal local governments to resolve. To address these issues, coastal local governments must adopt a more strategic and data-driven approach to regulatory management. By leveraging advanced technologies such as machine learning and data analytics, authorities can streamline regulatory processes, identify priority areas for intervention, and optimize resource allocation. This proactive stance is crucial for mitigating environmental risks, preserving marine biodiversity, and ensuring the sustainable development of coastal communities.

1.2. Current Status and Challenges of Marine Regulation by Coastal Local Governments

Coastal local governments hold a crucial role in marine regulation. Situated alongside the ocean, they shoulder substantial responsibilities in safeguarding marine ecological environments, promoting sustainable marine resource utilization, and upholding maritime security. Nevertheless, in the context of ongoing economic development and escalating human activities, coastal areas encounter a spectrum of challenges in marine regulation [7].

The degradation of the marine ecological environment stands as a paramount challenge confronting coastal local governments in marine regulation. Pressing issues such as overfishing, pollution discharge, and ecosystem degradation are increasingly conspicuous, posing grave threats to marine ecosystems' health and stability. For instance, research conducted by Issifu and Sumaila [8] revealed that millions of tons of plastic waste enters the oceans annually worldwide, inflicting severe damage on marine ecological environments. Coastal local governments must intensify regulatory endeavors and enact effective measures to curtail pollutant emissions, safeguard marine ecosystems, and enhance the sustainable development of marine ecological environments. Furthermore, overexploitation and irrational utilization of marine resources are notable concerns at present. As the global population grows and economic development progresses, the demand for marine resources escalates. However, issues such as overfishing, illegal fishing, and resource wastage have resulted in the continual depletion and inequitable utilization of marine resources [9]. Statistics indicate that over 30% of global fisheries resources have been overexploited, underscoring the imperative for coastal local governments to fortify fisheries management. By promoting the rational utilization and protection of fisheries resources, these governments can foster sustainable marine resource management. Coastal local governments play a crucial role in marine regulation, tasked with protecting marine ecosystems, promoting sustainable utilization of marine resources, and addressing key issues such as coastal erosion and mangrove conservation. Coastal erosion is a global problem, leading to the destruction of natural landscapes and potentially significant impacts on coastal communities and economic activities. Saengsupavanich et al. [10] conducted an analysis of coastal erosion in countries including Thailand, Malaysia, and Sri Lanka, examining the responsible government departments and their legal authorities [10]. They identified rapid urbanization, coastal infrastructure development, sea level rise from climate change, inadequate planning frameworks, sediment supply imbalances, and resource constraints as major challenges in coastal erosion management. Collaborative efforts among government agencies, researchers, local communities, and international organizations are essential for successful coastal erosion management in these regions. Mangroves are critical components of coastal ecosystems, providing habitats for marine organisms and acting as natural barriers against storm surges and sea level rise. Luom et al. [11] studied mangrove-based aquaculture (MBA) and related coastal protection challenges in Kien Giang Province, Vietnam, offering insights into the relationship between MBA and mangrove conservation [11]. They emphasized the importance of implementing MBA strategies across different coastal types. However, mangroves face habitat loss and degradation, necessitating increased protection and restoration efforts. Coastal local governments must adopt comprehensive strategies integrating scientific research, policy-making, and stakeholder engagement to address marine environmental challenges. This includes strengthening regulatory efforts, implementing effective measures to control pollutant emissions, protecting marine ecosystems, and promoting sustainable development. Addressing coastal erosion and mangrove conservation challenges requires scientific methods and innovative strategies. Rocha et al. [12] presented a comprehensive overview of current coastal vulnerability and risk assessment methodologies, encompassing various temporal and spatial scales to capture coastal processes [12]. Their approach involved categorizing these processes into different intervals and classifying the outcomes of each variable, thereby delineating a broad spectrum of vulnerability and risk levels. De Serio et al. [13] contributed to the field by developing a coastal vulnerability index that integrated geographic information systems with the analytical hierarchy process, facilitating an objective prioritization of key parameters [13]. Moreover, they explored the effectiveness of an Integrated Coastal Vulnerability Index in their study. Scardino et al. [14] delved into the relationship between sea surface temperatures (SSTs) and Mediterranean hurricane development [14]. Their research revealed a distinct pattern wherein SSTs exhibited a decrease before the formation of each Mediterranean hurricane, contrasting with strong temperate systems. Spectral analysis unveiled high continuous wavelet transform coefficients indicative of elevated SST energy content preceding Mediterranean hurricanes. These insights offer valuable cues for distinguishing Mediterranean hurricanes from typical seasonal storms. In light of these findings, coastal local governments must comprehensively factor in such considerations when formulating marine regulatory strategies. Effective management measures are imperative to address challenges such as coastal erosion, sea level rise, and extreme weather events. Achieving this requires a deep understanding of the causes and mechanisms underlying these phenomena through scientific research, coupled with the development of adaptive management strategies to bolster the resilience and sustainability of coastal areas.

In summary, coastal local governments face multifaceted challenges in marine governance, encompassing the degradation of the marine ecological environment, overexploitation and irrational use of marine resources, and maritime security concerns. Addressing these challenges demands robust marine governance measures aimed at protecting the marine ecological environment, fostering sustainable utilization of marine resources, and ensuring maritime security. These tasks represent urgent imperatives for coastal local governments.

1.3. Application of Machine Learning in Resource Optimization and Task Priority Setting

The utilization of machine learning for resource optimization and task prioritization represents a prominent focus in both research and practical spheres. As a pivotal subset of artificial intelligence, machine learning empowers computers to discern patterns and rules from data, thereby offering precise and efficient decision-making support. Within the realm of marine governance, the integration of machine learning technology holds considerable promise and untapped potential [15].

Machine learning technology can aid coastal local governments in scientifically and systematically prioritizing regulatory tasks. By analyzing historical data and regulatory requirements, employing machine learning algorithms to categorize and prioritize regulatory tasks can unveil their correlations and importance, thereby offering a scientific foundation for regulatory decision-making [16]. For instance, machine learning techniques can classify diverse regulatory tasks and subsequently prioritize them based on their significance and immediacy, thereby identifying which tasks to address initially and improving the efficiency and accuracy of regulatory efforts. Machine learning technology aids coastal local governments in intelligently allocating and optimizing regulatory resources. Given the limitations of regulatory resources, effectively distributing them among various tasks is a crucial challenge. By analyzing the characteristics and needs of regulatory tasks, machine learning predicts resource demands and allocation methods, thereby achieving intelligent resource allocation and optimization. For example, machine learning predicts resource demands and allocates them based on task priorities, maximizing resource allocation and utilization efficiency [17].

Moreover, machine learning technology can aid coastal local governments in automating and enhancing intelligence in the regulatory process. Traditional regulatory approaches often rely on manual expertise and fixed rules, which struggle to adapt to the dynamic marine environment. By training regulatory models, machine learning can automate and enhance the intelligence of the regulatory process. For instance, through the analysis and mining of marine regulatory data, machine learning can identify anomalies and regulatory risks in the marine environment, facilitating the timely implementation of regulatory measures to ensure marine safety and stability [18].

In conclusion, the utilization of machine learning technology for resource optimization and task prioritization offers substantial significance and value. Through machine learning techniques, coastal local governments can attain scientifically prioritized regulatory tasks, intelligent resource allocation, and automation in the regulatory process. This advancement enhances regulatory efficiency and resource utilization, fostering a more scientific, refined, and intelligent approach to marine regulatory work at the coastal local government level.

1.4. Research Objectives and Problem Analysis

Previous studies have predominantly delved into discussions concerning marine regulatory issues faced by coastal local governments, encompassing themes such as marine ecological environmental protection, sustainable utilization of marine resources, and maritime security. However, the existing research exhibits certain gaps and limitations. Firstly, with regards to the application of machine learning technology in marine regulation, most studies have been confined to surface-level task optimization and resource allocation, lacking in-depth exploration of specific application details and effectiveness assessment in regulatory endeavors. Additionally, when addressing challenges encountered by coastal local governments, such as coastal erosion, overdevelopment, and maritime security issues, prior research has primarily consisted of localized case analyses or macro-level policy recommendations, lacking targeted data support and empirical research. The primary impetus of this study is to amalgamate machine learning technology with the exploration of task prioritization and resource allocation strategies in the marine regulatory reform initiatives undertaken by coastal local governments in Qingdao, Dalian, and Xiamen. This study aims to address shortcomings in coastal local government marine oversight by employing machine learning to prioritize regulatory tasks and propose resource allocation strategies, thereby enhancing regulatory and resource efficiency. To achieve this objective, the study focuses on the following key aspects: First, this study seeks to determine the priorities of marine oversight for coastal local governments in a scientific and rational manner. Given the myriad and varied regulatory tasks, discerning primary tasks from secondary ones is crucial. This study investigates the application of machine learning techniques to prioritize regulatory tasks using historical data and regulatory criteria, aiming for resource allocation that is both scientifically informed and resource-efficient. Secondly, the study investigates how to effectively harness machine learning techniques for optimizing marine regulatory resources. Despite its potential, the application of machine learning in marine supervision is still nascent. For instance, in the realm of applying machine learning methods to marine regulatory technology, Scardino et al. [19] integrated machine learning and computer vision techniques with monitoring cameras to evaluate oceanic meteorological features. Their study involved employing a convolutional neural network (CNN) to categorize tidal phases and storm surges, along with utilizing optical flow techniques to assess wave currents and heights impacting the coastline [19]. Similarly, Scarrica et al. [20] utilized monitoring cameras affixed to drones in tandem with a CNN for the detection of beach litter [20]. This study aims to tackle the core challenge of applying these techniques to prioritize regulatory tasks and allocate resources. Various machine learning algorithms are explored, tailored to the characteristics and demands of regulatory tasks, to devise models and methodologies conducive to resource optimization in marine regulation. Thirdly, the study focuses on evaluating the efficacy and efficiency of machine learning techniques in optimizing marine regulatory resources. The credibility and practicality of research findings are pivotal for assessing research outcomes. Thus, the study devises objective evaluation criteria and methodologies to assess the practical effectiveness of machine learning techniques in optimizing marine regulatory resources. These evaluations can provide governmental decision-makers with scientific insights and references.

This study comprises several sections: Section 1 of this study is the introduction, which initially presents the research background and significance, delineating the challenges and issues encountered in marine supervision. It subsequently clarifies the study's purpose and problem statement, providing readers with insights into the core research objectives and critical issues to be addressed. Finally, a concise overview of the article's structure is provided. Section 2 comprises the literature review, which examines the current status and challenges of marine supervision by coastal local governments, along with the utilization of machine learning for resource optimization and task prioritization. By reviewing pertinent research findings and advancements, this section provides a theoretical foundation and serves as a reference for subsequent research. Section 3 encompasses the research methodology, meticulously detailing the questionnaire design and survey participants, data collection and processing methods, the application of machine learning algorithms in resource optimization, and the experimental design and model evaluation. Through transparent research methods, the scientific rigor and credibility of the study are upheld. Section 4 presents the research results, beginning with an analysis of the questionnaire survey findings, followed by an explanation of the utilization of machine learning algorithms for prioritizing marine supervision tasks. Subsequently, it introduces resource allocation schemes and evaluates their effectiveness. Section 5 is dedicated to discussion, offering an in-depth analysis and discourse on the research findings. It explores the practical application value of machine learning in marine supervision, interprets the results, conducts an analysis of potential influencing factors, and discusses research limitations and future directions. Section 6 comprises the conclusion, summarizing the main findings of the study, providing policy and practice recommendations, and delineating future research directions and their significance. Finally, the reference section lists relevant literature and materials cited in this study, offering readers further insights into related research fields.

2. Literature Review

Research and practice in marine supervision increasingly emphasize the application of machine learning technology to enhance supervision and resource utilization efficiency. Both domestic and foreign scholars have conducted numerous related studies in recent years, yielding significant advancements in the field of marine supervision. By employing machine learning, researchers have achieved intelligent and precise monitoring tasks, analyzing and extracting valuable insights from marine supervision data. For instance, Gamage et al. [21] utilized machine learning to analyze ship trajectory data, uncovering abnormal patterns indicative of illegal ship activities, thereby offering timely regulatory insights to marine authorities. Moreover, Mahrad et al. [22] applied machine learning to extract insights from marine environmental data, revealing dynamic trends in marine ecosystems and providing scientific foundations for environmental protection and management in marine environments. Researchers have further enhanced supervision effectiveness and resource utilization efficiency through the utilization of machine learning technology for task prioritization and resource allocation optimization. For instance, Ebrahimi et al. [23] employed machine learning to prioritize regulatory tasks, achieving intelligent allocation of regulatory resources and enhancing regulatory efficiency. Similarly, Durlik et al. [24] utilized machine learning to analyze and forecast regulatory data, enabling the dynamic adjustment of regulatory resources and further improving resource utilization efficiency. Moreover, there are endeavors aimed at exploring novel applications and methodologies of machine learning in marine supervision. For instance, Glaviano et al. [25] introduced a marine supervision model grounded in deep learning, facilitating real-time monitoring and early warning systems for the marine environment, thus offering innovative approaches to marine environmental protection and management. Additionally, Chen et al. [26] proposed an ocean supervision strategy based on reinforcement learning, fostering automation and intelligence in supervision tasks through the training of intelligent agents to learn optimal supervision strategies. Wang et al. [27] introduced an innovative approach to optimize the blockchain network system by employing smart contracts to construct a risk management system for online public opinion [27]. Additionally, they utilized risk correlation tree technology to track public sentiment. This work not only provides technical support for optimizing the dissemination mode of blockchain networks but also contributes to enhancing the current social networking environment. Deng et al. [28] conducted an evaluation of the economic development of coal-dependent cities within the context of low-carbon economic growth [28]. They initially analyzed the background of coal-dependent cities and the low-carbon economy. Subsequently, they established an economic resilience assessment system tailored to coal-dependent cities, characterizing the resilience of urban economies by analyzing the status of traditional and high-tech industries in resource-dependent cities. This study holds significant reference value for promoting urban resource management and enhancing economic efficiency. By bolstering government intervention and promoting public participation, the market vitality and economic resilience of resource-dependent cities can be effectively enhanced, thereby promoting sustainable urban development. Li et al. [29] assessed the correlation between China's low-carbon city pilot (LCCP) policy and urban entrepreneurial activities [29]. Their findings revealed that the LCCP policy inhibited entrepreneurial activities in high-carbon industries while encouraging such activities in emerging industries, thereby fostering changes and upgrades in industrial structure. This study provides new empirical evidence for the impact of the LCCP policy on entrepreneurial activities and changes in industrial structure. Li, Liang, Liang, and Wang [29] and Li et al. [30] explored the development path of clean energy in mining projects under the influence of big data. The proposed model for the development path of clean energy yielded positive results. This study, aimed to provide empirical support and decision-making references for the development of clean energy in mining projects, thereby promoting the sustainable development of the mining industry and achieving win–win economic and ecological benefits, which is crucial for protecting the ecological environment and achieving sustainable utilization of resources. Li et al. [31] investigated the impact of climate change on corporate environmental, social, and governance (ESG) performance [31]. The empirical results indicated that climate change significantly inhibits corporate ESG performance. Furthermore, the study found that continuously eliminating internal and external resource mismatches helps mitigate the adverse effects of climate change on ESG performance. Wang et al. [32] enhanced the anti-corruption effectiveness of grassroots governments using a big data platform management and "5W" analysis framework [32]. In summary, the combination of data platform management and multi-model methods effectively enhanced the anti-corruption capabilities of grassroots governments, providing insights for establishing transparent and efficient grassroots governance. Li, Tang, Liang, and Wang [31] and Li et al. [33] promoted corporate innovation by optimizing the financing environment and innovation conditions. They found that intellectual property pledge financing suppresses corporate innovation, especially innovation quality. This is because strict innovation conditions may weaken the innovation foundation of enterprises, and these enterprises are rarely affected by the fluctuations in funds obtained through intellectual property pledge financing.

In general, the application of machine learning technology in marine supervision has yielded significant results, advancing the scientific, intelligent, and refined development of marine regulatory practices. In the future, as machine learning technology continues to progress, the field of marine supervision is poised for further innovations and breakthroughs, offering enhanced technical support and assurances for the sustainable development and conservation of marine resources and the ecological environment.

3. Research Methodology

3.1. Application of Machine Learning in Resource Optimization and Task Priority Setting

The application of machine learning techniques in marine regulation is increasingly widespread, especially in optimizing resource allocation and setting task priorities, highlighting its growing importance. The BP neural network model, a significant tool in machine learning, plays a crucial role in marine regulation due to its robust data processing and pattern recognition capabilities. By learning from historical data and regulatory standards, this model can scientifically prioritize marine regulatory tasks, intelligently identifying which tasks are more urgent and important. Furthermore, the BP neural network model can predict resource needs, assisting regulatory agencies in achieving rational resource allocation to ensure that critical tasks receive adequate support. Additionally, the self-learning ability of a BP neural network allows it to continuously optimize the decision-making process over time, adapting to the dynamic changes in the marine environment and enhancing the efficiency and responsiveness of marine regulation. In this way, the BP neural network not only elevates the level of intelligence in marine regulation but also provides a solid technical foundation for the sustainable use of marine resources and the protection of marine ecosystems [34,35]. This section delves into the precise applications of machine learning algorithms in resource optimization and assesses their prospective value within the realm of marine regulation.

(1) Demand for Regulatory Resource Optimization

Marine regulatory endeavors encompass a myriad of tasks, ranging from fisheries management to ship safety monitoring and marine environmental protection, all amidst constraints of limited regulatory resources. Effectively allocating and optimizing these resources has emerged as a pivotal challenge within the marine regulatory domain. Conventional resource allocation methods, reliant on experience and predefined rules, often struggle to contend with the complexity and variability inherent in marine regulatory tasks. Consequently, leveraging machine learning algorithms to optimize regulatory resource allocation holds paramount significance.

(2) Application of Machine Learning Algorithms in Resource Optimization

Machine learning algorithms have the capacity to discern patterns and regulations from data and facilitate predictions and decisions based on the acquired knowledge, thus presenting extensive application opportunities in resource optimization. For instance, supervised learning algorithms enable model training to forecast resource needs for diverse regulatory tasks, leveraging historical data and regulatory requisites to achieve dynamic deployment and optimal allocation of regulatory resources. Concurrently, unsupervised learning algorithms unveil latent relationships and regulations within data, providing additional insights and guidance for the optimal allocation of regulatory resources.

Support vector machine (SVM), BP neural network models, and random forest (RF) algorithms are essential tools for optimizing marine regulatory resources. The application of these advanced machine learning models in resource optimization is vital, as they enable efficient data analysis and provide scientific decision support for coastal local governments. Firstly, SVM is a supervised learning model known for its excellent classification performance, especially in small sample scenarios. SVM achieves data classification by finding the optimal separating hyperplane in the feature space. In resource optimization, SVM helps identify and differentiate various regulatory tasks, thus providing a basis for prioritization and resource allocation. Secondly, the BP neural network model is a multilayer feedforward neural network that adjusts weights and biases within the network through the backpropagation algorithm. The BP neural network consists of an input layer, one or more hidden layers, and an output layer. Each layer comprises multiple neurons connected by weights. During the learning process, the network first calculates the output layer results through forward propagation. It then adjusts the network's weights and biases via the backpropagation algorithm based on the error between the actual output and the desired output, thus minimizing prediction error. BP neural networks excel in handling complex nonlinear problems and can accurately predict the prioritization and resource needs of regulatory tasks, providing effective solutions for resource optimization [36]. Lastly, RF is an ensemble learning method that constructs multiple decision trees and combines their prediction results to enhance model accuracy and robustness. RF is highly effective in processing large datasets and can evaluate the importance of various features. In resource optimization, RF can provide precise task prioritization and identify critical factors influencing resource allocation decisions. Given the advantages of these models, the BP neural network model was selected as the most suitable for the data characteristics and optimization goals of this study. The parameters were meticulously adjusted to ensure the scientific validity and practicality of the resource optimization scheme. The BP neural network model receives features related to marine regulatory tasks as the input, such as task urgency, importance, and historical resource allocation. Through training, the model learns the complex relationships between these features, regulatory task priorities, and resource demands. Subsequently, the model can predict new regulatory tasks, providing decision support for resource optimization. Multiple iterative training sessions and cross-validation were employed to evaluate the model's predictive performance. Additionally, to enhance the model's generalization ability, hyperparameters such as network structure and learning rate were adjusted. Through these methods, the BP neural network model demonstrated high predictive accuracy, offering effective technical support for optimizing marine regulatory resources for coastal local governments.

(3) Specific Application Scenarios

Machine learning algorithms find application in various scenarios for resource optimization in marine regulation. For instance, they can analyze marine environmental data to uncover evolving patterns and anomalies in the marine ecosystem, aiding in prioritizing regulatory tasks and devising appropriate resource allocation strategies. Furthermore, these algorithms can classify and categorize different regulatory tasks, establishing priorities for resource allocation based on task significance and urgency, thus facilitating intelligent resource allocation and optimal utilization in regulatory endeavors.

(4) Case Studies

Using fishery regulation as an example, employing machine learning algorithms to analyze and extract insights from data pertaining to fishing vessel behavior can unveil patterns indicative of illegal fishing activities, facilitating prompt regulatory intervention. Furthermore, leveraging machine learning algorithms to forecast the distribution and dynamics of fishery resources can aid fishery management authorities in devising judicious policies such as fishing quotas and seasonal fishing bans, thereby promoting the sustainable utilization of fishery resources.

3.2. Questionnaire Design and Survey Objects

In this study, a questionnaire was designed to assess the urgency and importance of different tasks in marine regulation by coastal local governments. To comprehensively gather data on marine regulation from coastal local governments, representative geographical locations were selected for case studies. Specifically, the survey covered the following coastal regions:

(1) Qingdao: As one of China's major marine cities, Qingdao has extensive experience and a unique position in marine resource development and marine environmental protection.
(2) Dalian: Located in Liaoning Province, Dalian boasts abundant marine resources and is a core area for marine economic development in the northeast region.
(3) Xiamen: Situated in Fujian Province along the southeastern coast, Xiamen's marine economy is a vital pillar industry and a pioneering area for innovation in marine regulation.

These regions are not only geographically representative but also have significant achievements and face challenges in marine regulation practices and resource optimization. Conducting case studies in these areas aims to provide an in-depth understanding of the practical issues coastal local governments encounter in marine regulatory reforms and explore effective resource optimization strategies.

The survey's scope of participants was initially determined by considering the involvement of various departments and fields in marine regulation. Specific departments and personnel that engage in marine regulatory activities, such as the Marine and Fisheries Bureau, Maritime Bureau, Environmental Protection Bureau, and marine fisheries management personnel, were selected as survey participants. A more comprehensive range of regulatory needs and opinions can be gathered by including individuals from diverse departments and positions.

Subsequently, the questionnaire content was designed. It primarily focuses on two aspects: firstly, assessing participants' perceptions and evaluations of current marine regulatory efforts, including the urgency and significance of regulatory tasks; secondly, eliciting participants' perspectives and requirements concerning task prioritization and resource allocation. This involved identifying which regulatory tasks participants deemed should be prioritized and which tasks require increased resource allocation. The questionnaire design utilizes a combination of multiple-choice and open-ended questions to ensure clarity, comprehensiveness, and ease of understanding.

In the third step, the questionnaire was distributed to the selected respondents via email, and their participation was invited. Throughout the survey period, proactive communication with respondents was maintained to address any queries they had and to encourage candid and unbiased responses. Additionally, the anonymity of the questionnaire was ensured to safeguard the privacy and data security of the respondents. In this study, respondents' email addresses were collected through the following methods. Firstly, collaborative relationships were established with coastal local governments and relevant marine regulatory agencies, obtaining contact information for potential respondents through these institutions. Secondly, professional social media platforms and industry forums were utilized to post survey notifications, inviting professionals in related fields to participate. These approaches facilitated the successful collection of email addresses from 200 respondents. To maintain ongoing communication with these respondents, several measures are implemented. Firstly, a dedicated project email account was set up to send out questionnaires and follow-up emails. Secondly, a mailing list management system was utilized to regularly send progress updates and thank you letters to the respondents, thereby nurturing good communication relationships. Thirdly, respondents were provided with a dedicated contact point, allowing them to raise questions or provide feedback at any time. Additionally, one-on-one communications were conducted with some respondents via phone or online meetings to promptly address their needs and concerns. Despite the relatively large group of 200 respondents, these measures enabled effective communication management, ensuring the smooth progression of the survey.

Upon completion of the questionnaire survey, retrieval was conducted to gather the questionnaires. Subsequently, the data underwent meticulous cleaning and screening to eliminate incomplete or invalid entries. This process involved assessing the completeness, consistency, and reasonableness of the data and addressing any anomalies to uphold data accuracy and credibility. Out of the 200 distributed questionnaires, 190 valid responses were obtained, yielding a recovery rate of 95%. In the conducted surveys, 63 staff members from the Marine and Fisheries Bureau completed the questionnaire, while the Maritime Bureau had 55 staff members who participated. Additionally, 40 staff members from the Environmental Protection Bureau and 32 individuals from other relevant departments also completed the questionnaire. The collected data were then organized, summarized, and subjected to statistical analysis using SPSS 26, encompassing descriptive statistical analysis and correlation analysis.

In this study, 190 valid questionnaires served as the dataset for training the machine learning models. As emphasized by Balki et al. [37], determining the sample size should consider the data diversity and model complexity [37]. While a larger sample size typically yields more robust results in model training, in specific contexts, 190 samples suffice to capture the essential characteristics of the data and train a well-performing model. Moreover, Azizi et al. [38] have highlighted that in resource-constrained scenarios, smaller sample sizes can be effectively utilized for model training by employing meticulously designed questionnaires and appropriate data preprocessing techniques [38]. The quality and diversity of the data here were ensured through meticulous feature engineering and data cleaning procedures, while the model's generalization capability was enhanced via techniques such as cross-validation. Throughout the model training phase, vigilant monitoring of potential issues such as overfitting was undertaken, and corresponding measures were implemented to optimize model performance. Therefore, the utilization of 190 responses is apt within the context of this study, providing adequate information for the models, and the efficacy of the models has been substantiated through experimentation.

3.3. Experimental Design and Model Evaluation

In the realm of marine regulation, the key challenge lies in optimizing the utilization of scarce regulatory resources to effectively prioritize tasks and allocate resources. The initial step involves data acquisition, encompassing historical regulatory records, marine environmental data, ship trajectory data, and similar datasets, which serve as training and testing sets for machine learning models. Following data collection, feature engineering is conducted to preprocess and transform raw data into suitable features for machine learning models, involving procedures such as data cleaning, feature selection, and transformation. Once the problem is defined, data are collected, and feature engineering is performed, the next step is to select an appropriate machine learning model to address the issue at hand. In this study, a BP neural network model was opted for, with the input layer comprising pertinent features of the regulatory task and the output layer representing the task's priority or the marine environment prediction outcome. Subsequently, the BP neural network model underwent training using the assembled data. The training process employed a backpropagation algorithm to adjust network parameters, aiming to minimize the disparity between model output and actual values. Finally, model optimization was conducted through cross-validation and other techniques to identify the optimal network structure and parameters, thereby enhancing the model's predictive and generalization capabilities. Figure 1 illustrates the BP neural network model for optimizing marine regulatory resources.

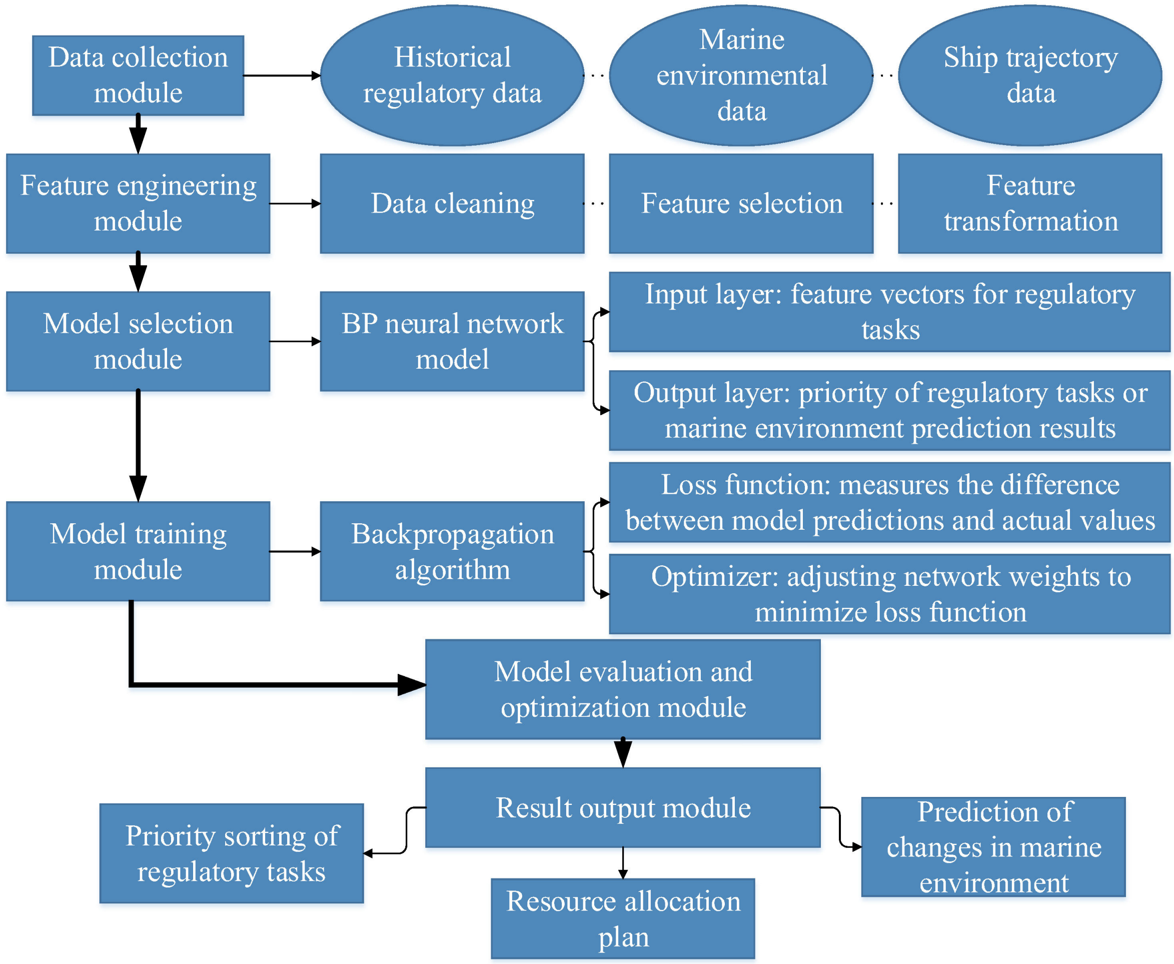

Figure 1. BP neural network model for ocean supervision resource optimization.

The subsequent phase involved training the model with the provided training data. This training procedure aimed to fine-tune the model parameters, enabling it to closely match the training data and make precise predictions regarding new data instances. When assessing a model's performance, a range of performance metrics can be employed to gauge its predictive efficacy. The metrics selected for evaluation in this study encompassed accuracy, precision, and recall.

Accuracy, a frequently employed metric for assessing classification models, quantifies the proportion of accurately classified samples out of the total. In essence, accuracy signifies the percentage of samples predicted correctly by the model. The metric reported here was computed as Equation (1):

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision signifies the ratio of true positive cases predicted by the model to all positive cases in the sample. A higher precision rate suggests a lower likelihood of the model incorrectly classifying samples as positive, indicating a more accurate identification of positive instances. It was computed using Equation (2):

$$\text{precision} = \frac{TP}{TP + FP} \quad (2)$$

Recall denotes the ratio of true positive cases accurately identified by the model to all actual positive cases, serving as a metric to gauge the model's capability in detecting positive instances. It was computed using Equation (3):

$$\text{recall} = \frac{TP}{TP + FN} \quad (3)$$

In the above equations, *TP* represents the number of positive cases correctly predicted by the model, *TN* indicates the number of negative cases correctly predicted by the model, *FP* accounts for the number of negative cases incorrectly classified as positive by the model, and *FN* signifies the number of positive cases erroneously classified by the model as negative.

4. Research Findings

4.1. Analysis of Questionnaire Survey Results

(1) An analysis was conducted on the gender, age, and education level of the respondents. The results indicate an equal distribution of males and females, each constituting 50% of the respondents. In terms of age, 40% of individuals were aged 18–30, 30% were aged 31–45, 20% were aged 46–60, and 10% were over 60 years old. Regarding educational attainment, 30% of respondents had a high school education or below, 50% held a bachelor's degree, and 20% held a master's degree or higher. This is depicted in Figure 2 below.

(2) The urgency and importance ratings of various regulatory tasks were acquired through the questionnaire survey as follows. Task 1: Marine Ecological Conservation and Restoration involves monitoring the health of marine ecosystems, implementing ecological restoration projects, and formulating and executing measures to protect marine biodiversity. Task 2: Rational Development and Utilization of Marine Resources focuses on balancing the development and protection of marine resources, ensuring their sustainable use, and promoting the healthy development of the marine economy. Task 3: Marine Pollution Control and Environmental Governance centers on reducing pollutant emissions, improving marine environmental quality, and addressing marine pollution incidents to protect the marine environment from damage. Task 1: Urgency—3.8, Importance—4.2; Task 2: Urgency—4.5, Importance—3.9; Task 3: Urgency—3.2, Importance—4.6. Analyzing these ratings enabled the determination of the priority of each regulatory task, facilitating the formulation of a rational resource allocation plan. Figure 3 depicts the specific scores for the urgency and importance of different regulatory tasks.

Through the questionnaire, insights into the knowledge and expectations regarding machine learning technology were gathered, revealing the following results: Knowledge level—Understand (30%), Understand some (50%), Do not understand (20%); Willingness to use—Willing to try (60%), May try (30%), Do not want to try (10%); Expected effects—Improve the efficiency of supervision (40%), Improve the accuracy of prediction (30%), Reduce labor costs (20%), Others (10%). By analyzing these findings, it became possible to assess the feasibility and priority of applying machine learning techniques in marine regulation, as well as to identify the focus and direction of application. Figure 4 depicts the statistical outcomes of the survey respondents' overall attitude towards and expectations for machine learning technology.

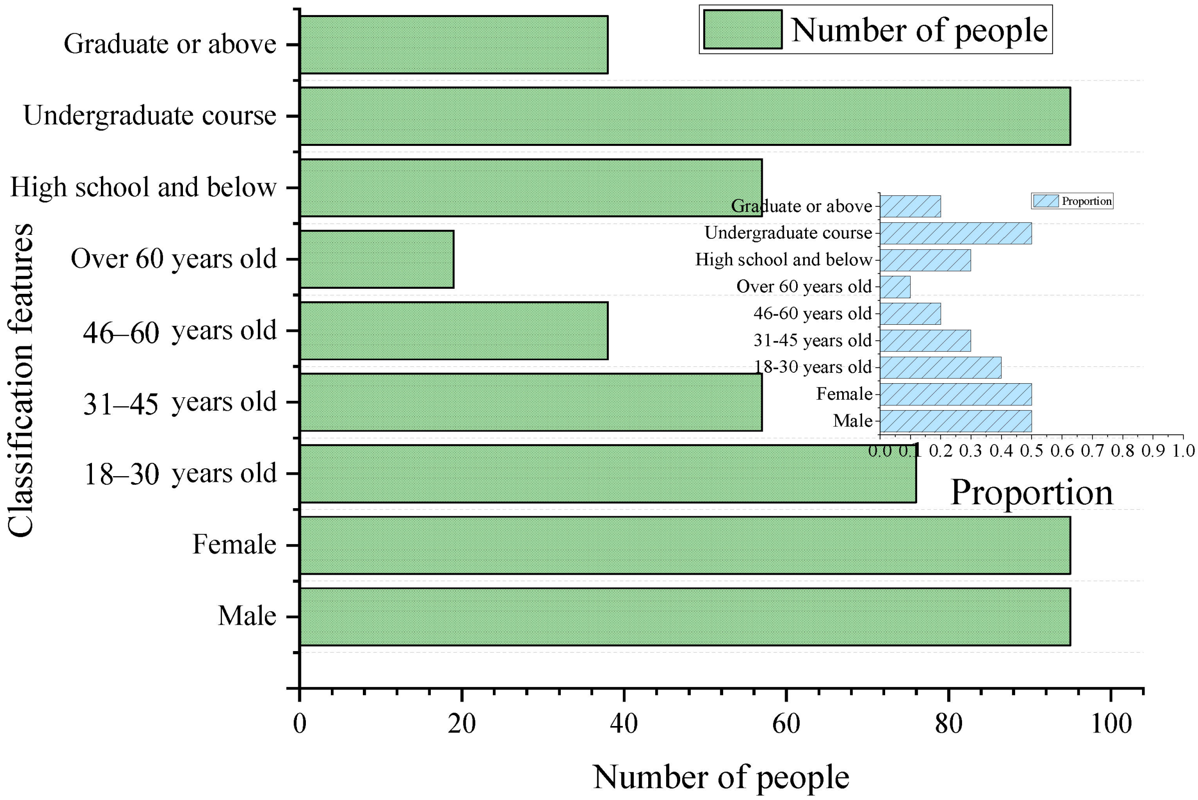

Figure 2. Statistical overview of respondents' demographic information.

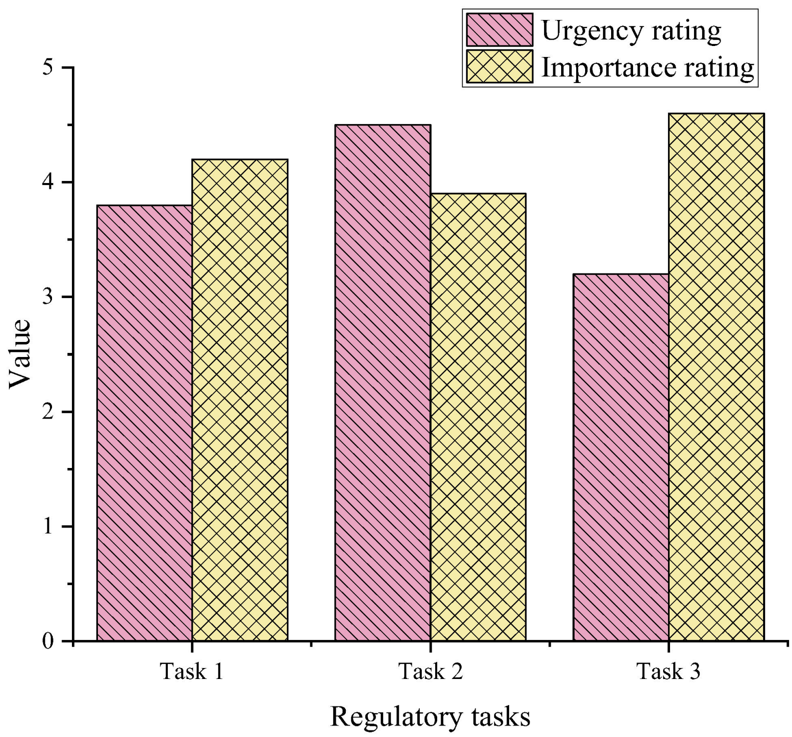

Figure 3. Scores for the urgency and importance of different regulatory tasks.

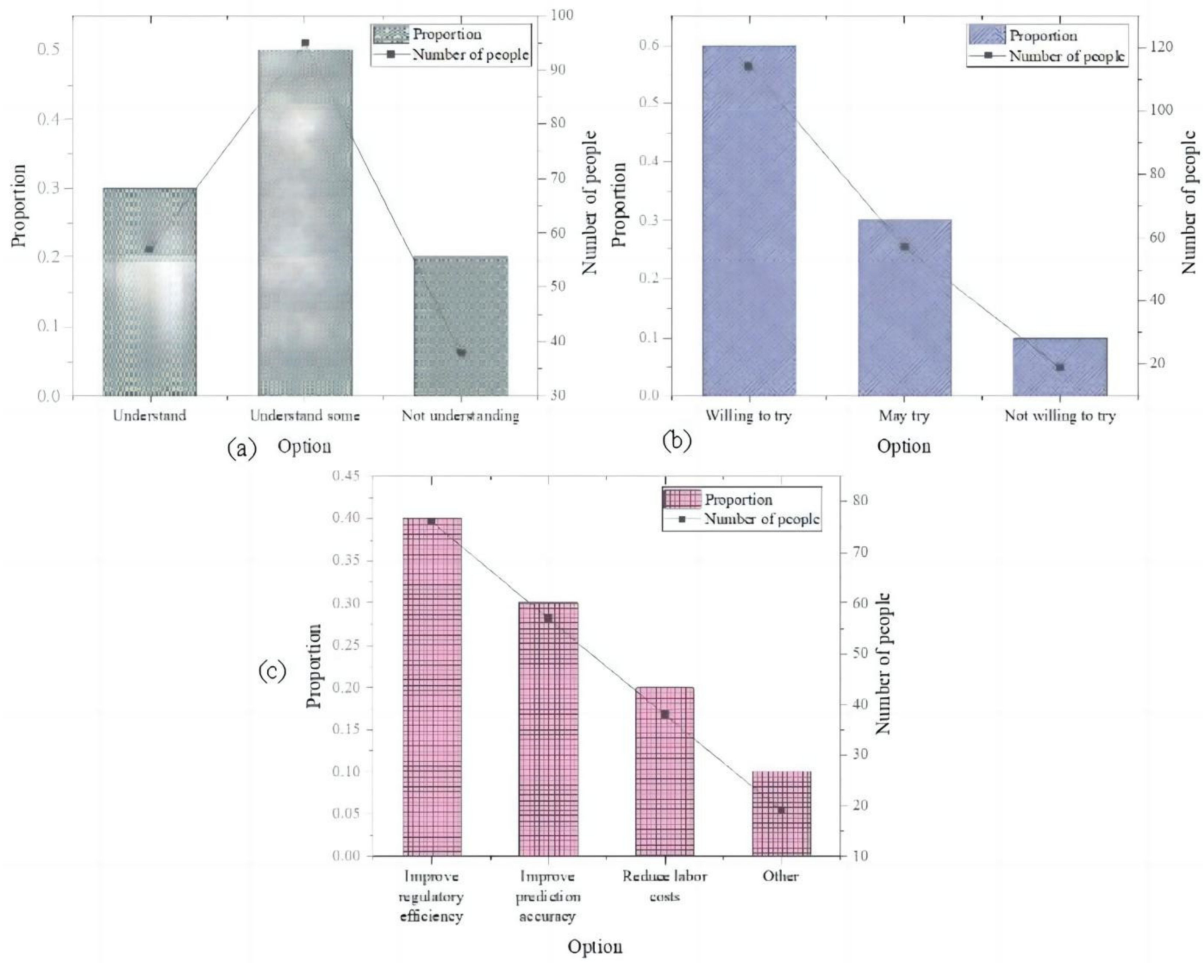

Figure 4. Survey respondents' overall attitude towards and expectations for machine learning technology: (**a**) Awareness level; (**b**) Willingness to use; (**c**) Expected outcomes.

4.2. Evaluation of Model Effects in Resource Allocation Plans

(1) In this study, the training of the BP neural network model involved utilizing a training set comprising 800 samples. These samples encompassed various features pertinent to marine regulatory tasks, including task urgency, importance, and historical resource allocation. Sourced from information collected through questionnaire surveys and relevant historical records of marine regulation and marine environmental data, the sample data underwent feature engineering, data cleaning, selection, and transformation to ensure the effectiveness of the input features for predicting task priorities and resource requirements. Before initiating model training, normalization of the data was performed to mitigate the influence of differing dimensions and magnitudes, thereby enhancing the model's convergence and generalization capability. Additionally, cross-validation techniques were employed to evaluate the predictive performance of the model, and model parameters were adjusted to optimize predictive outcomes. To assess the model's generalization ability on unknown data, a separate test set of 200 samples was selected for evaluation of model performance.

The characteristics of regulatory tasks and their priority scores as predicted by the BP neural network model are presented in Table 1. Task 1 demonstrated high urgency and importance scores, indicating its critical nature. Despite a moderate level of historical resource allocation, the model assigned Task 1 a priority score of 0.75, suggesting it warrants considerable attention and resource allocation. Task 2, although exhibiting a slightly lower urgency score compared to Task 1, shared a comparable importance score. With high historical resource allocation, the model predicted a priority score of 0.70 for Task 2, underscoring its significance but implying a marginally lower resource requirement compared to Task 1. Task 3 recorded the highest urgency score but a comparatively lower importance score and historical resource allocation. Consequently, the model assigned Task 3 a priority score of 0.65, signifying that while it demands prompt action, its overall priority is relatively lower due to its diminished importance and historical resource allocation.

Table 1. Feature input of the regulatory task and its priority score predicted by the BP neural network model.

Regulatory Task	Urgency Score	Importance Score	Historical Resource Allocation	Predicted Priority Score
Task 1	0.8	0.9	Moderate	0.75
Task 2	0.7	0.8	High	0.70
Task 3	0.9	0.7	Low	0.65

Our analysis revealed an accuracy of 0.85 for the training set and 0.82 for the test set. The precision was 0.88 for the training set and 0.84 for the test set. The recall rate was 0.82 for the training set and 0.79 for the test set. The model demonstrated high accuracy, precision, and recall rates on the training set, indicating its strong predictive ability. Similarly, on the test set, the model maintained high levels of these metrics, demonstrating a good generalization ability. By comparing the metrics on both sets, any issues with overfitting or underfitting can be identified, allowing for adjustments to the model structure and parameters to enhance performance and generalization. Figure 5 illustrates the performance results of the BP neural network model on the training and test sets.

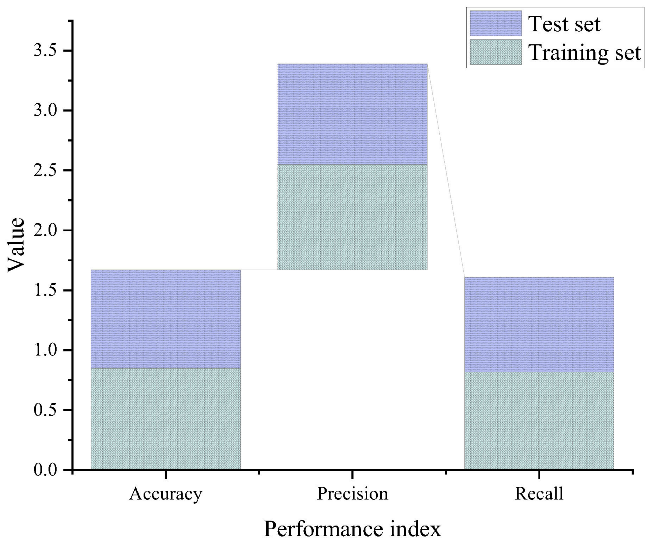

Figure 5. Performance of the BP neural network model on the training and test sets.

(2) The evaluation results of the BP neural network model were further dissected based on distinct sample characteristics such as managerial level. For managers, the accuracy rate stood at 0.85, the precision rate at 0.88, and the recall rate at 0.82. At the supervisor level, the accuracy rate was 0.81, the precision rate was 0.83, and the recall rate was 0.78. Meanwhile, at the employee level, the accuracy rate was 0.79, the precision rate was 0.81, and the recall rate was 0.76. The results are illustrated in Figure 6 below.

(3) Next, an analysis was conducted based on the years of service, with the following results: for 0–5 years of service, the accuracy was 0.82, precision was 0.84, and recall was 0.79; for 5–10 years of service, the accuracy was 0.83, precision was 0.86, and recall was 0.80; and for more than 10 years of service, the accuracy was 0.85, precision was 0.88, and recall was 0.82. Figure 7 shows the performance metrics of the BP neural network model on samples considering different years of work experience.

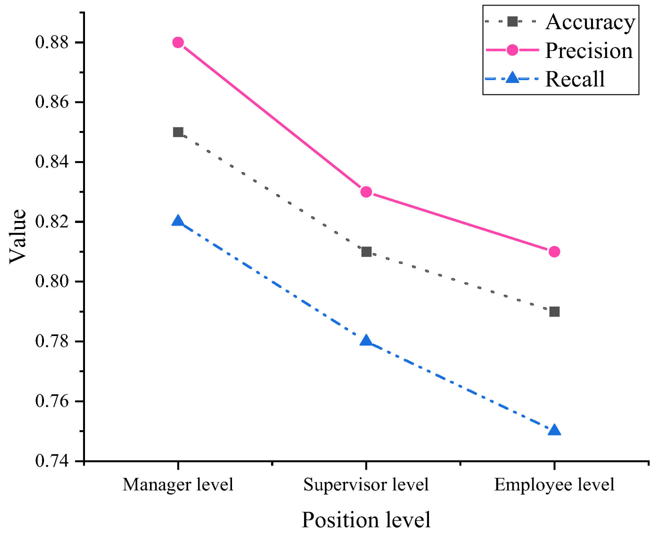

Figure 6. Performance of the BP neural network model on samples at different job levels.

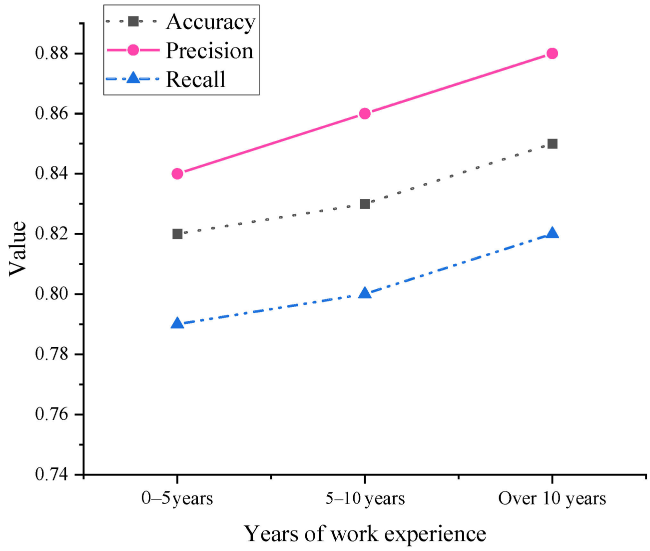

Figure 7. Performance of the BP neural network model on samples considering different years of work experience.

5. Discussion

This study conducted an in-depth analysis of resource optimization and task prioritization in coastal local government marine regulatory reform through the application of a BP neural network model. Firstly, this study determined that the BP neural network model exhibited a strong predictive capability on the training set and demonstrated a good generalization performance on the test set. This observation underscores the effective application of machine learning techniques in prioritizing tasks and allocating resources in marine regulatory tasks, thereby providing coastal local governments with precise and scientifically informed decision support. Secondly, by comparing the evaluation results of samples from various management levels, differences in accuracy, precision, and recall among management, supervisory, and staff levels were identified. This disparity elucidates distinct needs and preferences across different management levels concerning resource allocation and task execution, thereby laying the groundwork for the development of tailored management strategies. Moreover, variations in the performance of employee samples with differing lengths of work experience were observed during model evaluation. This phenomenon may stem from the influence of work experience on task comprehension and resource requirement judgment, thus further validating the applicability and effectiveness of the BP neural network model across diverse experience groups.

This study employed machine learning techniques to analyze marine regulatory data, facilitating the prediction of the urgency and importance of regulatory tasks. Additionally, it conducted an analysis of abnormal situations in the marine environment, offering crucial insights for regulatory decisions. The prioritization and allocation of resources in marine regulatory tasks are pivotal for coastal local governments to effectively manage marine resources. The findings of this study underscore that through machine learning models, the urgency and importance of regulatory tasks can be quantitatively assessed, providing a scientific basis for resource allocation. For instance, tasks associated with ecological protection and restoration, characterized by high urgency and importance scores, warrant priority consideration and a higher allocation of resources. Moreover, resource allocation strategies should account for variances in task comprehension and execution among employees at different management levels and with varying lengths of work experience to achieve precise resource allocation. The application of machine learning technology has revolutionized the field of marine regulation. Through big data analysis and pattern recognition, machine learning techniques can forecast trends in marine environmental changes and detect abnormal behaviors such as illegal fishing and vessel collisions, thus enhancing regulatory efficiency and response speed. Additionally, machine learning technology aids decision-making by optimizing the allocation of regulatory resources through intelligent algorithms, thereby achieving automation and intelligence in regulatory tasks. Optimizing the allocation of regulatory resources is a potent means to bolster the capability and efficiency of marine regulation. This study showcases how resources can be intelligently allocated based on task priority using the BP neural network model. Future research could delve into combining multi-objective optimization algorithms to strike a balance in resource allocation, encompassing regulatory efficiency, cost-effectiveness, and environmental protection. In contrast, Amiri et al.'s [39] findings suggest that machine learning models can discern and adapt to diverse patterns based on different data attributes [39]. Similarly, this study's model exhibited varying evaluation effects from employee samples with differing levels of work experience, underscoring the model's capacity to capture the differential impacts of work experience on marine regulation, thus further validating the efficacy of machine learning in personalized decision support. By scoring and ranking the urgency and importance of marine regulatory tasks using the BP neural network model, not only does it bolster the scientific execution of regulatory tasks, but it also enhances the accuracy of resource allocation. This resonates with Peng et al.'s [40] discovery that machine learning substantially enhances regulatory efficiency and quality in environmental regulation by streamlining the decision-making process [40]. Integrating machine learning technology into marine regulatory reform pragmatically equips coastal local governments with robust decision support tools, fostering the progression of marine regulation toward a more scientific and refined trajectory. In conclusion, this study aptly showcases the application potential of machine learning technology in optimizing marine regulatory resources, offering fresh perspectives and methodologies for future research and practice in related domains. With the continual advancement of data analysis technology and the enhancement of computational capabilities, machine learning is poised to play an increasingly pivotal role in public policy arenas such as marine regulation.

Moreover, it is acknowledged that for the effective deployment of machine learning technology in China's marine regulation sector, ensuring that government officials possess the requisite technical knowledge and data literacy is paramount. This necessitates specialized training and education to acquaint officials with the fundamental principles of AI technology and equip them with operational proficiency. Additionally, officials must cultivate the capacity to analyze and interpret data, a skill crucial for both training and evaluating machine learning models. To bolster the application of AI technology, the Chinese government should develop essential infrastructure, including high-speed internet and cloud computing platforms, to provide the requisite hardware support for technology operations. Concurrently, establishing data sharing platforms will streamline the integration and dissemination of marine regulatory-related data, providing rich data reservoirs for model training. Further, governmental support for AI technology research and development, coupled with incentivizing innovation and providing funding and technical backing, is imperative. Moreover, the formulation of lucid regulations and policies, encompassing guidelines and regulatory frameworks for AI technology utilization, is equally pivotal to ensure its legality and security. Interdepartmental collaboration mechanisms will foster information exchange and resource sharing among diverse government entities, fostering a collaborative approach to advancing AI technology application. It is believed that through these measures, machine learning technology will assume a pivotal role in China's marine regulation domain, augmenting regulatory efficiency and precision, promptly identifying problems and risks, and providing scientific decision support for marine resource management and protection. Despite certain challenges, concerted efforts from the government and various societal sectors augur promising application prospects for machine learning technology, heralding positive transformations in China's marine regulation landscape.

In this study, machine learning methods were employed to optimize the prioritization and resource allocation of marine regulatory tasks. However, this approach encounters several challenges, particularly concerning the availability of training data. Firstly, the accessibility of training data is pivotal for the success of machine learning models. In China, despite the government's concerted efforts in promoting digital transformation, data pertaining to marine regulation may not be as readily available as in other sectors. This scarcity stems from the intricate nature of data collection and integration, coupled with constraints on data sharing and openness. To mitigate this challenge, multifaceted strategies are imperative. Strengthening collaboration with marine research institutions, leveraging modern technologies such as satellite remote sensing for data acquisition, and fostering interdepartmental data sharing mechanisms are essential steps. Secondly, the proficiency of Chinese government officials in utilizing machine learning methods poses another challenge. Presently, some officials may lack familiarity with machine learning and data analysis. Overcoming this obstacle necessitates enhancing training and educational initiatives for officials to bolster their data literacy and adeptness with new technologies. Additionally, deficiencies in technical proficiency among officials can be remedied by establishing dedicated professional teams or fostering partnerships with specialized institutions.

Insufficient training data can compromise the performance of machine learning models, presenting challenges to the reliability of coastal resource management. In such scenarios, several considerations merit attention:

(1) Utilizing alternative data sources: Exploring alternative data sources such as social media data, online news reports, and reports from non-governmental organizations to complement official data shortcomings.
(2) Transfer learning: Employing transfer learning techniques involves utilizing models pre-trained in other domains or regions as a foundation and fine-tuning them to suit local marine regulation requirements.
(3) Ensemble methods: Employing ensemble methods by combining multiple machine learning models enhances model generalization capability and robustness.
(4) Expert knowledge: Integrating expert knowledge and experience through expert systems can aid decision-making in data-scarce scenarios.
(5) Continuous data collection: Establishing mechanisms for ongoing data collection and updates allows for the gradual accumulation of data resources to support model training and optimization.

In conclusion, despite these challenges, there is optimism surrounding the application of machine learning methods in marine regulation. Continuous technological innovation, policy backing, and talent development are key factors in overcoming these obstacles. Collaboration among government, academia, and industry stakeholders is vital in navigating these challenges and advancing the modernization and intelligence of marine regulation.

6. Conclusions

This study employed machine learning techniques to analyze marine regulatory data and effectively predicted the urgency and importance of regulatory tasks, thereby providing a scientific basis and decision support for regulatory authorities. By prioritizing tasks, regulatory resources can be optimized and scheduling can be improved, enhancing regulatory efficiency and precision. Analysis of marine environmental data enables the identification of anomalies and potential risks, offering insights for marine resource conservation and environmental management. Timely detection and resolution of environmental issues contribute to safeguarding the stability and sustainable development of marine ecosystems, as well as preserving biodiversity and ecological balance. Furthermore, this study underscores the widespread application prospects and potential value of machine learning technology in marine regulation. With continuous advancements in data collection and processing, the application of machine learning in marine regulation will broaden, providing robust support for intelligent marine regulatory systems. These systems ensure the sustainable utilization and protection of marine resources while adapting to evolving environmental challenges and regulatory needs. The integration of machine learning into marine regulatory frameworks holds promise for enhancing regulatory decision-making processes. Through advanced predictive analytics, regulatory authorities can anticipate emerging issues and allocate resources effectively to address them proactively. This proactive approach can lead to more efficient and targeted interventions, ultimately fostering greater resilience and adaptability in the face of changing environmental conditions and human activities impacting marine ecosystems.

This study has certain limitations. Due to constraints in data availability and sample size, the research results may be influenced by these limitations, potentially failing to fully capture the diversity and complexity of marine regulation. Although the machine learning models demonstrated good performance in predicting marine regulatory tasks and environmental anomalies, there is still room for further optimization and improvement to enhance their accuracy and stability. Future efforts will prioritize refining and innovating machine learning models and integrating advanced technologies such as deep learning to enhance predictive ability and generalization. This will enable more precise regulatory predictions and environmental analyses. Additionally, efforts should be directed towards expanding the scope of data collection to encompass a wider range of variables and scenarios, ensuring a more comprehensive understanding of marine regulatory dynamics and environmental conditions. Collaborative initiatives among researchers, regulatory agencies, and industry stakeholders can facilitate the acquisition of diverse datasets, fostering the development of robust and adaptable machine learning frameworks for effective marine regulation and ecosystem management. More data can be checked in Appendix A.

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Data Availability Statement: The data that support the findings of this study are available upon reasonable request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Dear Participants:

To gain a deeper understanding of the resource allocation strategies and priority settings of coastal local governments in marine regulatory reforms, we have designed a comprehensive questionnaire survey for this study. Your input is invaluable to our research and will aid us in better understanding the current situation and needs of marine regulation. Please fill in the following questions based on your actual experience.

All responses in the questionnaire will be treated with strict confidentiality, and the data will only be used for academic research purposes, with your personal information remaining undisclosed.

I. Basic Information

1. Gender:
    A. Male
    B. Female
2. Age range:
    A. 18–30 years old
    B. 31–45 years old
    C. 46–60 years old
    D. 60 years old and above
3. Education level:
    A. High school and below
    B. Bachelor's degree
    C. Master's degree and above

II. Perception and Evaluation of Marine Regulatory Work

4. How urgent do you perceive the current marine resource management to be? (Rate from 1 to 5, with 5 indicating extremely urgent)
    A. 1
    B. 2
    C. 3
    D. 4
    E. 5
5. How important do you consider the current marine resource management to be? (Rate from 1 to 5, with 5 indicating extremely important)
    A. 1
    B. 2
    C. 3
    D. 4
    E. 5
6. Please rank the following marine regulatory tasks in terms of priority:
    A. Marine pollution control
    B. Fisheries resource management
    C. Vessel traffic management
    D. Ecological protection area delineation
7. Which of the above tasks do you believe require additional resource allocation? (Multiple choices allowed)
    A. Marine pollution control
    B. Fisheries resource management
    C. Vessel traffic management
    D. Ecological protection area delineation

III. Awareness and Expectations of Machine Learning Technology

8. How familiar are you with machine learning technology?
    A. Completely unfamiliar
    B. Somewhat familiar
    C. Quite familiar
9. Are you willing to try using machine learning technology for marine regulatory work?
    A. Willing to try
    B. Might try
    C. Not willing to try
10. What do you believe are the potential effects of applying machine learning technology in marine regulation? (Multiple choices allowed)
    A. Improve regulatory efficiency
    B. Enhance prediction accuracy
    C. Reduce manpower costs
    D. Other (please specify)

IV. Personal Work Background

11. How many years have you been engaged in marine regulatory work?
    A. 0–5 years
    B. 5–10 years
    C. More than 10 years
12. What department are you affiliated with?
    A. Marine and Fisheries Bureau
    B. Maritime Bureau
    C. Environmental Protection Bureau
    D. Other related departments (please specify)

V. Feedback and Suggestions

13. What suggestions do you have for improving the current marine regulatory system?

VI. Conclusion

Thank you for dedicating your time to participate in this survey. Your feedback is immensely valuable to our research. Please review the completed questionnaire for accuracy before submission. Thank you once again!

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