ISSN: 1813-4890

Research on Ship Recognition Technology Based on Neural Networks

Taizhi Lv*, Zewen Zhang, Xin Zhang

College of Information Engineering, Jiangsu Maritime Institute, Jiangsu Nanjing, 211170, China

Abstract

Currently, artificial intelligence technology has deeply integrated into every aspect of our lives, extensively penetrating into various fields such as family education, biomedical science, autonomous driving, and transportation. In water transportation management, ship recognition technology plays a crucial role. It not only enables real-time monitoring of surrounding waters to effectively prevent collision accidents and ensure navigation safety, but also plays an indispensable auxiliary role in disaster rescue and other aspects. In recent years, with the continuous advancement and popularization of deep learning technology and computer vision, ship recognition technology has also been continuously optimized. This paper aims to explore ship recognition technology based on Convolutional Neural Networks (CNN) and MobileNet, leveraging the TensorFlow framework to enhance the accuracy of ship detection and classification, while striving to reduce manual intervention. By constructing and training neural network models specifically designed for ship recognition, this study seeks to verify whether different networks can accurately identify and classify various types of ships when processing large-scale datasets.

Keywords

Ship recognition, neural network, TensorFlow, convolutional neural network, MobileNetV3.

1. Introduction

With the continuous increase in global trade, water transportation management has become particularly important. Ship recognition technology has gained increasing attention under this backdrop, serving as a crucial tool for safeguarding maritime order and security [1]. Modern maritime transportation carries about 90% of global trade in goods; therefore, real-time monitoring and management of maritime traffic flow are not only related to economic benefits but also to environmental protection and public safety. Furthermore, with the rise in maritime illegal activities such as smuggling, illegal fishing, and illegal immigration, how to effectively monitor and identify ships at sea has become an urgent issue for countries to address [2].

Traditional ship recognition methods mainly rely on radar, AIS (Automatic Identification System), but these methods have certain limitations. For instance, radar and AIS are susceptible to environmental interference and signal coverage restrictions, while visual observation depends on human judgment, which is inefficient and prone to errors. With the development of computer vision and deep learning technologies, especially in recent years, more and more research has been dedicated to improving ship recognition algorithms to enhance the accuracy and real-time performance of recognition. For example, the YOLO (You Only Look Once) series of algorithms, through improving model structures and optimizing feature extraction processes, have significantly increased recognition accuracy while improving detection speed [4]. Accurate ship recognition helps enhance maritime traffic management and prevent illegal

ISSN: 1813-4890

activities. Automated ship recognition technology can promptly detect and address potential safety threats, ensuring the safety of maritime navigation; it can assist marine resource management departments in monitoring fishing boat activities, preventing illegal fishing, and promoting sustainable fisheries development; it can also timely detect and stop behaviors that may cause pollution and damage to the marine environment, contributing to the protection of the marine ecological environment. In summary, the continuous advancement of ship recognition technology not only provides strong support for maritime traffic management and safety assurance but also opens up new paths for intelligent marine monitoring and national security defense.

This paper employs a neural network to achieve ship type recognition using the deep learning framework TensorFlow. Traditional feedforward neural networks exhibit significant fluctuations in ship recognition and have poor convergence capabilities. Based on this, this paper improves the convolutional neural network model by modifying the activation functions and network structure of the convolutional layers and tests the model's performance, achieving relatively stable results. However, there are still limitations in recognition capabilities. This paper makes appropriate improvements based on MobileNetV3 and achieves high recognition rates and generalization capabilities through experimental analysis.

2. Computational Framework and Ship Image Dataset

2.1. TensorFlow Framework

TensorFlow is an open-source deep learning framework that supports distributed training methods and is one of the most popular deep learning frameworks on GitHub [3]. TensorFlow 2 integrates the Keras high-level neural network API, allowing users to easily build, debug, and train neural network models.

2.2. Ship Image Dataset

The dataset used in this paper's research is the Ship_classification_dataset from Kaggle, which contains images of ten different types of ships [5]. The original training dataset includes a total of 8,534 images, while the test dataset includes 781 images. Due to a large number of duplicate and blurry images, after processing, the remaining training dataset consists of 1,000 images, and the test dataset consists of 200 images. Figure 1 shows some examples of cargo ship images.

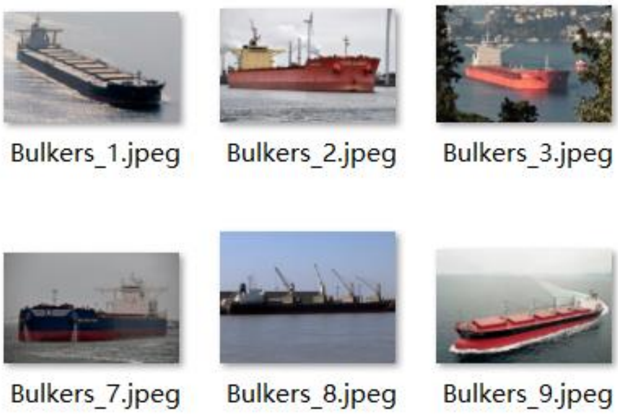


Figure. 1: The image examples

As seen from Figure 1, the image sizes in the dataset are not uniform. Therefore, during image preprocessing, the images are first resized to a uniform size (600×416 pixels). Secondly, while saving the image data as numpy arrays, the pixel values are normalized to accelerate convergence and improve model performance during training.

3. Ship recognition based on Convolutional Neural Network

3.1. Convolutional Neural Network

The convolutional neural network is a neurocognitive model inspired by visual neural mechanisms. It is specifically designed to process grid-structured data [6]. Image data can be viewed as grid data composed of pixels. The core technologies of CNN mainly include local perception, weight sharing, and pooling.

3.2. Ship Recognition Experiments

In this paper, a convolutional neural network model is constructed as shown in Figure 2. A set of convolutional layer and max-pooling layer is inserted between the second max-pooling layer and the third convolutional layer. The convolutional layer contains 8 convolutional kernels of size 3×3, and the max-pooling layer has dimensions of 2×2.

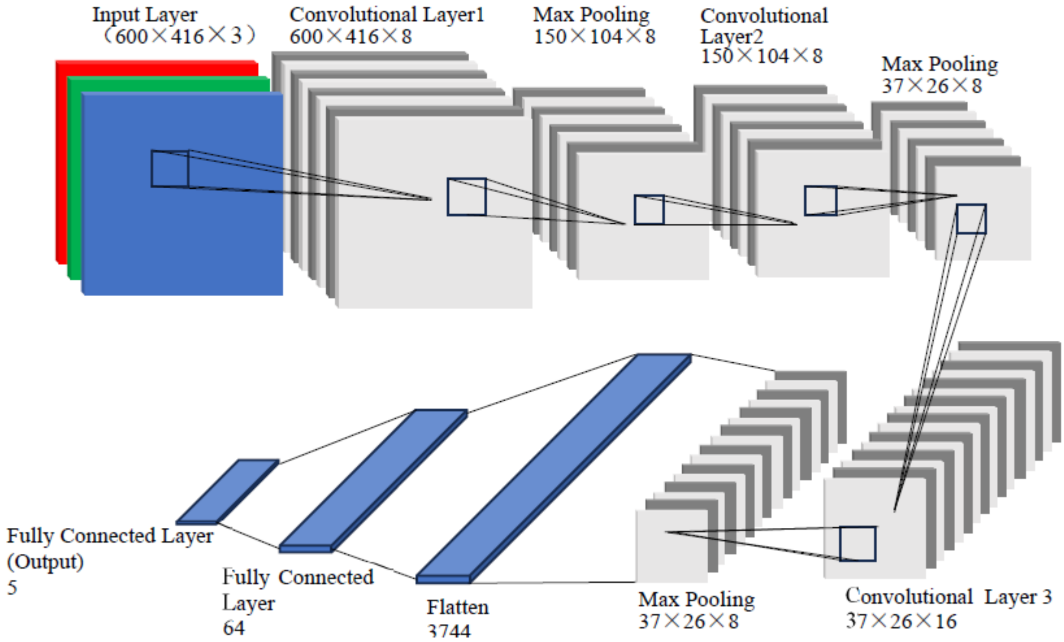


Figure. 2: The convolutional neural network

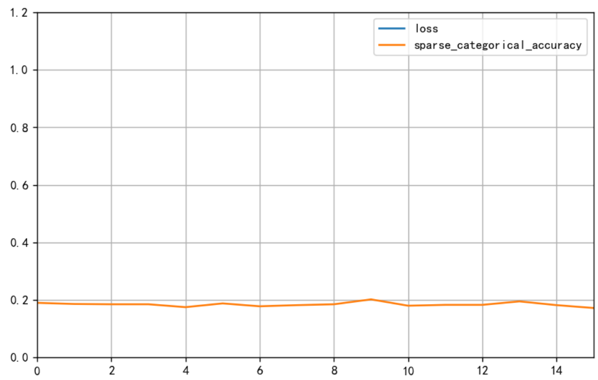
The experiment employs a mini-batch gradient descent method with a batch size of 32 for iterative optimization of model parameters. The number of iterations is set to 16 and 32 for comparative experiments. The dataset is shuffled before each training session, and training logs are saved. The experiment compares the performance and generalization ability of three different activation functions, with the results presented in Table 1. From the table, it can be observed that the sigmoid model fails to perform the classification task when recognizing ship images, as it exclusively identifies bulk carriers and is unable to recognize other types of ships. On the other hand, both the $relu$ model and the $tanh$ model exhibit relatively high accuracy in identifying different categories of ships. Additionally, it is found that their ability to recognize container ships is superior to that of other types of ships.

Table. 1: The test accuracy rates for different types of ships

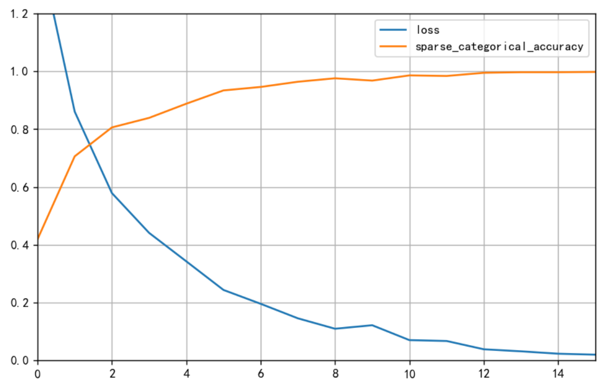
Excitation function / Ship Type	$sigmoid$	$relu$	$tanh$
aircraft carrier	0.0000e+00	0.8500	0.8000
bulk carrier	1.0000	0.8500	0.8250
vehicle carrier	0.0000e+00	0.8500	0.8500
container ship	0.0000e+00	0.9000	0.9250

cruise ship	0.0000e+00	0.8500	0.8750
total loss value	1.6096	0.5374	0.5365
overall accuracy rate	0.2000	0.8600	0.8550

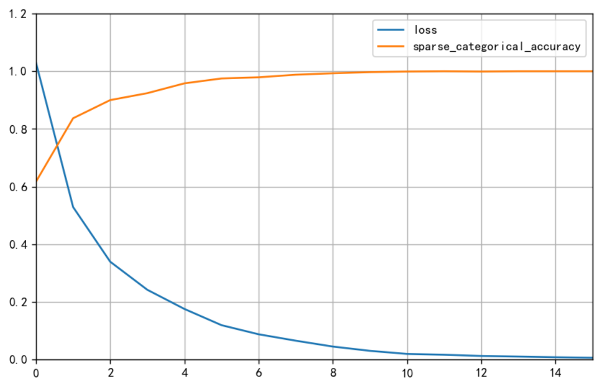
From Figure 3, it can be observed that the sigmoid function exhibits severe gradient vanishing when dealing with multi-classification problems, with its loss value consistently stabilizing at a relatively high level and its accuracy stabilizing at a relatively low level. Both the $relu$ model and the $tanh$ model demonstrate good performance during training, and the $tanh$ model converges faster than the $relu$ model. During testing, the accuracies of $relu$ and $tanh$ are comparable. Both the $relu$ model and the $tanh$ model exhibit good stability in ship recognition tasks and perform well in handling image classification problems.



$sigmoid$



$relu$



$tanh$

Figure. 3: The training results under different activation functions

4. Ship Recognition Based on MobileNetV3

4.1. MobileNetV3

MobileNet, proposed in 2017, focuses on optimizing computational efficiency and model size for operation on resource-constrained devices. Compared to traditional convolutional neural networks, MobileNetV1 has a significant advantage in its lightweight nature, making it more suitable for scenarios with limited computational resources. In 2019, the Google team further optimized the model structure by building upon the advanced methods of V1 and V2, combining neural architecture search and the NetAdapt algorithm [7]. Additionally, V3 introduces an attention mechanism, adding the SE (Squeeze-and-Excitation) attention module within the bottleneck layers, and redesigns the activation function, replacing the original ReLU function with a new activation function, h-swish, in these bottleneck modules. The network architecture of MobileNetV3 is shown in Table 5-1, where *Input* represents the image input size for each feature layer, *Operator* represents the network structure that the feature maps will pass through, *Expsize* indicates the number of channels after expansion in the bottleneck module, *#out* indicates the number of channels in the output feature maps, *SE* indicates whether the squeeze lightweight attention mechanism is used in MobileNetV3, *NL* represents the type of activation function (HS for h-swish activation function, RE for *relu* activation function), and *Stride* represents the convolution stride.

4.2. Ship Recognition Experiments

After the model construction and training stages, line graphs depicting the loss value and accuracy were plotted based on the training log files, as shown in Figure 4. The figure reveals the changes in loss value and accuracy during the training process. As training progressed, the loss value gradually decreased, while the accuracy steadily increased, indicating an improvement in model performance. In the early stages of training, the loss value dropped sharply, and the accuracy rose rapidly, suggesting that the model was able to quickly capture important features in the data during the initial learning phase. Although there were some fluctuations in loss value and accuracy during the training process, the overall trend indicated continuous improvement in the model's performance. As can be seen from the figure, the final training accuracy of the model reached over 98%, demonstrating the model's efficiency and accuracy. The loss value gradually decreased during the training process and eventually stabilized, indicating that the model performed well in reducing errors and did not exhibit obvious overfitting. Furthermore, the accuracy curve also tended to stabilize after reaching a high point, indicating that the model was able to maintain stable prediction performance after learning the data distribution characteristics.

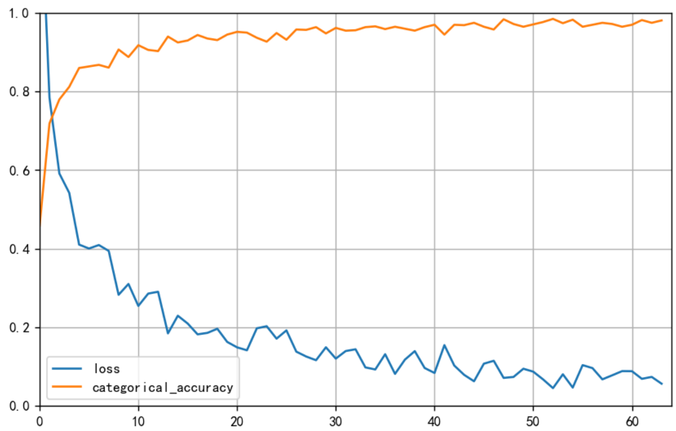


Figure. 4: The training results

Using the trained model to test different types of ships, the results are shown in Table 2. It can be observed that the vehicle carrier category had the lowest loss value and the highest accuracy, reaching 100%, indicating that the model performed extremely well in this category and was able to accurately identify all samples of vehicle carriers. However, the aircraft carrier category had a significantly higher loss value and the lowest accuracy, with only 70%. This suggests that the model encountered difficulties in recognizing aircraft carriers. Through analysis of the aircraft carrier sample tests, it was found that the reason for the model's inaccurate predictions was that it misidentified aircraft carrier images as bulk carriers and cruise ships. This means that the features of aircraft carriers have a significant overlap with those of bulk carriers and cruise ships, leading to misclassification by the model. Although bulk carriers, container ships, and cruise ships could not be perfectly predicted, their loss values and accuracies were still at a high level. Overall, the model's total loss value was 0.5275, with an accuracy of 92.5%. The overall performance was good, but the difficulty in recognizing aircraft carriers affected the overall performance.

Table. 2: The test accuracy rates for different types of ships

Ship Type \ Metrics	$loss$	$accuray$
aircraft carrier	2.1584	0.7000
bulk carrier	0.1648	0.9750
vehicle carrier	0.0220	1.0000
container ship	0.1407	0.9750
cruise ship	0.1516	0.9750
total	0.5275	0.9250

5. Conclusion

This paper systematically studies ship recognition technology using convolutional neural networks and MobileNetV3. CNNs significantly improve recognition accuracy through local receptive fields and shared weights, but they have high computational complexity. The improved MobileNetV3 model, while maintaining recognition accuracy, greatly reduces the demand for computational resources, achieving more efficient and accurate ship recognition. Ship recognition plays a crucial role in the future development of the transportation industry. Therefore, how to apply ship recognition technology to real-life scenarios using various neural network algorithms is a promising task, but it also comes with significant challenges.

Acknowledgements

This work was financially supported by the funding of the Natural Science Foundation of the Jiangsu Higher Education Institutions of China (22KJB580002), the Jiangsu Province Insitute Students Innovation and Entrepreneurship Training Program (G-2023-0409), and the Excellent Teaching Team for QingLan Project of the Jiangsu Higher Education Institutions of China (Big Data Technology Teaching Team with Shipping Characteristic)..

References

[1] Barnes, Paul, and Richard Oloruntoba. "Assurance of security in maritime supply chains: Conceptual issues of vulnerability and crisis management." *Journal of international Management* 11.4 (2005): 519-540.

[2] Xiao, Yi, Zhuo Chen, and Levi McNeil. "Digital empowerment for shipping development: A framework for establishing a smart shipping index system." *Maritime Policy & Management* 49.6 (2022): 850-863.

[3] Pang, Bo, Erik Nijkamp, and Ying Nian Wu. "Deep learning with tensorflow: A review." *Journal of Educational and Behavioral Statistics* 45.2 (2020): 227-248.

[4] Jiang, Peiyuan, et al. "A Review of Yolo algorithm developments." *Procedia computer science* 199 (2022): 1066-1073.

[5] Di, Yanghua, Zhiguo Jiang, and Haopeng Zhang. "A public dataset for fine-grained ship classification in optical remote sensing images." *Remote Sensing* 13.4 (2021): 747.

[6] Taye, Mohammad Mustafa. "Theoretical understanding of convolutional neural network: Concepts, architectures, applications, future directions." *Computation* 11.3 (2023): 52.

[7] Koonce, Brett, and Brett Koonce. "MobileNetV3." *Convolutional Neural Networks with Swift for Tensorflow: Image Recognition and Dataset Categorization* (2021): 125-144.