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Satellite Image Recognition for Smart Ships Using A Convolutional Neural Networks Algorithm

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ABSTRACT

In recent years, along with the development of artificial intelligence technologies and related technical products, the evolution of smart ship has accelerated. Smart ship has become the main development direction of ship industry in the future. In this paper, we proposed a CNN model to recognize ships in bay and sea area. Data sets of Ships in Satellite Imagery data and Airbus data were employed for model training and testing and features are pixel data of images and used in the classification problem. We used labels either "ship" or "no-ship" as our dependant variable to train the CNN model. Finally we get high accuracy of 98.125% for ship satellite images recognition. Through the performance metrics, including precision, recall and F1-score, we proved the reliability of this CNN model. Moreover, our CNN model is able to identify real bay and sea satellite images as well. The results make a great contribution for the development of smart ship and carve out the possibilities for fully automated operation of ship and ports.

Keywords: Smart Ships, Satellite Image Recognition, Vehicle Collision Warning System, Deep Learning, CNN.

INTRODUCTION

Smart Ship refers to the use of sensor system, communication and information system, the Internet and other technical means to automatically detect and obtain information and data on the ship, the marine environment, logistics, ports, etc., and based on computer technology, automatic control technology, big data processing and analysis technology. The intelligent operation of the ship is carried out in aspects of navigation, management, maintenance and cargo transportation, so that the ship transportation will be safer, more environmentally friendly, more economical and more reliable. The functions of Smart Ship mainly include intelligent navigation, intelligent hull, intelligent cabin, intelligent energy efficiency management, intelligent cargo management and intelligent integration platform. In the level of technology, it has many similarities with the more developed self-driving technology. Smart ship is to use artificial intelligence to empower the ship to make decisions without human control. Moreover, vehicle collision warning system is the focus of smart ship.

The core technology of self-driving vehicle is also vehicle collision warning system. Self-driving vehicle is a vehicle that is competent of sensing its surrounding environment and moving safely without human operator. Among many artificial intelligence technologies, image recognition technology has played a decisive role in the development of smart vehicles. Researches on self-driving have experienced a substantial enhancement due to improvements in deep learning methods. In the area of computer vision, deep neural networks and convolutional neural networks have emerged as a powerful tool for image segmentation, detection and classification. Inspired by autonomous driving, we can know that the technical advances of smart ship also depend on image recognition.

In 2001, Paul Viola and Michael Jones invented a simultaneous face detection algorithm to fulfill human figure identification according to their facial traits, which marked the emergence of image recognition technology. In the following decades, the applications using clustering model, support vector machine (SVM) and random forests had been appeared to process image recognition.

After that, the performance of convolutional neural network increased the identification accuracy for image recognition. It has led to a major leap in application technologies of other fields on the basis of image recognition.

LITERATURE REVIEW

With the economic development of the trade ports, the optimization of ship resource scheduling and the ship collision avoidance have always been the popular research topics. In 2009, genetic algorithm, simulating the biological model, was used by Tsou et al. to recommend a plan on economic view for the shortest route of ship collision avoidance, with the usage of Geographic Information System (GIS). Sung and Park (2015) proposed a prediction analysis on ship manoeuvring performance, which estimate the bare hull manoeuvring coefficients by RANS based on virtual captive model tests. In 2016, Park et al. discussed a semi-analytical approach for estimating the ship collision probability on trajectory uncertainties, performed a probability flow model for a variety of maritime traffic situations and demonstrated the practical feasibility of the proposed model. To avoid ship collision, a reliability-based structural design framework was presented in the study (Koh et al. 2017), in which the probabilistic distribution of accidental loads can be predicted according to the occurrence probabilities of different situations of ship loads and a structural analysis is practiced for the limit from structural resistance. Ramos, Utne and Mosleh (2019) explored the human factor on collision avoidance in the operations of maritime surface autonomous ship, took analysis using Hierarchical Task Analysis and established model for task classification. A majority of researches on multiple aspects of ship transportation are still being applied in combination with other technologies.

Compared to the evolution of the maritime transport, autonomous driving has made more progresses with artificial intelligence and deep learning technologies. YOLO model, which is a Computer Vision model, has been conducted to detect the pedestrian before the actual accident (Kohli and Chadha 2019). In this research, even though various image enhancement and processing techniques were used, they found that neither of these two methods can improve the detection rate. Based on an End-to-End algorithm proposed by NVIDIA, Chen et al.(2019) designed Auxiliary Task Network (ATN), a novel network structure, to enhance the driving performance with the strength of minimal training data and image semantic segmentation was used for navigation as an auxiliary task. Farag (2019) performed a Behavior Cloning CNN model with seventeen-layer architecture, trained by Adam's optimization algorithm, to process driving image data, even though this implemented approach has some shortcomings, including that the neural network is not able to build on previous states to make the current decision because of its non-memory. Furthermore, inspired by the researches in the field of self-driving, smart ship has emerged and become a research topic discussed increasingly by some experts and scholars. In 2018, Li et al. designed an integrated information platform for Smart Ship, which is on the basis of the cloud computation sub-system and supported by the OPC UA data transmission protocol and finally is able to realize data interaction and data visualization for the shipbuilding and sailing. A maritime decision support system was presented in the study of Sarvari et al. (2019). This maritime decision support system was come up with a three-module decision support system (DSS) for ferryboat emergency evacuation planning under different emergency conditions. The Smart Ship also conducted related research on decision support. Xue et al. (2019) solved fuzziness and uncertainty problems with a novel piloting decision recognition model, based on the fuzzy Iterative Dichotomiser 3 (ID3), to realize an automatic smart ship piloting systems, involving simulation of the pilot's behavior. In this study, a reliable method of mining key factors of piloting decisions and the standardization principle of piloting decision-making factors were proposed as well. To realize automatic collision avoidance and navigation, Deep Reinforcement Learning (DRL) was applied for the model training of complicated navigational situations, incorporating ship manoeuvrability, human experience and navigation rules etc.. A variety of analytical models and technologies are continuing to advance the application of Smart Ship.

As a robust algorithm technology of artificial intelligence, Convolutional Neural Network (CNN) has been widely applied in multiple areas for many supervised learning problems, most of which covered image recognition, speech recognition, natural language processing and other types of cognitive learning. In 2016, Liu et al. demonstrated through their experiments that

CNN algorithm was able to successfully address the food image recognition for Computer-Aider Dietary Assessment system. The Convolutional Networks on time series radio signal data also showed viable and outstanding performance (O'Shea et al. 2016). Moreover, CNN algorithm frame is effective in Natural Language Processing. CNN was combined with sentiment analysis to predict user satisfaction according to Twitter data. CNN can extract information with its convolutional layer and the high accuracy on tweets sentiment classification has showed its advantage. In voice recognition, CNN still has remarkable strengths. Alu, Zoltan & Stoica (2017) designed and implemented CNN model to obtain emotional-related response from robots and the high accuracy of 71.33% has indicated its applicability. Besides, CNN models has been continuously bettering to fit face recognition. In Wu et al.'s study, a Light CNN framework was presented to learn a compact embedding on the large-scale face data with massive noisy labels. It extracted one face representation using about 121ms on a single core, which proved this model's great efficiency. The results of the experiment verified that the Light CNN framework has prominent value for face recognition systems.

DATA SUMMARY

The demand for global trade is driving huge growth in ship traffic in the worldwide oceans. More ships increase the chances of traffic infractions at sea, including ship accidents, piracy, illegal fishing in protected marine areas, illegal cargo shipping and maritime drug smuggling, which has forced relevant organizations to carry out more effective methods of monitoring ships in the sea.

In this study, the data is obtained from two sources on Kaggle. One is the data of Ships in Satellite Imagery collected over the San Francisco Bay and San Pedro Bay areas of California. This data was offered by commercial imagery providers that captured image using constellations of small satellites to help solve the difficulties of detecting large ships' location in satellite images. The other is the Airbus data available from Airbus Ship Detection Challenge. The organizer Airbus Defence and Space Company, a global leading provider of optical & radar satellite imagery, offers comprehensive maritime monitoring services by implementing effective solutions with technologies and capabilities. The goal of this challenge held by Airbus is to enhance the accuracy and speed of automatic ship detection and to support the maritime industry on threats anticipation, trigger alerts and efficiency improvement at sea.

The difference between these two data sources of satellite imagery is that the first data source contains more bay ship images and the second more maritime ship images. Ship in Satellite Imagery Data consists of 4000 80×80 RGB images with either "ship" or "no-ship" label, which has "ship" labeled 1000 images and "no-ship" labeled 3000 images. The pixel value data for each 80×80 RGB is stored in row-major order with a list of 19,200 integers. The dataset is distributed as a JSON formatted file, shown as Table 1. The specific data attributes include pixel data, labels, locations and scene_ids. Airbus Data contains totally 192,556 satellite images, in which 65% of them are no ship images and 35% are ship images. An example of an image record with the corresponding data attributes in its csv file dataset is summarized in Table 2.

Table 1 An example of an image record on Ship in Satellite Imagery Dataset

Attribute	Data
pixel data	[62 71 68 ... 64 63 74]
labels	0
locations	[-122.34261421096728, 37.68377118462645]
scene_ids	20170730_181044_103d

Table 2 An example of an image record on Airbus Imagery Dataset

Attribute	Data
ImageId	000155de5.jpg
EncodedPixels	264661 17 265429 33 266197 33 266965 33 267733 33 268501 33 269269 33 270037 33 270805 33 271573 33 272341 33 273109 33 273877 33 274645 33 275413 33 276181 33 276949 33 277716 34 278484 34 279252 33

In our study, Ship in Satellite Imagery Data is used as training data to train our model. The pixel data can be separated to three parts: the first 6400 red channel values, the second 6400 green channel values and the third 6400 blue channel values. Scene_id is the specific identifier of the PlanetScope visual scene extracted from the image chip. The longitude and latitude coordinate parameters of the image center point are the whole location data of the dataset.

"Label" in this dataset is valued 0 or 1, respectively representing the "no-ship" class and "ship" class. The 3000 "no-ship" class images cover those that only contain a part of a ship, those that are diverse landcover features, involving water, vegetion, bare earth, buildings, etc. Some example “no-ship” class images are shown in Figure 1.

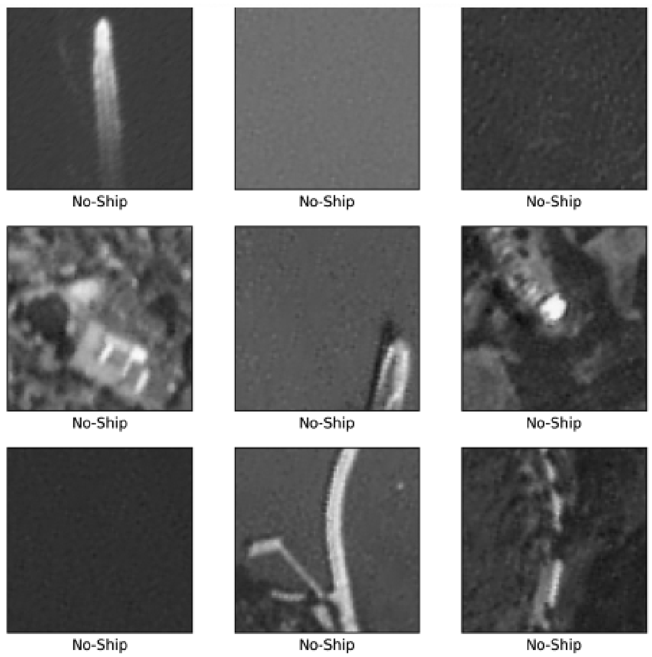

Figure 1. Labeled No-Ship

Each ship of the 1000 “ship” class images is almost centered. The images of this class are shown in Figure 2, in which we can see different color for the ship.

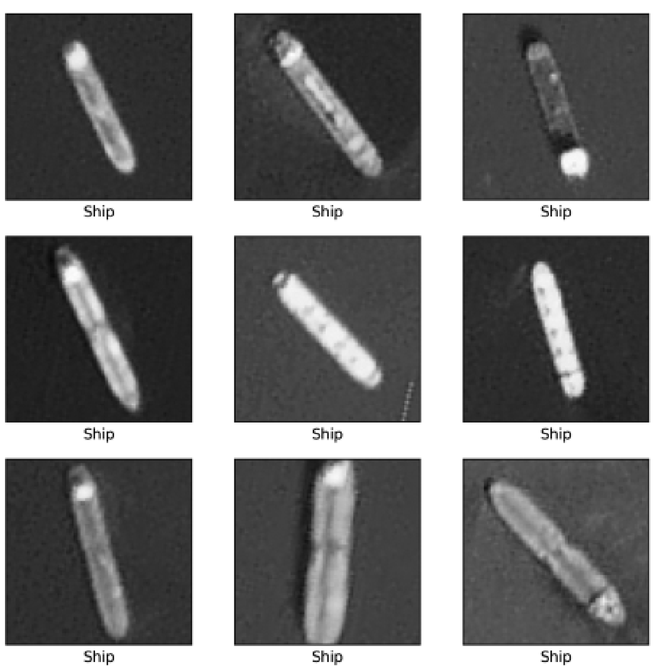

Figure 2. Labeled Ship

METHODOLOGY

We considered the problem of ship imagery classification as a binary problem. For each satellite image, we classified whether it will show a ship or not ship by performing satellite image recognition. This satellite image recognition was achieved by targeted model training and test set prediction. We randomly split Ship in Satellite Imagery Data into training (80% of data) and testing (20% of data) sets. The targeted model was built on training set and then used for prediction on the testing data set, the dependent variables. Besides, 6 satellite images on the sea were chosen from Airbus data as predictors as well, which were identified by the targeted model we trained. The purpose of this practice is to evaluate how the model will perform with new data.

The essence of satellite image recognition is image recognition on a binary problem. In many fields, CNN model has achieved successful results. In health area, Liang et al. (2016) proposed an image analysis model based on a convolutional neural network (CNN) to automatically classify single cells in thin blood smears on standard microscope slides as either infected or uninfected. In aviation area, Zhang et al. (2016) presented a CNN-based model to locating the aircraft with higher detection accuracy than the other methods, which is more efficient and accurate in large-scale VHR images. Sladojevic et al. established plant disease recognition model based on leaf image classification, by the use of convolutional neural networks. This developed model is able to discern plant leaves from their surroundings and to identify if plant leaves are either healthy or unhealthy from different types of plant diseases. In different fields, the CNN model is indeed a powerful algorithmic framework for image recognition on the binary problem.

In our study, we recognized the satellite image as either ship or no-ship, which is also typically image recognition on binary problem. Therefore, we defined a CNN model based on Ship in Satellite Imagery Data and set pixel data as our features. The output of this model would be the binary classification of the dependant variable, indicating whether a ship is detected or not.

Convolutional neural network (CNN) is a class of deep neural networks, most commonly utilized for the application of visual imagery analysis. CNN is applied to automatically and adaptively learn spatial hierarchies of features through convolution layers, pooling layers, and fully connected layers.

In CNNs, during the training process we decide the weights of the convolutional layer being used for feature extraction as well as the fully connected layer being for classification. The advanced CNN network structures lead to save memory and further to maintain a better performance for applications of computation complexity.

Compared to CNN, a simple neural network has many limitations during model applications. The substantive number of training data was strictly required. Inadequate parameters in feature extraction will lead to poor performance. Additionally, simple neural network is the optimal framework because of its longer convergence times and ignorance of key properties of images. In a CNN framework, convolution layers play the important role of feature extractor, which effectively minimize computation to a great extent without any essence loss of the data and guarantee the accuracy of image classification as well. The advantages and characteristics of CNN model framework and its remarkable achievement in image recognition have proven that the CNN model is the best model framework for processing satellite image recognition.

We established a CNN model trained with the training dataset split from Ship in Satellite Imagery Data. Pixel data was extracted as feature and labels were regarded as target value in this model. Each image pixel data in the CNN model is constructed by using the following algorithm:

- Input each 80×80 image into convolution layer.
- Adjust parameters, implement filters with strides, and conduct padding depending on case. Perform convolution on the image and apply ReLU activation to the matrix.
- Carry out pooling to fulfill dimensionality reduction. Pooling layers work together with convolution to extract features.
- Iterate as many convolutional layers until get satisfaction.
- Flatten the model output and feed into a fully connected layer (FC Layer) to classify those features.
- Specify the training deviation between the predictions and true labels through loss layer. A variety of loss functions can be used properly to deal with different tasks. To forecast a single class of two mutually exclusive classes (ship or no-ship), Softmax loss is used in our model.

RESULT

In this section we report the experimental results obtained by the CNN model. The performance metrics that were used to evaluate the CNN model's performance are accuracy, precision, recall, and F1-score.

We first calculate the prediction accuracy for the test dataset using the formula as below:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Our model get accuracy score for ship detection is 98.125%.

In order to understand the prediction performance of each class, we second analyze classification parameters as Table 3. We can see class "0" has a precision of 0.99, which means when it predicts no-ship image is "no-ship", it is correct 99%. Precision of 0.95 on class"1" indicates that it is 95% accuracy when identify ship image as "ship". Recall of 0.99 on class "0"means that it correctly identifies 99% of all no-ship images, while 0.96 on class"1" represents that 96% of all ship images are detected accurately. F1-score 0.99 on class "0" and 0.96 on class "1" both are high enough, which proves both precision and recall of each classifier indicate good results.

Table 3. Performance Results.

	Precison	Recall	F1-score	Support
0	0.99	0.99	0.99	628
1	0.95	0.96	0.96	172
Avg / total	0.98	0.98	0.98	800

We continually use our trained CNN model to recognize a real satellite image on bay area as Figure 3. In Figure 3, although all the ships in the water are pointed out correctly, detection errors also appear. We can see at coordinate position (1400, 1800) a ditch was identified as "ship". At the coordinate position (600, 1200) , the land area was recognized as "ship", which was an obvious identification error. The coordinate position (800, 500) was regarded as "ship", while it's shore area. Two ships are lined up side by side at coordinate position (900,400), however no identification mark was put. At coordinate position (1000, 1400) it is a ship launching area for shipbuilding and it were not supposed to be marked as ship. Extra recognition error is at coordinate position

(2600, 100), where the shore area was falsely classified as "ship".

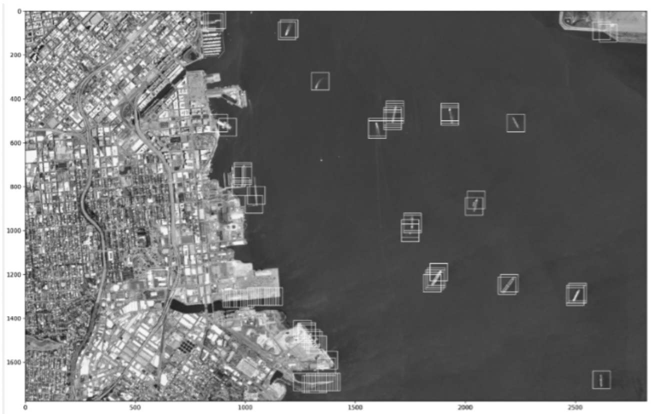

Figure 3. Satellite Image Recognition on Bay area.

We further discussed if our targeted CNN model is able to discern the ships on the sea. We chose parts of satellite images from Airbus Data to test the model as Figure 4. (a) is a cloudy calm sea, (b) is calm sea with ship, and (c) is night sea with wind and waves. All these three images were recognized correctly, especially for (b) image with ship. (d) is sea crossed by the ship, (e) is the sea passed by ship, and (f) the sea with two ships driving in different directions. These three images showed identification errors.

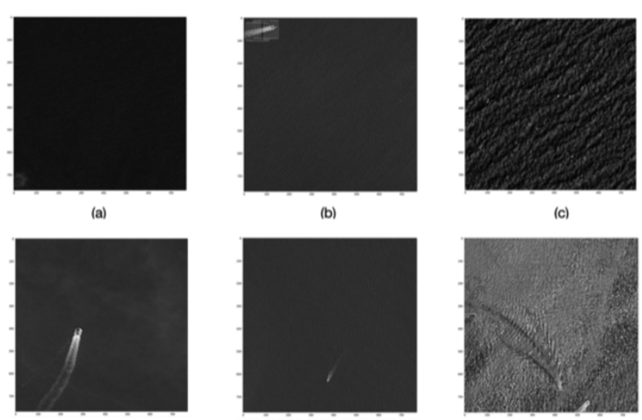

Figure 4. Satellite Image Recognition on the Sea.

In general, our trained CNN model had high reliability of ship detection on both bay and sea areas. For bay area, it can correctly identify all the ships in the water, even though some of the areas of shore, ditch and ship launching were discerned as "ship". Three of the six satellite on the sea were correctly recognized, that means we get 50% accuracy on the prediction of Airbus testing data.

DISCUSSION AND CONCLUSION

In this research, we established a CNN model on a binary problem to recognize Ship in Satellite images as either "ship" or "no-ship". We obtained the results with the high accuracy 98.125% and the trained model is able to detect the ship on sea as well. However, the experiment has some flaws.

In Ship in Satellite Imagery Data, parts of pixel data were wrongly labeled. We can see in Figure 1 the first picture in the first row actually is a ship and the second picture in the second row is a ship as well, even though it exposed half of a ship. These mistakes in data have influenced the accuracy of the model training process, which led to the model couldn't detect the ship on the sea from our test images as (d) in Figure 4. Besides, compared these two sources of images, we can find out different scales were used in their satellite images. The satellite image (e) in Figure 4 is much smaller than each image in Figure 1 or Figure 2. A constructive solution for these data mistakes is to re-label the pixel data more carefully.

In the study, we have shown that our approach significantly improved ship satellite detection accuracy. The research has made a significant contribution to the development of smart ships. Using clouding computing and big data analysis, it can transmit reliable ship positioning information to the shore control center and promote semi-automatic navigation of the ship. In further research, port logistics information may be added to achieve a seamless connection between ship and shore information. This will further facilitate fully automated shipping and automated port loading and unloading and logistics.

Biographical Notes

Hang Xiao is a project manager in SSGM at State Street Corporation. He earned a M.S. in Information System from Northeastern University since 2012. His research interests include IoT, AI, Big Data and Operational Research.

Xin Wang earned her M.S. in Data Science since 2018 and kept doing research in the IntelligentRabbit AI and Big Data Lab since 2019. She will start her Ph.D. in 2020.

Peng Zhao is a data science professional with experience in industry teaching, and research. He has a broad range of practical data science experience in different industries, including finance, mobile device, consumer intelligence, big data technology, insurance, and biomedical industries. He is a leading machine learning expertise in a Big Data & AI company in New Jersey. He also manages a data scientist team providing a variety of data consulting services to individuals, businesses and non-profit organizations.

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