YOLO BASED SHIP IMAGE DETECTION AND CLASSIFICATION

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Abstract - Considering the important apps in the military and the civilian domain, ship identification and based on optical remote sensing images considerable observation in the sea surface remote sensing filed. An improvement algorithm of SVM (support vector machine) with CNN algorithm is proposed here for fine tuning system. Multi class Image classification using CNN and SVM on a Kaggle data set. Please clone the data set from Kaggle using the following command. The deep convolutional neural network (DCNN) technique takes the feature extraction of input images for input. The features are acquired from the convolutional neural network and are moved to the support vector machine (SVM) classifier. In this research claimed that replacing the trainable classifier (the conventional SoftMaxfunction) of a CNN model with an SVM classifier can raise the classification performance. Its improve the accuracy of system (98percent)

Key Words: Deep Learning, CNN

1. INTRODUCTION

The maritime vessel classification, verification and identification are critical and challenging problems regarding national defense and marine security for coastal countries. These countries have to control the traffic and they are constantly trying to improve efficiency on ports for economic growth. There are also other threats such as stealing, sea pollution and illegal fishery. Most of these issues are not only related with countries individually, but also they need to be observed in a global perspective. That's why the International Maritime Organization (IMO) was established. IMO is a special agency of the United Nations, whose purpose is to create regulatory framework for the safety and maintenance of shipping and also protect marine pollution caused by ships. These systems can be used in control centers for assist.

Vessel verification round is deciding whether two vessel images belong to same ship or not. The main application area of this task is marine time surveillance, where vessel passing then it is strictly tracked in straits. In this kind of applications, two separate camera systems are placed to both entry and exit point. The images gathered from those systems are compared to infer whether the ship is still passing through or it has completed its passing.

1.1 METHODLOGY

DEEP LEARNING

Traditional machine learning methods struggle to perform as the dimensionality of the input data increases. For example, in image classification input images may contain thousands of pixel values. This problem is called the curse of dimensionality to overcome this problem, traditional methods require manual feature engineering of raw data in order to decrease the input dimensions. However, in practice, engineering these features from a mass of data is hard without specific domain expertise. This is where deep learning steps in.

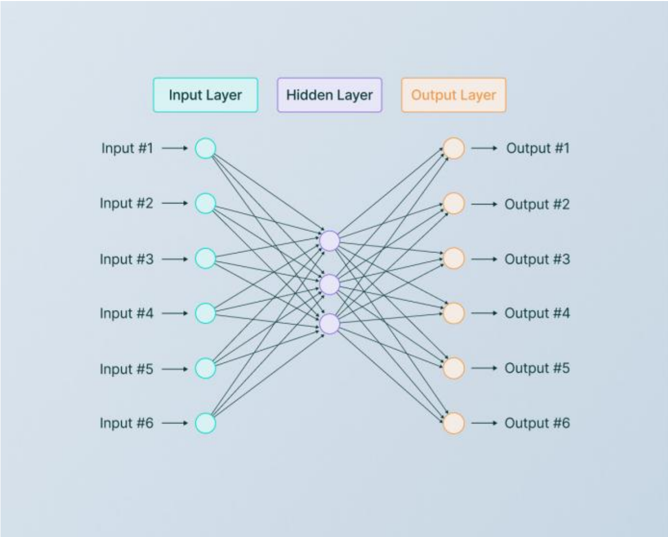
Deep learning solves the curse of dimensionality by learning hierarchical representations of the data with complex models of multiple layers. This is achieved with representation learning. In representation learning, no feature engineering is used. Instead, a model learns by itself which features of the mass of data are relevant for the task. When a deep learning model is trained, the model learns abstract representations of the data by observing the data patterns. The first layers of a deep learning model learns more simple features of the data, whereas the last layers learn more specific features of the data.

1.2 Convolutional Neural Network(CNN)

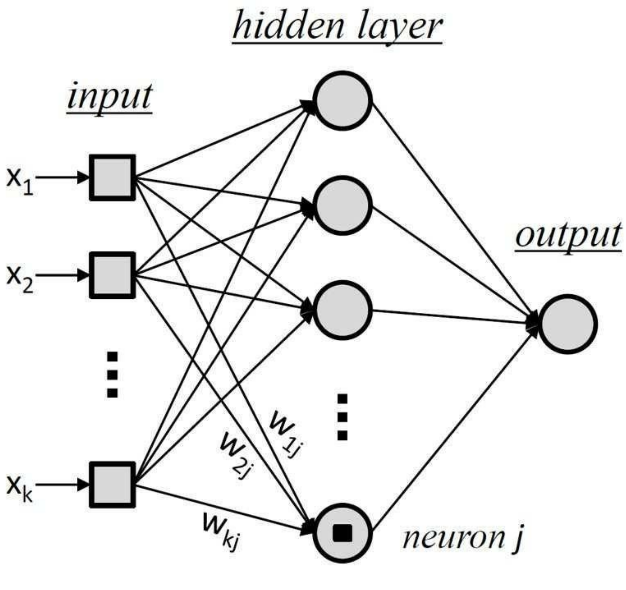
In deep learning, a convolutional neural network (ConvNet) is a class of deep neural networks, most commonly applied to analyze visual image. Now we think of a neural network we think about matrix multiplications but that is not that case with ConvNet. It uses a special technique called Convolutional. Now in mathematics convolution is a mathematical operation on two functions that produces a third function that show how the shape of one is modified by other.

2. Neural Network

The history of neural networks is quite old. Rosenblatt (1958) was a psychologist and he proposed "the perceptron" which is a mathematical model heavily inspired by biological neurons in human brain. As we can see in Figure 2.1, the model has n binary inputs and exactly same number of weights. Each input value is multiplied by the corresponding weight. If the sum of these products is larger than zero, the perceptron is activated and it outputs a signal whose value is generally +1. Otherwise it is not operated with an output value of 0. This is the mathematical model for a single neuron, the most fundamental unit for neural networks



Since the perceptron model has a single output, it can perform binary classification. A stronger structure called "a layer" has been formed with connecting many perceptrons in parallel fashion. Thus, this enables to work for identification tasks with many categories. This structure is called Single–Layer Neural Network.



However, single unit perceptrons are only small amount of learning linearly separate tasks. Minsky and Papert (1969) popularly showed that it is impossible for a single layer perceptron to learn a major XOR function. They also stated that this issue could be overcame by adding in the intermediate layers called hidden layers. That architecture is now called Multi-Layer Perceptron or Multi-Layer Neural Network. But the real problem was that Rosenblatt's learning algorithm did not work for multiple layers and how to adjust the weights of hidden layers at that time. After a long stagnation period in artificial intelligence field, Werbos (1982) utilized the back-propagation algorithm to train multi-layer neural networks.

3. CONCLUSIONS

We propose a novel and unified approach named SPAN utilizing the SAR imaging mechanism for oriented ship detection and classification. The strong backscattering points are extracted by the specifically designed SFE module and provide the basis for the subsequent classification tasks. The presented RRM combined with low-level contiguous information helps the SPAN obtain higher location precision and it will improve the recall rate. Furthermore, the RoI-AG module extracts ship features with axis-alignment to avoid the adjacent background interferences in ship classification.

4. FUTURE WORK

REFERENCES

[1] L. Du, H. Dai, Y. Wang, W. Xie, and Z. Wang, "Target discrimination based on weakly supervised learning for high-resolution SAR images in complexscenes," IEEE Trans. Geosci. Remote Sens., vol. 58, no. 1, pp. 461–472, Jan. 2020.

[2] W. Boerner, "Recent advances in extra-wide-band polarimetry, interferometry and polarimetric interferometry in synthetic aperture remote sensing and its applications," IEE Proc., Radar Sonar Navig., vol. 150, no. 3, pp. 113–124, 2003.Though the SPAN has a satisfactory detection and classification performance, there still exist several limitations. The ant interference and classification ability need to be further improved. For example, the ghosts of land And cross-side lobes of ships result in recognition errors and some false alarms. Further suppressing these interferences to get a more accurate oriented box and classification result will be investigated in our future work.

[3] J. Jiang and S. Cao, "Real-time disaster monitoring system by using SAR," inProc. Microw. Instrum. Satell. Photogram. Remote Sens. Earth., vol. 2313, 1994,pp. 91–95.

[4] H. Li, T. Celik, N. Longbotham, and W. Emery, "Gabor feature based unsupervised change detection of multitemporal SAR images based on two-level

clustering," IEEE Geosci. Remote Sens. Lett., vol. 12, no. 12, pp. 2458–2462, Dec.2015.

[5] Z. Zhang, W. Guo, S. Zhu, and W. Yu, "Toward arbitrary-oriented ship detection with rotated region proposal and discrimination networks," IEEE Geosci. Remote Sens. Lett., vol. 15, no. 11, pp. 1745–1749, Nov. 2018.

[6] S. Brusch, S. Lehner, T. Fritz, M. Soccorsi, A. Soloviev, and S. Van, "Ship surveillance with TerraSAR-X," IEEE Trans. Geosci. Remote Sens., vol. 49, no. 3, pp. 1092–1103, Mar. 2011.

[7] H. Dai, L. Du, Y. Wang, and Z. Wang, "A modified CFAR algorithm based on object proposals for ship target detection in SAR images," IEEE Geosci. Remote Sens. Lett., vol. 13, no. 12, pp. 1925–1929, Dec. 2016.

[8] X. Wang and C. Chen, "Ship detection for complex background SAR images based on a multiscale variance weighted image entropy method," IEEE Geosci. Remote Sens. Lett., vol. 14, no. 2, pp. 184–187, Feb. 2017.

[9] J. He, Y. Wang, and H. Liu, "Ship classification in medium-resolution SAR images via densely connected triplet CNNs integrating fisher discrimination regularized metric learning," IEEE Trans. Geosci. Remote Sens., vol. 59, no. 4, pp.3022–3039, Apr. 2021.

[10] C. Bentes, D. Velotto, and B. Tings, "Ship classification in TerraSAR-X images with convolutional neural networks," IEEE J. Ocean. Eng., vol. 43, no. 1,pp. 258–266, Jan. 2018.