International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 11 Nov. 2022, pp: 312-316 www.ijaem.net ISSN: 2395-5252

Review of Object Detection Algorithms

Arun Chauhan, Premnath S

Submitted: 01-11-2022 Accepted: 12-11-2022

I. INTRODUCTION:

- In Deep Learning, many algorithms are used for object detection. From those, most of the algorithms play very well. But it also has demerits that should be avoided.
- Here, we're going to review which algorithm is best for object detection.

Motivation and Need for the Study:

- Early, there were different algorithms to do deep learning.
- No sufficient data and exact data are shown in those algorithms.
- To find which algorithm is the best based on almost exact output.

II. LITERATURE REVIEW AND RESEARCH CHALLENGES:

24 convolution layers will be present in the original YOLO design, which is followed by two completely connected layers. Non-maxima suppression is the practice of selecting the bounding boxes with the highest Intersection Over Union (IOU) [1] with the ground truth out of the various bounding boxes that YOLO will predict for each grid cell.

It introduces the idea of assessment criterion as well as a few publicly available datasets[2] of object detection. Following that, it will review recent developments in object detection research and theories, summarizing significant advancements and outlining possible future approaches.

We suggest a better YOLO-V3[3] model for spotting apples at various stages of development in orchards with varying lighting, complicated surroundings, and overlaying apples, branches, and leaves. Images of young, growing, and ripe apples are the first things that are gathered. These photos will then be enhanced using blur computation, rotational modification, chroma balancing, and luminosity transformation. Training sets will be made using augmented photos.

These new methods are multifunctional[4] and do not have drawbacks. Due to the sensitivity and tunability of AMs, MIT can be used in low fields and at low frequencies, meeting the criteria for long-range media penetration.

We suggest a better YOLO-V3[3] model for spotting apples at various stages of development in orchards with varying lighting, complicated surroundings, and overlaying apples, branches, and leaves. Images of young, growing, and ripe apples are the first things that are gathered. These photos will then be enhanced using blur computation, rotational modification, chroma balancing, and luminosity transformation. Training sets will be made using augmented photos.

These new methods are multifunctional[4] and do not have drawbacks. Due to the sensitivity and tunability of AMs, MIT can be used in low fields and at low frequencies, meeting the criteria for long-range media penetration

We are going to calculate the saliency map for the entire image with SPP-net[5] just once, and then we pool features in any region (sub-images) to create fixed-length approximations for the sensors' training. This approach eliminates having to compute the convolutional features repeatedly. Our approach will be 24-102 times better than the R-CNN approach for analyzing image patches, and on Pascal VOC 2007 we get a similar or better performance.

The work of improving underwater photographs[6] is challenging and presents particular difficulties. These images struggle with a variety of vision tasks, including object detection, classification, and segmentation, necessitating processing in order to improve their quality.

These concepts were further developed into the AlexNet architecture[7] , where convolution processes were repeated numerous times between max-pooling operations, enabling the network to learn richer features at all spatial scales.

Networks working together will perform better than working alone. It is impossible to deploy since it is computationally expensive. Our objective is to apply an ensemble's performance[8] and generalization to a smaller network through distillation.

RoIMix, an enhancement technique, will

describe interactions between images. The proposals are combined after being derived from various photos. In contrast to other approaches of data augmentation [20], RoIMix[9] is applied to a number of images to produce enriched samples that serve as training data.

The feature pixel cannot be recovered, the background color is constant in slow motion, the time complexity is large, and the noise resistance performance is subpar. When compared to conventional machine learning methods, deep learning[10] has the benefits of large data volume, robust scalability, good flexibility, and simple conversion.

The method depends on the connection of the target's AC magnetic signature with the spin-polarized, processing atomic vapor of a radio-frequency[11] optical atomic magnetometer. The power spectrum of the atomic sensor can be modified to prevent noisy bands that would otherwise hinder detection. These sidebands correspond to the AC magnetic fingerprints[19] of rotating machinery or electric motors.efficiently learned using a synthetic underwater picture database[12].

Our model directly reconstructs the clear latent underwater image by leveraging on an automatic end-to-end and data-driven training mechanism[18], in contrast to the existing works that impose rigid frameworks applicable only for specific scenes or require the parameters of underwater imaging model estimation.

The issue of underwater image restoration[13] can be reduced to single-image dehazing, where all color channels have the same attenuation coefficients[16]. This is because the blue-red and blue-green color channels have different attenuation ratios.

We outline a method for deciphering an indoor scene's main surfaces, objects, and supporting relationships from an RGBD image[14]. The majority of current research overlooks physical interactions or only applies to neat rooms and halls.

Images taken underwater suffer from contrast loss and color divergence due to light scattering and coloralteration[17]. the haze around the school of carangids, the diver, and the reef in the background is due to light scattering, whereas the yellow fish in the upper-right[15] corner and the brown coral reef at the bottom have bluish tones because of color change.

Problem Statement:
To Find the best Algorithm for Object Detection Using Deep Learning with Efficient Results.

Objectives:

Achieved and precise item identification has been a significant point in theprogress of computer vision frameworks with the appearance of profound learning methods, the immaculateness of objectrecognition has expanded radically.

The paper intends to a comprehensive cutting-edge method for item identification with the objective of getting high precision with constant

execution. A significant test in a large number of the item identification framework is the submission of other PC vision methods for aiding the profound learning-based point of view, which leadsto slow and insignificant execution. In this paper, the best suitable deep learning algorithm is to be found with more accuracy in a real-time and easy way to establish the deep learning into Object Detection and run it in real-time applications.

Proposed Methodology:

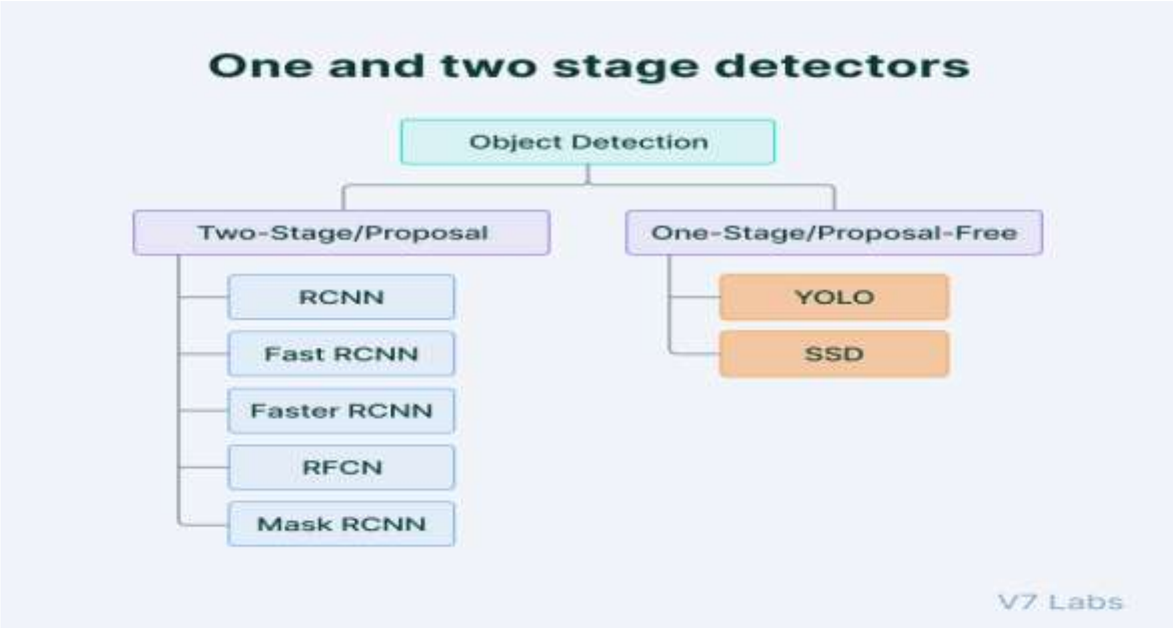
Object Detection techniques for the most part fall into either Machine Learning or Deep Learning approaches. For Machine Learning, it is important to initially characterize attributes utilizingone of the accompanying strategies and afterward utilize a procedure, for example, the Support Vector Machine (SVM) todo the classifications. And Deep learning procedures can perform end-end object detection without explicitly characterizing highlights, and are ordinarily founded on convolutional neural networks (CNN).

Deep learning approaches:

convolutional neural networks (CNN
Region suggestions (R-CNN, Fast R-CNN, Faster R-CNN,3D-CNN)
Darknet is an open-source neural network framework
You Only Look Once (YOLO)
Generative adversarialnetworks (GANs) (Machine Learning Approach)

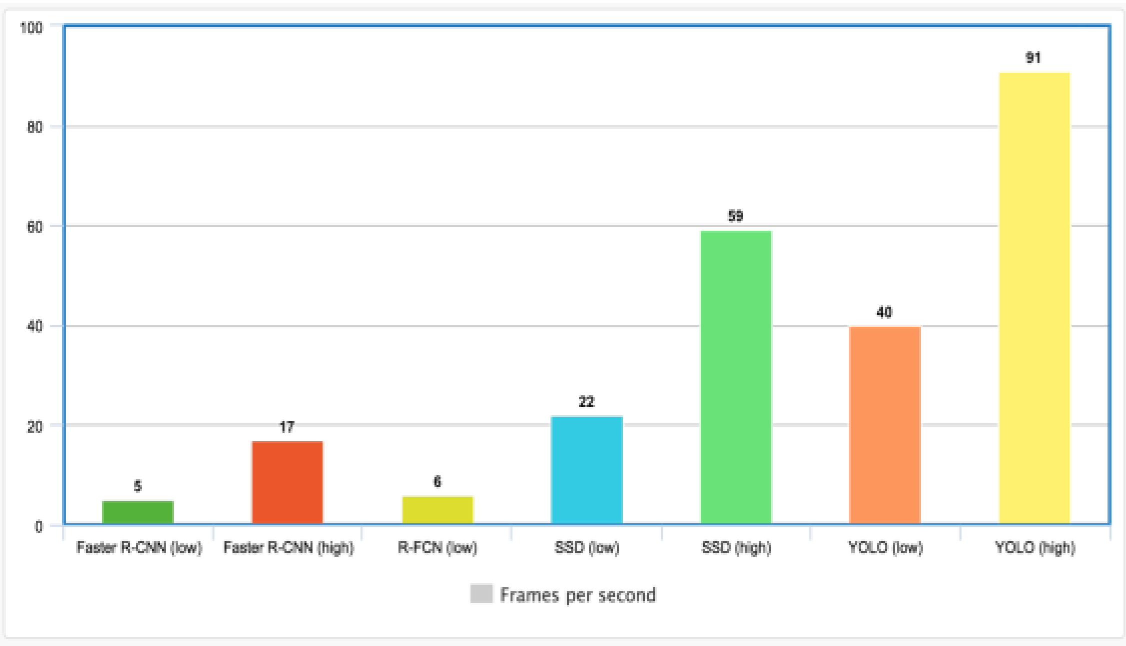
The use of methods in Machine Learning and Deep Learning Approaches are taken and trained and **The Most Efficient Algorithm and The Most Best Method are to be Reviewed.**

III. DATA SET:



https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.v7labs.com%2Fblog%2Fyolo-object-detection&psig=AOvVaw0TvPJ7BRvus_erKBvQ5Xru&ust=1668105524014000&source=images&cd=vfe&ved=0CBAQjRxqFwoTCJDxnrzfofsCFQAAAAAdAAAAABAJ

Where they all have their own data set and different algorithms to run. The test of the accuracy of YOLO is equal to CNN's Result but YOLO has less time requirement and less system requirements when compared to the rest of the Algorithms.



https://www.google.com/url?sa=i&url=https%3A%2F%2Fjonathan-hui.medium.com%2Fobject-detection-speed-and-accuracy-comparison-faster-r-cnn-r-fcn-ssd-and-yolo5425656ae359&psig=AOvVaw20PUerCUwkJyHPUVNpFkE&ust=1668105929011000&source=images&cd=vfe&ved=0CBAQjRxqFwoTCIj-kf3gofsCFQAAAAAdAAAAABAS

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 11 Nov. 2022, pp: 312-316 www.ijaem.net ISSN: 2395-5252

IV. CONCLUSION:

Object Detection is a Key function for most of computers and robot vision frameworks. Although Great progress has been made in these years and future. (for example face detectionfor cell phones) or have been coordinated intodriver help innovations, we are still quite far from reaching individuals via virtual it might help the innovation to grow marvellously.

The review of this paper is to compare all the possible algorithms and find the best and most efficient algorithms for object detection from the comparison of results both CNN and YOLO has more than the same accuracy but the use of YOLO in the system and time complexity is better than CNN's performance.

REFERENCE:

[1]. Peiyuan Jiang, DajiErgu*, Fangyao Liu, Ying Cai, Bo Ma. "A Review of Yolo Algorithm Developments," The 8th International Conference on Information Technology and Quantitative Management (ITQM 2020 & 2021),

[2]. Zhiqiang, W., & Jun, L. (2017, July). A review of object detection based on convolutional neural network. In 2017 36th Chinese Control Conference (CCC) (pp. 11104-11109). IEEE.

[3]. Tian, Y., Yang, G., Wang, Z., Wang, H., Li, E., & Liang, Z. (2019). Apple detection during different growth stages in orchards using the improved YOLO-V3 model. Computers and electronics in agriculture, 157, 417-426.

[4]. Deans, C.; Marmugi, L.; Renzoni, F. Active Underwater Detection with an Array of Atomic Magnetometers. Appl. Opt. 2018, 57, 2346.

[5]. He, K.; Zhang, X.; Ren, S.; Sun, J. Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition. IEEE Trans. Pattern Anal. Mach. Intell. 2015, 37, 1904–1916.

[6]. Uplavikar, P.; Wu, Z.; Wang, Z. All-In-One Underwater Image Enhancement Using Domain-Adversarial Learning. arXiv 2019, arXiv:1905.13342

[7]. Chollet, F. Xception: Deep Learning with Depthwise Separable Convolutions. In Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 21–26 July 2017; pp. 1800–1807.

[8]. Hinton, G.; Vinyals, O.; Dean, J. Distilling the Knowledge in a Neural Network. arXiv 2015, arXiv:1503.02531.

[9]. Lin, W.-H.; Zhong, J.-X.; Liu, S.; Li, T.; Li, G. ROIMIX: Proposal-Fusion Among Multiple Images for Underwater Object Detection. In Proceedings of the ICASSP 2020—2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona, Spain, 4–8 May 2020; pp. 2588–2592.

[10]. Hu, K.; Lu, F.; Lu, M.; Deng, Z.; Liu, Y. A Marine Object Detection Algorithm Based on SSD and Feature Enhancement. Complexity 2020, 2020, 5476142.

[11]. L. Marmugi, L. Gori, S. Hussain, C. Deans, and F. Renzoni, "Remote detection of rotating machinery with a portable atomic magnetometer," Appl. Opt. 56, 743–749 (2017).

[12]. Saeed Anwar, Chongyi Li, and FatihPorikli. Deep underwater image enhancement. CoRR, abs/1807.03528, 2018.

[13]. D. Berman, T. Treibitz, and S. Avidan. Diving into hazelines: Color restoration of underwater images. In Proceedings of the British Machine Vision Conference. BMVA Press, 2017.

[14]. Pushmeet Kohli Nathan Silberman, Derek Hoiem and Rob Fergus. Indoor segmentation and support inference from rgbd images. In ECCV, 2012.

[15]. He, K.; Zhang, X.; Ren, S.; Sun, J. Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition. IEEE Trans. Pattern Anal. Mach. Intell. 2015, 37, 1904–1916.

[16]. Uplavikar, P.; Wu, Z.; Wang, Z. All-In-One Underwater Image Enhancement Using Domain-Adversarial Learning. arXiv 2019, arXiv:1905.13342

[17]. Chollet, F. Xception: Deep Learning with Depthwise Separable Convolutions. In Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 21–26 July 2017; pp. 1800–1807.

[18]. Hinton, G.; Vinyals, O.; Dean, J. Distilling the Knowledge in a Neural Network. arXiv 2015, arXiv:1503.02531.

[19]. Lin, W.-H.; Zhong, J.-X.; Liu, S.; Li, T.; Li, G. ROIMIX: Proposal-Fusion Among Multiple Images for Underwater Object Detection. In Proceedings of the ICASSP 2020—2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona,

Spain, 4–8 May 2020; pp. 2588–2592.

[20]. Hu, K.; Lu, F.; Lu, M.; Deng, Z.; Liu, Y. A Marine Object Detection Algorithm Based on SSD and Feature Enhancement. Complexity 2020, 2020, 5476142.

[21]. Uplavikar, P.; Wu, Z.; Wang, Z. All-In-One Underwater Image Enhancement Using Domain-Adversarial Learning. arXiv 2019, arXiv:1905.13342

[22]. Chollet, F. Xception: Deep Learning with Depthwise Separable Convolutions. In Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 21–26 July 2017; pp. 1800–1807.

[23]. Hinton, G.; Vinyals, O.; Dean, J. Distilling the Knowledge in a Neural Network. arXiv 2015, arXiv:1503.02531.

[24]. Lin, W.-H.; Zhong, J.-X.; Liu, S.; Li, T.; Li, G. ROIMIX: Proposal-Fusion Among Multiple Images for Underwater Object Detection. In Proceedings of the ICASSP 2020—2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona, Spain, 4–8 May 2020; pp. 2588–2592.

[25]. Hu, K.; Lu, F.; Lu, M.; Deng, Z.; Liu, Y. A Marine Object Detection Algorithm Based on SSD and Feature Enhancement. Complexity 2020, 2020, 5476142.