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Comparative Study of Ship Image Classification using Feedforward Neural Network and Convolutional Neural Network

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Abstract

In autonomous navigation systems, the need for fast and accurate image processing using deep learning and advanced sensor technologies is paramount. These systems rely heavily on the ability to process and interpret visual data swiftly and precisely to ensure safe and efficient navigation. Despite the critical importance of such capabilities, there has been a noticeable lack of research specifically focused on ship image classification for maritime applications. This gap highlights the necessity for more in-depth studies in this domain. In this paper, we aim to address this gap by presenting a comprehensive comparative study of ship image classification using two distinct neural network models: the Feedforward Neural Network (FNN) and the Convolutional Neural Network (CNN). Our study involves the application of both models to the task of classifying ship images, utilizing a dataset specifically prepared for this purpose. Through our analysis, we found that the Convolutional Neural Network demonstrates significantly more effective performance in accurately classifying ship images compared to the Feedforward Neural Network. The findings from this research are significant as they can contribute to the advancement of core source technologies for maritime autonomous navigation systems. By leveraging the superior image classification capabilities of convolutional neural networks, we can enhance the accuracy and reliability of these systems. This improvement is crucial for the development of more efficient and safer autonomous maritime operations, ultimately contributing to the broader field of autonomous transportation technology.

Keywords: *Ship Image Classification, Feedforward Neural Network, Convolutional Neural Network.*

1. Introduction

Autonomous navigation systems refer to technologies that enable transportation means such as vehicles, drones, and ships to navigate and control automatically without human intervention [1]. The rapidly advancing autonomous driving technology in vehicles is driven by improved sensor performance and computer vision and object recognition algorithms based on deep learning.

Maritime situational awareness refers to the technology that integrates and processes heterogeneous sensor

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data from cameras, radar, etc., and utilizes artificial intelligence processing techniques to accurately detect and recognize maritime objects, including ships [2]. This technology aims to advance the level of autonomy in autonomous ships and minimize human error-related maritime accidents, which constitute a significant proportion of maritime accident causes. By providing comprehensive information on navigation situations and potential collision risks to the ship's navigation system, it supports rapid decision-making.

2. Background

The rapidly advancing autonomous driving technology in vehicles is based on improved sensor performance, computer vision, and object recognition algorithms powered by deep learning. Deep learning-based computer vision and object recognition algorithms are mostly trained using large-scale publicly collected datasets, which enable the deep learning models to learn and recognize various objects in diverse environments [3].

From this background, in this paper, we apply feedforward neural network model and convolutional neural network model for ship image classification. The dataset we used are Kaggle Ship Images Dataset prepared by Caner Baloglu [4] (shown in Fig. 1).

Figure 1. Ship Images

The resolution of an image in the dataset is 128x128. The dataset has 6,177 training images, which can be categorized into five classes, 'Cargo' (2,120), 'Carrier' (916), 'Cruise' (776), 'Military' (1,148), and 'Tanker' (1,217) (shown in Fig. 2). The number of test images is 2,755.

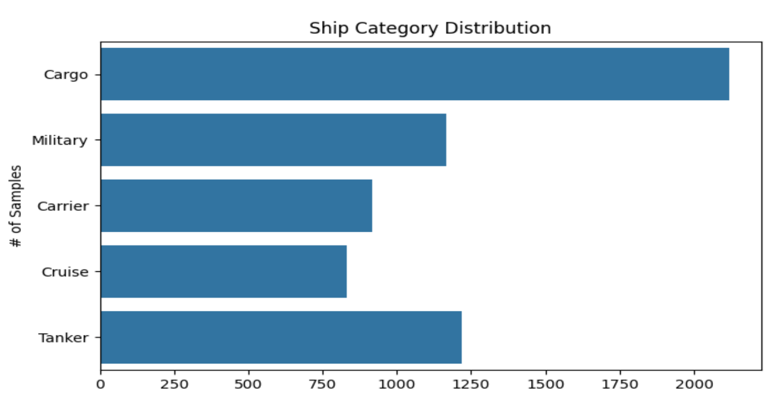

Figure 2. Image Dataset Distribution

For the purpose of classifying the ship images, we implemented and applied two distinct neural network models: the Feedforward Neural Network (FNN) model and the Convolutional Neural Network (CNN) model. The FNN model, with its straightforward architecture, processes the images by passing them through multiple layers of neurons in a sequential manner. In contrast, the CNN model, known for its hierarchical structure, employs convolutional layers to effectively capture spatial features and patterns within the images, thus enhancing its ability to accurately classify them. Through the application of these two models, we aimed to compare their performance and determine the most effective approach for ship image classification.

3. Feedforward Neural Network and Convolutional Neural Network

For the classification of the ship images, we applied Feedforward Neural Network model and Convolutional Neural Network model.

3.1 Feedforward Neural Network

Firstly, we applied Feedforward Neural Network model for ship image classification. The feedforward neural network we have designed and implemented is a simple neural network with one hidden layer. We have implemented the neural network model from the scratch.

3. 2 Convolutional Neural Network

Fig. 3 shows the architecture of Convolutional Neural Network model we have used [5].

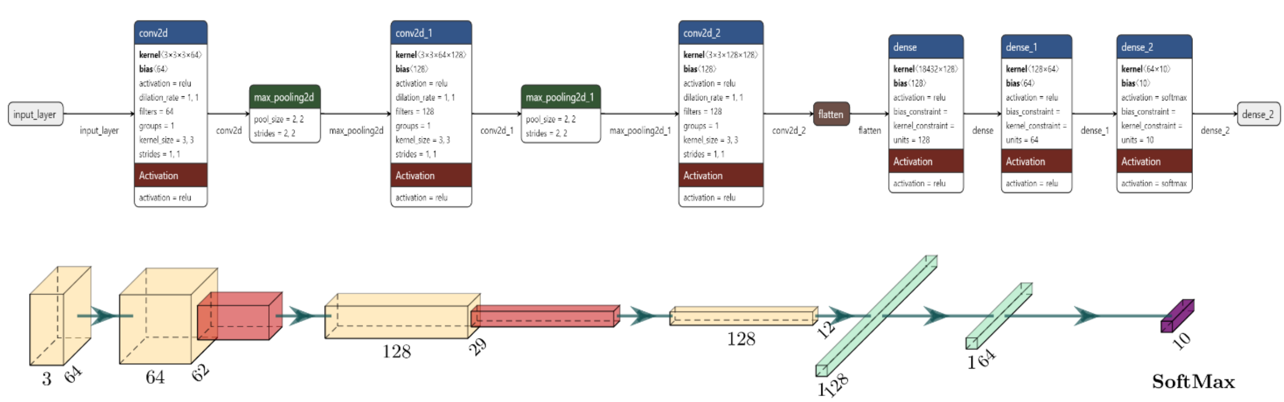

Figure 3. Architecture of Convolutional Neural Network

Note that the input is passed through a conv2d layer. The kernel configuration of conv2d layer is 3x3x3x64. The kernel size is 3x3. The size of bias is also 64. Its activation function is ReLU.

After conv2d operation, the result is transferred to a max_pooling2d layer. The pool size is 2x2, and the strides is also 2x2.

After that, the result is submitted to conv2d_1 layer. The kernel configuration of conv2d_1 layer is 3x3x64x128. The kernel size is 3x3.The bias is a vector with 128 values. Its activation function is ReLU.

After conv2d_1 operation, the result is transferred to a max_pooling2d layer. The pool size is 2x2, and the strides is also 2x2.

After that, the result is submitted to conv2d_2 layer. The kernel configuration of conv2d_1 layer is 3x3x128x128. The kernel size is 3x3.The bias is a vector with 128 values.

Finally, the resulting feature map is flattened. Three dense layers are used for classification.
The input and output for the first dense layer, dense, is 18432x128. Its activation function is ReLU.
The input and output for the second dense layer, dense_1, is 128x64. Its activation function is ReLU.
Finally, the input and output for the last dense layer, dense_2, is 64x10. Its activation function is Softmax.

4. Results

Fig. 4 shows the accuracy and loss graph of feedforward neural network. Note that, overall, the training process is not stable due to too simple architecture of feedforward neural network.

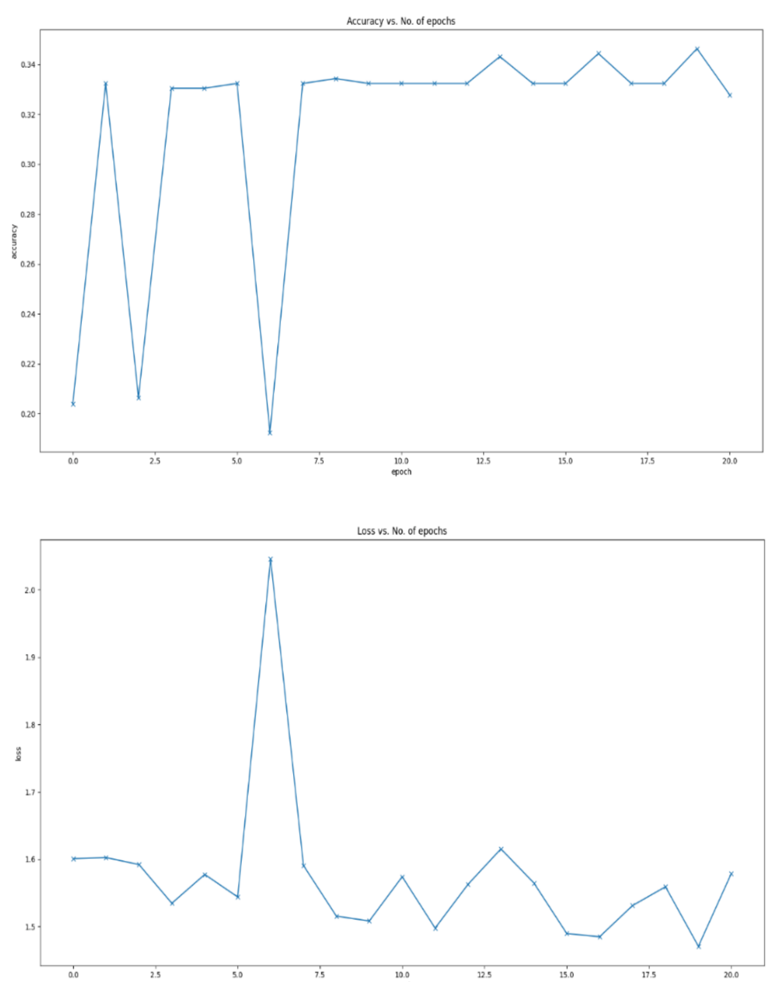

Figure 4. Accuracy and loss graph of Feedforward Neural Network

Fig. 5 shows the accuracy and loss graph of convolutional neural network. Note that, overall, the training process is very stable.

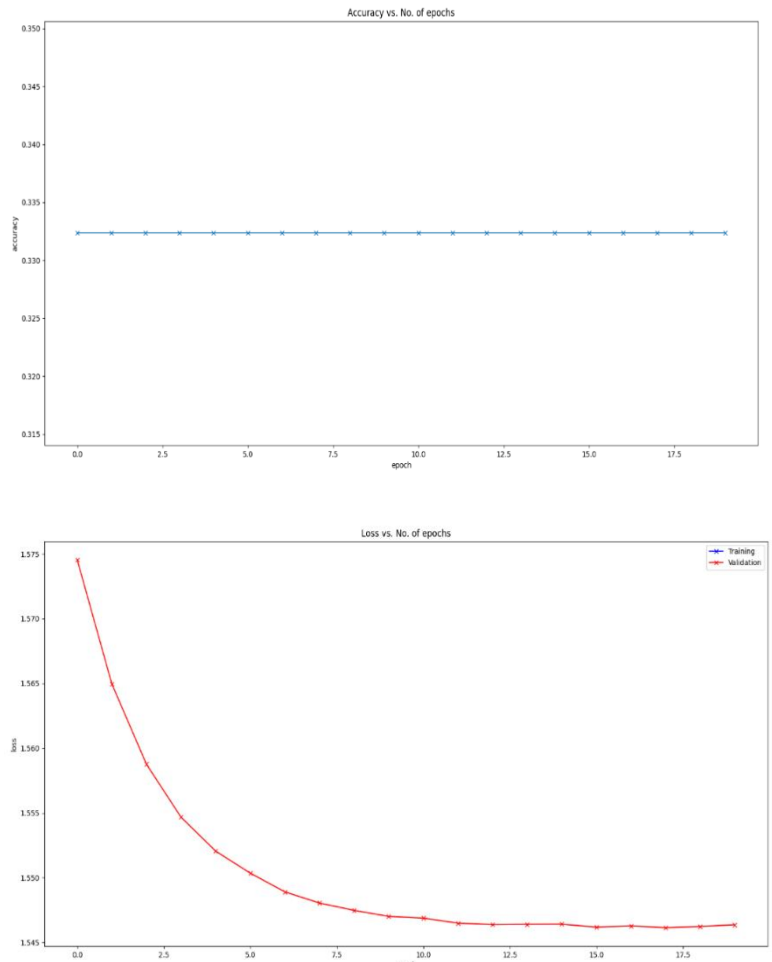

Figure 5. Accuracy and loss graph of Convolutional Neural Network

Fig. 6 shows a few examples of the classification results of our CNN model.

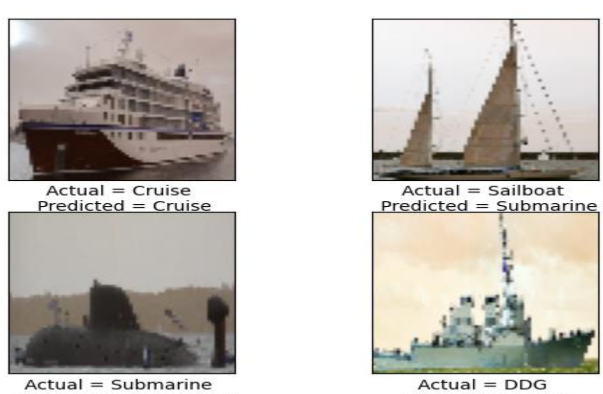

Figure 6. Classification Results

Table 1 shows the validation loss and validation accuracy of feedforward neural network and convolutional neural network. It can be seen that convolutional neural network outperform feedforward neural network.

Table 1. Validation Loss and Validation Accuracy of Feedforward Neural Network and Convolutional Neural Network

Epoch	Feedforward Neural Network		Convolutional Neural Network	
	Validation Loss	Validation Accuracy	Validation Loss	Validation Accuracy
1	1.6026	0.3323	1.5746	0.3323
2	1.5923	0.2064	1.5650	0.3323
3	1.5348	0.3304	1.5588	0.3323
4	1.5775	0.3304	1.5547	0.3323
5	1.5441	0.3323	1.5520	0.3323
6	2.0460	0.1924	1.5503	0.3323
7	1.5908	0.3323	1.5489	0.3323
8	1.5156	0.3343	1.5480	0.3323
9	1.5084	0.3323	1.5475	0.3323
10	1.5741	0.3323	1.5470	0.3323
11	1.4979	0.3323	1.5469	0.3323
12	1.5629	0.3323	1.5465	0.3323
13	1.6154	0.3431	1.5464	0.3323
14	1.5649	0.3323	1.5464	0.3323
15	1.4898	0.3323	1.5464	0.3323
16	1.4851	0.3443	1.5462	0.3323
17	1.5314	0.3323	1.5463	0.3323
18	1.5592	0.3323	1.5461	0.3323
19	1.4709	0.3463	1.5462	0.3323
20	1.5789	0.3277	1.5464	0.3323

5. Conclusion

In this paper, we present an in-depth comparative study focused on ship image classification utilizing two distinct types of neural networks: the Feedforward Neural Network (FNN) and the Convolutional Neural Network (CNN). Our study involves the application of both the feedforward neural network model and the convolutional neural network model to the task of classifying ship images. The dataset employed for this research is the Kaggle Ship Images Dataset, which was meticulously prepared by Caner Baloglu.

Through our analysis, we observe that the Convolutional Neural Network demonstrates significantly more effective performance in the accurate classification of ship images compared to the Feedforward Neural Network. The superior performance of the CNN can be attributed to its ability to capture spatial hierarchies in images, making it exceptionally well-suited for image recognition tasks.

The findings of this research hold substantial implications for the advancement of core source technologies in maritime autonomous navigation systems. By leveraging the robust image classification capabilities of convolutional neural networks, it is possible to enhance the accuracy and reliability of autonomous navigation systems in maritime environments. This improvement could lead to more efficient and safer autonomous maritime operations, contributing to the broader field of autonomous transportation technology.

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