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Research Article

Design and Implementation of a Damage Assessment System for Large-Scale Surface Warships Based on Deep Learning

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Artificial intelligence technology and image recognition technology are playing an increasingly important role in information warfare, while battlefield image recognition and information processing are at the heart of information processing in warfare. This research will use deep learning image recognition technology and QT development platform, combined with target damage tree analysis and Bayesian network inference method, to research and develop the design of large-scale surface warships damage assessment system. A large-scale surface warships damage assessment system was designed. The system can quickly identify the target large-scale surface warships type with an accuracy rate of over 91%. On this basis, damage assessment is carried out in terms of target vulnerability, combatant power analysis, and bullet-eye rendezvous. A new damage classification is established. The system can improve the efficiency of large-scale surface warships damage assessment, can be well combined with the front-line information collection pictures to assess, and overcome the traditional large-scale surface warships damage assessment and problems of slow and inaccurate manual processing of raw data. It provides a new way of thinking for large-scale surface warships damage assessment research.

1. Introduction

The destruction assessment research of large-scale surface warships is an important research direction in the military research at home and abroad. At present, the damage evaluation of large-scale surface warships are mostly based on simulation calculation and calculation combining with test data and empirical formula [1]. Since the 1970s, the European and American countries, mainly represented by the United States, have carried out in-depth research on the destruction assessment technology, achieved relatively mature theoretical results, and developed various destruction assessment systems to be used in actual combat training. After a long period of development, foreign destruction evaluation research has rarely discussed the underlying evaluation methods and evaluation models, and in the context of the destruction evaluation system research, various application-level evaluation systems have been established, especially the US military has established much destruction evaluation systems to conduct data analysis of different training modes. Glenn Dickinson[2] developed a system to automatically assess the effects of destruction. Sirmalis et al. [3] have developed a destruction assessment system for real-time assessment of missile attacks. The system uses photographic communications equipment carried by missiles fired over enemy targets, separating from the missile before attacking, and transmitting images of the missile attack in real-time. Conley and Gamache have developed a large missile explosion and damage assessment system [4]. Mainly through the sensor to collect and analyze the shock department explosion wave damage, combat forces can report enemy forces and their own killing capabilities to the database in real time, and the system timely calculates the damage information. The French THETIS system [5] is a damage assessment system that specifically analyzes ship viability. The assessment includes the safety and stability of the hull from the beginning of the ship design, to the direct damage effect of suffering from a weapon hit, and the second damage caused by explosions, shock waves, and fires. The THETIS system uses the

functional tree structure to describe the relationship between the systems and components of the ship and simulates the damage effect of the system target in the image way, and analyzes the bullet point and broken armor damage under different weapon attacks. According to the mission and function requirements, Hou et al. [6] proposed a design idea of ship damage effect assessment system. By building target ships, ammunition, and reasoning rules and other databases, physical, functional, and system efficiency damage were evaluated, respectively. Zeng [7] studied the overall damage assessment method of the ship when subjected to the underwater explosive load, focused on the analysis of the bottom components and the destructive mode of the ship, and summarized the destruction law of the explosion water depth, the explosion azimuth and other parameters on the overall structure of the ship. Wang [8] took typical antiship weapons as an example to study the deformation characteristics, the damage situation, and damage range of the superstructure of large-scale surface warships under the action of contact and explosion and to provide an engineering calculation reference for the local damage to large ship structures under contact and explosion.

With the development of science and technology, information warfare has become the main combat mode in the contemporary military. Information war is a form of war that makes full use of information resources and relies on information. One of the main directions of the current military research is how to quickly discover the information that commanders are interested in the massive amount of combat feedback information and use this information to study effective conclusions. On the other hand, with the development and progress of artificial intelligence technology and image recognition technology, it provides a reliable research mean for battlefield image recognition and battlefield image information processing. In recent years, the image recognition technology based on deep learning has made rapid development, and it has relatively mature applications in remote sensing image recognition, face recognition, communication, biomedicine, machine vision, and other fields [9–13]. In recent years, machine learning techniques are being implemented in several applications to solve real-world problems. Yanget al. [14, 15] applies deep learning to a power system. To improve the security of federated learning, a secure federated learning scheme is designed by combing Paillier cryptosystem with federated learning. And he proposes a novel deep-learning intelligent system incorporating data augmentation for STVSA of power systems. Pham Binh et al. [16] applies deep learning to flood risk assessment, he proposed a novel approach for flood risk assessment, which is a combination of a deep learning algorithm and multicriteria decision analysis (MCDA). Hu et al. [17] applies deep learning to medical services. He designs and implements a medical Q&A system based on deep learning. Jena et al. [18] applies deep learning to seismic risk assessment, this study develops a convolutional neural network (CNN) model for earthquake probability assessment in NE India. Vasit et al. [19] applies deep learning techniques to agriculture, to develop a raw imagery-based deep learning approach for field-scale yield prediction. Computer vision is an essential application of artificial intelligence [20–22]. Many other scholars have applied deep learning in intelligent transportation systems [23–26]. The study mainly included destination prediction, traffic flow prediction, travel time estimation, predicting traffic accident severity, predicting the mode of transportation, and navigation.

Unfortunately, deep learning techniques have so far rarely been used in the damage assessment of large-scale surface warships. The current study, and almost 70% of the damage assessment system for large-scale surface warships is based on traditional techniques. However, most of the systems studied now cannot be quickly and effectively analyzed with the pictures of the actual battlefield feedback, so that the information feedback in the actual battlefield takes a long time, and it is easy to miss the best judgment opportunity, resulting in military delay. In order to bridge this gap, based on our existing work, this study applies the deep learning image recognition technology to the large-scale surface warships damage evaluation, which can greatly improve the evaluation efficiency and provide some reference for the damage analysis and research of large-scale surface warships. This study addresses the following questions: (i) establish a highly accurate large-scale surface warships' identification model, (ii) formulate and improve the large-scale surface warships damage assessment method, and (iii) design and develop a set of large-scale surface warships damage assessment platform.

2. Materials and Methods

2.1. General Design of the Damage Assessment System for Large-Scale Surface Warships

2.1.1. System Design Principles

(1) Robustness, the software can judge that the input other than the specification requirements does not meet the requirements of the specification and can have a reasonable processing way.

(2) The system should have a friendly interface, good man-machine interaction, and meet the required man-machine interaction interface. The 3D images and 2D ICONS displayed are more intuitive and convenient for the war fighters to use.

(3) The system should adopt a consistent interface, should standardize the description form, and should have a good expansion.

(4) The design of the database should fully consider the scalability and accessibility.

2.1.2. Database Establishment. The database of the large-scale surface warships damage assessment system is mainly divided into four parts: target database, target damage database, combat department database, and evaluation result database.

(1) Target Database. This database mainly stores the model information of large-scale surface warships, including the three-dimensional images of the large-scale surface warships

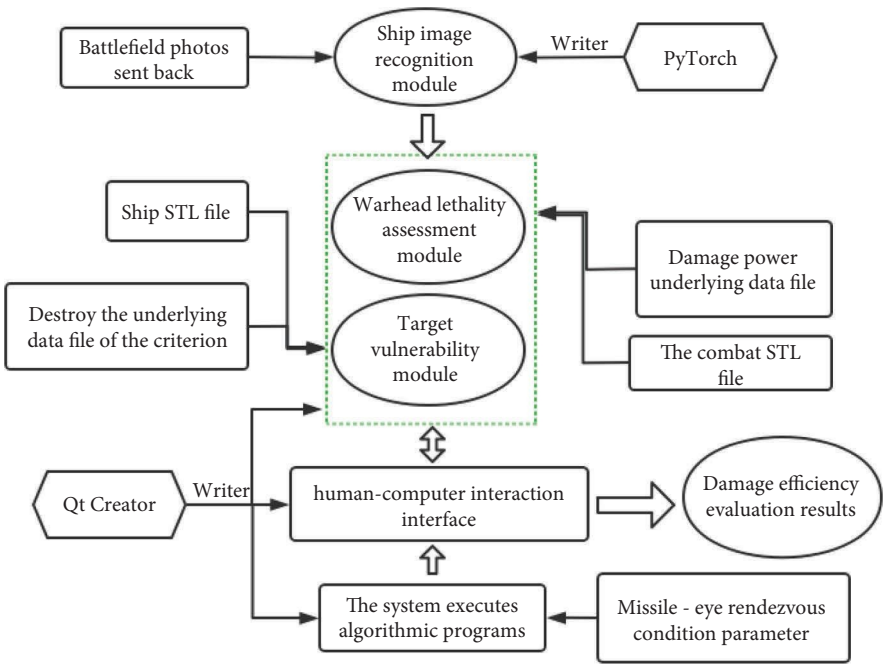

Figure 1: Flow chart of the damage efficiency assessment software algorithm.

and the material information used in each cabin. 3D image data can be directly imported to the display interface and can be rotated at any angle, zoom in, and out. Damage parts can be manually added to provide basic ship information for damage assessment.

(2) Target Damage Database. This database is mainly to store the established large-scale surface warships damage tree, the relationship among the subordinates, the damage weight of each component, to provide the basic data of the damage tree for the later damage assessment.

(3) Combat Department Database. This database is used to store the performance parameters of antiship weapons and some data reflecting the characteristics of destructive power, providing the basic data for the bullet rendezvous module.

(4) Evaluation Results Database. This database only stores the results information completed by the previous evaluation to be viewed directly next time.

2.1.3. System Architecture. The design of the large-scale surface warships damage assessment system is mainly divided into five modules, system management module, large-scale surface warships image recognition module, warhead lethality assessment module, target vulnerability module, and damage efficiency assessment module. The flow chart is shown in Figure 1.

(1) System Management Module. The main function of the system management module is to complete the registration and authentication function of user login. System users are divided into administrators and operators. The administrator's permission is the increase, deletion, and permission setting of the overall user. The operator's authority can only query the database, add the basic data, and complete the large-scale surface warships damage assessment and analysis.

(2) Large-Scale Surface Warships Image Recognition Module. Object recognition module is mainly based on the combat information sent back to the picture information, and identifies the damaged analysis target large-scale surface warships model according to the deep learning image recognition technology.

(3) Target Vulnerability Module. Target vulnerability module is mainly in the computer image identified large-scale surface warships model, began to related large-scale surface warships target vulnerability analysis. First, import the STL file of the large-scale surface warships model. The STL file mentioned here is a 3D model of large-scale surface warships in professional modeling software (such as UG and Soilworks). STL files mainly describe common properties of 3D models of closed faces or bodies, such as geometry. STL files come in two formats: ASCII plain format and binary format. The STL file structure in ASCII format is shown in Figure 2, and the STL file structure in binary format is shown in Figure 3. It is much more common because the binary code format is simple. The 3D model diagram is displayed, then the tree is established, and then the tree logical relationship is completed.

(4) Warhead Lethality Assessment Module. Combat department power analysis module mainly analyzes the mathematical characterization of shock wave peak, shock wave positive pressure action time, shock wave ratio impulse, secondary pressure wave peak pressure, bubble

```
solidfilenamestl  //File path and name
facetnormalxyz    //The three components of the normal vector of a triangular surface
outerloop
vertexxyz         //The first fixed point coordinate
vertexxyz         //Second fixed point coordinate
vertexxyz         //The third fixed point coordinate
endloop
endfacet          //Complete the definition of a triangular surface

`****`            //Other facets
endsolidfilenamestl  //The entire STL file definition ends
```

Figure 2: Structure diagram of the STL file in ASCII format.

```
UINT8 //Header
UINT32 //Numberoftriangles
//foreachtriangle
REAL32[3] //Normalvector
REAL32[3] //Vertex1
REAL32[3] //Vertex2
REAL32[3] //Vertex3
UINT16 //Attributebytecountend
```

Figure 3: Structure diagram of the STL file in binary format.

maximum radius, and time of underwater explosion. By inputting the explosive equivalent of the combat department, the explosive distance, and other basic values, the damaging power of the combat department is intuitively displayed in the form of charts.

(5) Damage Efficiency Assessment Module. We determine the attack position coordinates of the combat department, set the relevant parameters including the attack speed, angle, and the close blast distance of the proximity fuse, and calculate the damage probability of the submarine target under different strike schemes. The display of the evaluation results should be concise and clear, so that the commander can see the result of the large-scale surface warships damage at a glance. Figure 4 shows the picture of the software development.

2.2. Key Technologies for the Damage Assessment System for Large-Scale Surface Warships

2.2.1. Construction of the Convolutional Neural Network Model. At present, there are three typical deep learning models: deep model based on restricted Boltzmann machines (RBM), recurrent neural networks (RNN), and convolutional neural networks (CNN) [27]. Among them, CNN model is a feedforward-forward artificial neural network that can be applied to process grid information (such as image), mainly using image recognition and audio processing. Meanwhile, CNN is compared with general information recognition methods, with strong robust and generalization ability. The typical CNN model is mainly composed of input layer, convolutional layer, activation function, pooling layer, full connection layer, and output layer. The simple diagram is shown in Figure 5.

The convolutional layer is composed of many convolutional units, and the basic parameters of each convolutional unit are optimized by using the back propagation algorithm. The main purpose of the convolution calculations is to obtain different properties of the input. The first convolutional layer only obtains a lower level feature, such as boundaries, curves, and angles, while more multilayer networks can iterate more complicated features in the underlying features. The convolution process is shown in Figure 6.

Deep models based on CNN have begun to develop rapidly, and more optimized and more mature deep convolutional neural network models have been proposed successively, such as AlexNet [28], ZF-Net [29], VGGNet [30], GoogleNet [31], ResNet [32], R-CNN, Fast R-CNN, Faster R-CNN, and Mask R-CNN.

The technology used in this design is Yolov5, and YOLO (you only look once) is an end-to-end deep convolutional neural network proposed by Redmon at the 2016 Computer Vision (CVPR2016). By solving the object detection as a regression problem, the proposed method no longer needs to extract the candidate regions but instead divides the image into a fixed-size grid, and then makes the prediction within each grid. It predicts the probability of the confidence of the target and the border area belonging to different categories, and regression on the whole image to get the position and category of the target border, resulting in that the running speed is greatly improved [33]. The target identification process of YOLO is shown in Figure 7. The training model and the detected target in YOLO are carried out in a separate grid, which greatly improves the speed, the performance, and the accuracy, while reducing the background misdirection rate.

The hardware platform for the experiment is AMD Ryzen 7 5800H with Radeon Graphics@3.20 GHz with 16 GB of memory. In view of the lack of public in-depth knowledge training samples on large-scale surface warships, we make and train and test sample sets by network query and large-scale surface warships model shooting. Figure 8 shows the sample large-scale surface warships test results in the large-scale surface warships identification module in this development system. The sample large-scale surface warship is an Ali Burke-class destroyer.

2.2.2. Performance Analysis of the Model. In order to detect the performance of the network algorithm, the intersection ratio between the true value of the bounding box and the predicted box is used to indicate the accuracy of the prediction. Generally, IOU > 0.5 is the correct detection result. The precision rate P, the recall rate R, the weighted harmonic average $F1$, and the average precision rate (mAP) are used as comprehensive evaluation indicators, and the frame rate FPS (that is, the number of pictures that can be detected per

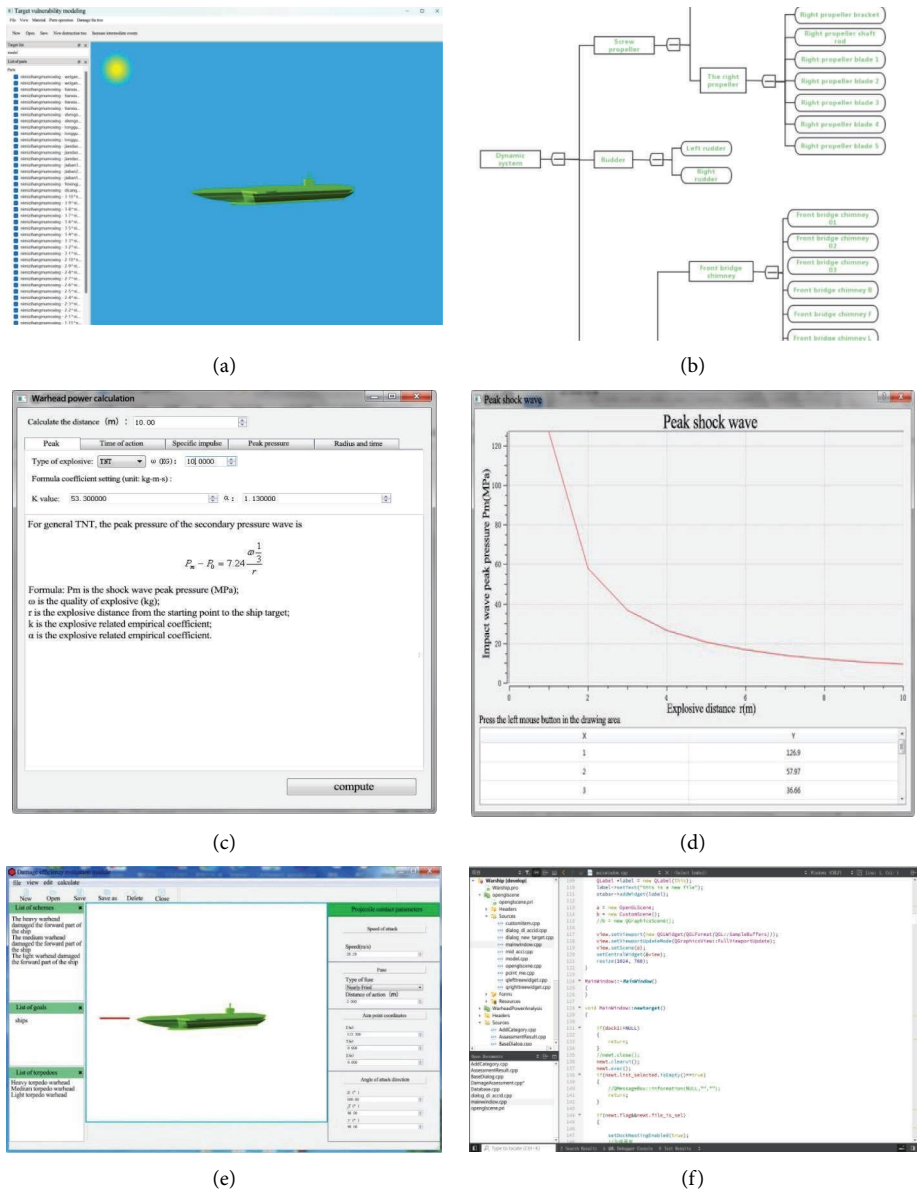

Figure 4: Schematic diagram of the software effect. (a) Target vulnerability interface. (b) Damage tree interface rendering. (c) Combat department power model head interface. (d) Chart of shock-wave mathematical models. (e) Disruptive analysis interface. (f) Software development interface.

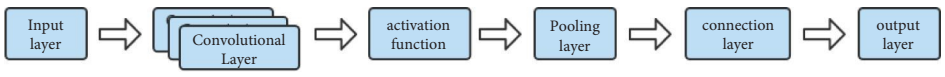

Figure 5: A typical CNN model constitutes a simple diagram.

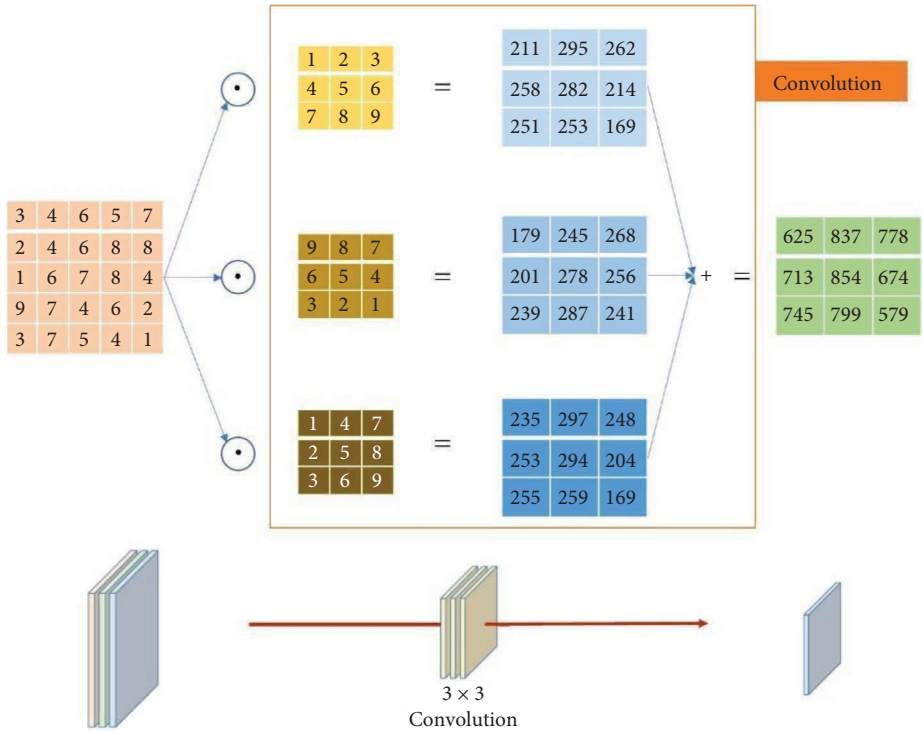

Figure 6: Schematic diagram of the convolution process.

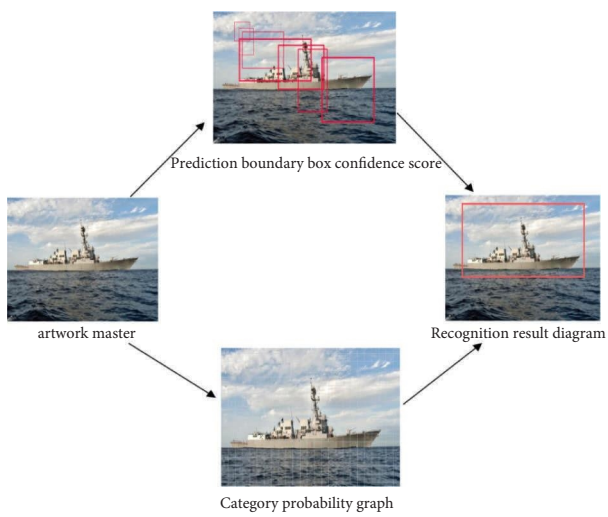

Figure 7: YOLO target ID flow chart.

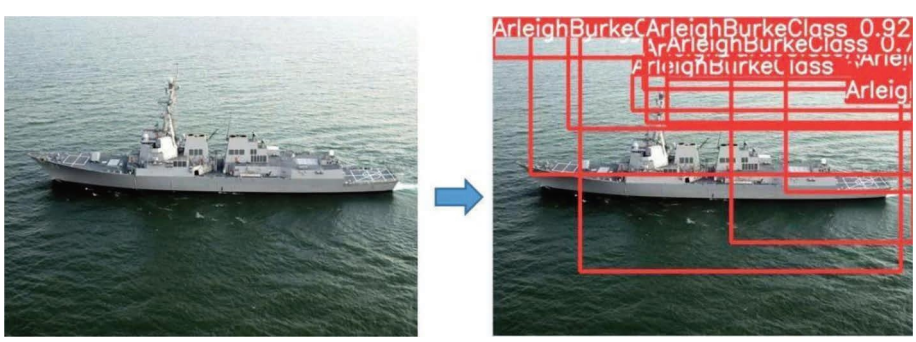

Figure 8: Schematic diagram of the sample large-scale surface warships identification results.

Table 1: Model performance test results.

Model	P (%)	R (%)	mAP (%)
YOLOv5	93.28	89.92	91.48

second) is used to evaluate the detection speed of the target detection network. The corresponding calculation formula is as follows:

$$P = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}},$$
$$R = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}},$$
$$F_1 = \frac{2\mathrm{PR}}{P + R}, \tag{1}$$
$$AP = \int_0^1 P(R)\mathrm{d}R,$$
$$mAP = \frac{\sum_{i=1}^{N} AP_i}{N}.$$

In the formula TP is the number of real samples, indicating the number of samples that the detected ship category is the real ship category; FP is the false positive sample, indicating the number of samples that the detected ship category does not conform to the real ship category; FN is the false negative sample, indicating the number of samples that real ships exist but have not been detected by the network model; AP is the average precision rate; and N is the number of all types of ships.

As can be seen from Table 1, the average detection accuracy mAP have reached 91.48%. Therefore, the designed algorithm has a good detection effect.

2.3. Computational Cost and Runtime. The main mode of this environment configuration is based on Anaconda + PyTorch (GPU version) + CUDA + cuDNN + Qt Creator 5.0.2. The preliminary work mainly collected the large-scale surface warships pictures, used the gradient descent algorithm of yolov5 framework to do the model training, and obtained the model files. The model files was used for the AI operations. Overall design and development of software was based on QT platform. The large-scale surface warships type is determined based on the AI recognition results, and each recognition operation is about 30 s–40 s. The identified large-scale surface warships model is then imported from the damage identification system developed by Qt to complete the damage assessment through the system operation. The evaluation time is about 3–5 minutes.

3. Destruction Assessment

3.1. Destruction Assessment Method. The system designed and developed this time is to evaluate the damage effect of the target large-scale surface warships by combining the damage tree analysis method and the Bayesian network reasoning method [34]. Damage tree analysis is a kind of top-down, from the top composition event in the analysis target as the starting point of analysis, and then step analysis to determine which event or which event combination caused the destruction, until the initial underlying event is found. Damage tree is an inverted tree figure drawn by a series of specific meaning of special symbols according to certain rules, indicating the logical relationship between various cause events and target destruction [35].

Bayesian network is, just popular in recent years, an uncertain logic reasoning development tool, it can be based on unknown or incomplete information to explore the problem of more accurate inference, and these characteristics of Bayesian networks are also very suitable for damage assessment and analysis on the battlefield. In the case of multiple unclear or incomplete target damage information, the target damage efficiency can be comprehensively evaluated.

Table 2: Cole explosion parameters of different charges.

Explosive	TNT	THL	HBX-1	PENT	NSTHL
k	53.3	63.48	53.51	56.21	67.08
α	1.13	1.144	1.18	1.194	1.26

3.2. Combat Department Power Analysis. The characteristic parameters of the underwater blast shock wave are mainly the peak pressure and the specific impulse. The calculation of the peak underwater shock wave pressure can be estimated by the empirical formula of the spherical charge explosion shock wave, and the corresponding empirical peak formula of the underwater shock wave pressure at different burst distances in a large number of tests is as follows [36, 37]:

$$P_{\mathrm{m}} = \mathrm{k}\left(\frac{\sqrt[3]{\omega}}{r}\right)^{\alpha}. \tag{2}$$

In the formula P_m is the shock wave peak pressure (MPa), ω is the quality of explosive (kg), r is the explosive distance from the starting point to the ship target, k is the explosive related empirical coefficient, and α is the explosive related empirical coefficient. For different explosives, the associated Cole explosion parameters k and α are shown in Table 2.

The characterization parameters involved in bubble pulsation mainly include bubble pulsation cycle and bubble maximum radius. Since only the destructive effect of the first bubble pulsation is considered, only the first bubble pulsation cycle and bubble maximum radius are selected for calculation. For TNT loading, the bubble pulsation cycle is calculated as follows [38]:

$$T = 2.11 \times \frac{\sqrt[3]{m_\omega}}{(h_b + 10)^{5/6}}. \tag{3}$$

In the formula T is the first bubble pulsation cycle (s), m_ω is the quality of explosive (kg), and h_b is the equivalent water depth corresponding to the bubble expansion (m). The maximum radius of the bubble is also the bubble radius

Table 3: Grade table of large-scale surface warships damage.

Damage grade	Definition	Phenomenon description
S1	The large-scale surface warships sank	The large-scale surface warships breaks, and the hull completely loses its vitality
S2	The large-scale surface warships were severely damaged	Most of the large-scale surface warships was damaged and basically lost its vitality
S3	Medium destruction of large-scale surface warships	Part of the large-scale surface warships structure is damaged and cannot fully function as the system
S4	The large-scale surface warships was slightly damaged	A very small part of the large-scale surface warships structure is damaged and does not affect the large-scale surface warships operations

reached when the bubble first pulsates. The relevant calculation formula is as follows [38]:

$$\mathrm{Rm} = \mathrm{KR}\sqrt[3]{\frac{\omega}{10P_0}}. \tag{4}$$

In the formula Rm is the maximum bubble radius (m); KR is the charge correlation coefficient, TNT charge is 1.63; the charge mass (kg); and P_0 is the absolute hydrostatic pressure (MPa) at the burst point, and the calculated value depends on the underwater depth H of the charge, namely $P_0 = 0.103(1 + 0.1H)$.

3.3. Large-Scale Surface Warships Structure Damage Level. At present, there are many studies of the damage level of large-scale surface warships, but the damage level standards are not uniform. The number of grades varies, most of which are 3–6 grades. The levels are expressed, according to the ABCDE grading expression, according to I, II, III, IV, and V. They are also divided by moderate and mild to severe severity. For example, Zhu and Feng [39] divided the damage level into five grades according to the condition of ship equipment and repair time. And Zhang and Liu [40] of PLA Unit 91493 and others carried out numerical simulation and analysis based on the damage to underwater near-field explosion targets. The results determine the degree to large-scale surface warships damage caused by the explosion in the water, and it is divided into four grades according to the degree of plastic deformation. Through extensive simulation experiments and underwater contactless explosion damage conditions, we divided the large-scale surface warships structural damage classes into four grades (S1, S2, S3, and S4). See Table 3 for the specific grade classification.

4. Conclusion

Finally, we developed independent large-scale surface warships evaluation software. This paper implements a large-scale surface warships damage evaluation system based on deep learning. To the best of the authors' knowledge, this is the first time that deep learning has been applied to large-scale surface warships damage assessment. Compared with the traditional evaluation methods, the designed system can not only analyze and identify ships reliably, but also determine the damage probability by damage tree analysis. The damage assessment system of large-scale surface warships based on deep learning ship identification technology can quickly and accurately evaluate the damage degree of ships according to battlefield operational information.

The study aims at develop and test a practical, visual digital tool for naval commanders to provide them with assistance in maritime integrated operations and provide a scientific basis for their decisions to complete their operational analysis efficiently, thus increasing the possibility of gaining an advantage in the battlefield.

However, the system has some limitations in some aspects. Due to the specificity and high quality requirements of different large-scale surface warships damage assessment content, in practice, users are currently limited to select or input the combat department and part of the target information, to achieve the most effective use of the system. And the database information still needs to be further updated and improved. In the next step, the system needs to improve the data in real time and upgrade the model according to the actual combat situation.

In the future we will expand our approach to handle damage assessment work on more targets, including but not limited to submarines and tanks. We will also expand the variety of combat departments to be not limited to underwater blasting. The types of extended damage elements are not limited to shock waves, including but not limited to fragment and jet [41].

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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