

A Novel Method for Using Deep Reinforcement Machine Learning to Identify Objects

Ankit Mehta, Ramender Singh

Deptt. of Computer Science and Engineering, R D Engineering College, Ghaziabad, U.P., India

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Abstract- Object identification in computer vision enables systems to interpret real-world images by recognizing, localizing, and classifying objects within them. This task becomes complex when multiple objects are present in a single image, requiring advanced methods to simultaneously reduce training time and computational cost. Traditional approaches relied on feature extraction techniques using color, shape, and texture information, often supported by classifiers like support vector machines. However, limitations in processing power and insufficient datasets hindered progress until the emergence of multicore processors and GPUs around 2010. These technological advancements, along with large annotated datasets like ImageNet, have enabled deep learning models to significantly improve object recognition capabilities. Despite these improvements, developing efficient algorithms for resource-constrained environments remains a challenge, highlighting the complexity of replicating human-like visual recognition in machines.

I. Introduction

People can swiftly draw conclusions based on their ability to identify, recognize, and categorize objects thanks to computer vision's ability to define tasks computationally based on what we see in the real world. Object identification can often be difficult when many elements are included in a single picture [2]. Localization and classification are combined in the task of object identification [50]. The method locates the instance of the object, builds a localization window over it, and then characterizes the object's class using the instance score.

The issue is decreasing the model's training time and computational cost, despite the fact that object identification has been the subject of several research in the literature [19]. Furthermore, when working with large datasets, this method is challenging to use on devices with constrained resources. Up until around 2000, multicore processing systems and GPU graphics processing units were not doing well on jobs since there were not enough images for neural network training. To solve the issue, research has shifted to feature extraction [109]. For object recognition, both low-level and high-level feature extraction are accessible; usually, color, shape, and texture information are required to identify a successful item. Support vector machines categorize features by using data vectors as its basis [120].

With the development of multicore and GPU technology around 2010, it became easy to have training datasets such as ImageNet[114], which are handled by neural networks. The object identification system may recognize objects in any photo by comparing a database image of an object with a picture of an object of a priori sort. This problem is quite complex since it requires a number of functions and algorithms. People are eager to call things out since they have a tendency to pick things up quickly. It has been really difficult to understand this machine application algorithmically.

Identification of Convolutional Objects

This chapter examines and contrasts convolutional neural network-based special object recognition methods. Specifically, we will see algorithms that connect CNNs based on the categorization of region proposals.

Neural Network Convolution

Among the several types of deep neural networks, convolutional neural networks have received the most research attention.

Overview

Numerous CNN architectural variations may be found in various works. However, their underlying mechanisms are quite similar. Specifically, every neuron in a feature map is connected to a group of nearby neurons in the previous layer. In the earlier layer, this area is referred to as a neuron's receptive field. By using a learnt kernel to convolve the input and applying an element-wise nonlinear activation function to the convolved result, the new feature map may be calculated.

Four factors may be used to categorize the CNN's core features.

The input layer's goal is to retain the image's pixel cost, much like in other kinds of ANNs.

By calculating the scalar product between the weights of the neurons and the area associated with the input level, the convolutional layer will determine the output of neurons connected to particular parts of the provided input.

The pooling layer will then further reduce the number of parameters inside that activation by just performing down sampling in addition to the spatial dimensionality of the set input.

Next, the completely linked layers will carry out the identical work that started in conventional ANNs with the goal of producing class scores using the classification activation functions.

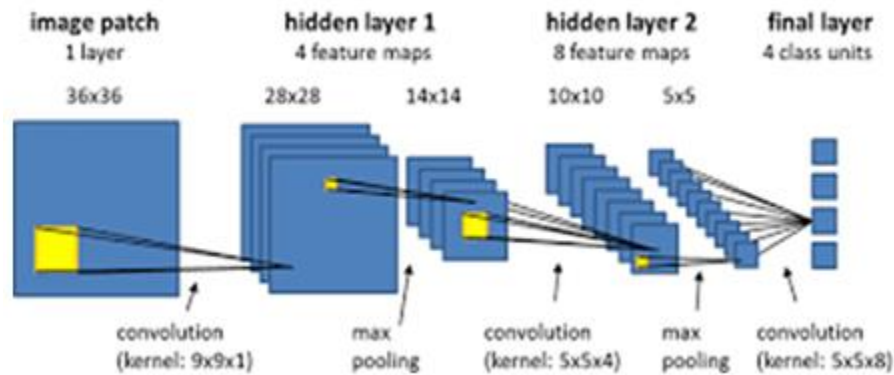


Figure 3.1 Convolutional Neural Networks with Multiple Hidden Layers

Deep Reinforcement Learning-Based Object Identification Model Proposal

It is evident from the aforementioned chapter that when researchers work with object recognition algorithms, quality and accuracy of identification present major obstacles. All of the issues covered in the previous chapter are better addressed by the suggested effort, which also addresses issues outside translation. Additionally, it categorizes the item. We put forth ODDRL-net, a unique model that detects objects in the fewest possible steps. The idea of methodology and the suggested model will be explained in the next part.

Proposed ODDRL-Net Model

As shown in the figure, we proposed an object detection deep reinforcement learning - network (ODDRL-Net), an improved and efficient model that predicts fast object identification.

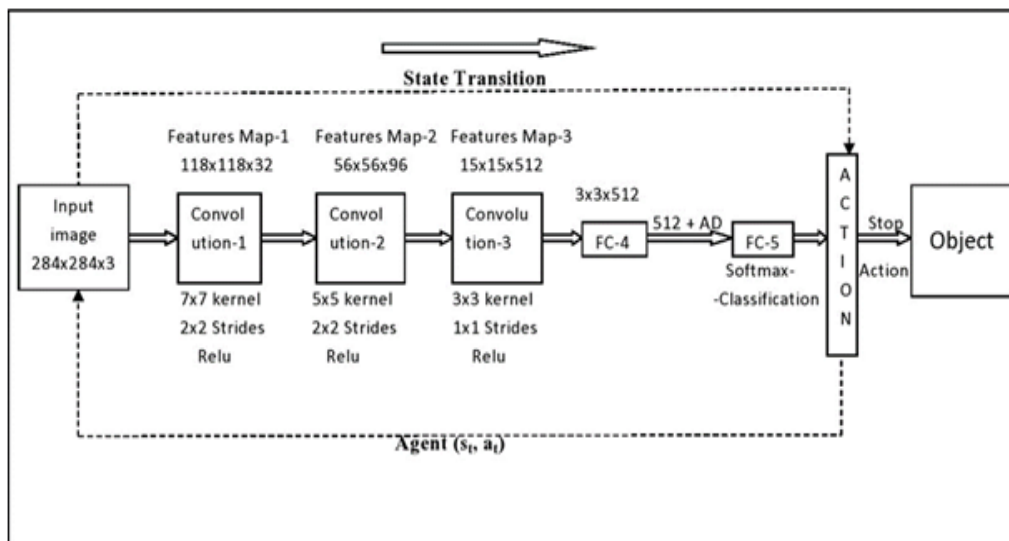


Figure 1 Proposed Object Detection Deep Reinforcement Learning - network (ODDRL-net)

The model contains three convolution layers {convol1, convol2, convol3}, which are identical to the model using features for object identification like VGG-M net [127], etc. Sang doo Yun [111] used to initialize their model with VGG-M net as a pre-trained model. Also, they took the different layers as motivated by this model for giving a tracker.

Experimental Setup and Implementation

Every object identification model adheres to a set of guidelines to ensure that it is suitable for identification. However, there are a few crucial factors that indicate how much your model has created. The suggested study takes into account all of the metrics indicated for calculating performances and compares results with other approaches in the literature. Each parameter, such as average precision (AP), recall, IoU (intersection over union), and classification accuracy, is crucial for identification. We covered performance evaluation and comparison using several methods in Chapter 6. Nevertheless, this chapter included the assessment measures and environment needed to demonstrate the model's true performance.

II. Results and Discussion

Computation of mAP with Proposed work for Pascal Voc Dataset 20 category

The calculation of mAP was covered in the previous chapter since the Q-network's scores, which represent action costs rather than discriminative scores, are useless for evaluating object detection. We have designed a detector based on the Softmax classifier, which scores every region in a single search step, using the basic idea of RCNN. The actual processed picture for the top five classes is shown in Figure 2.

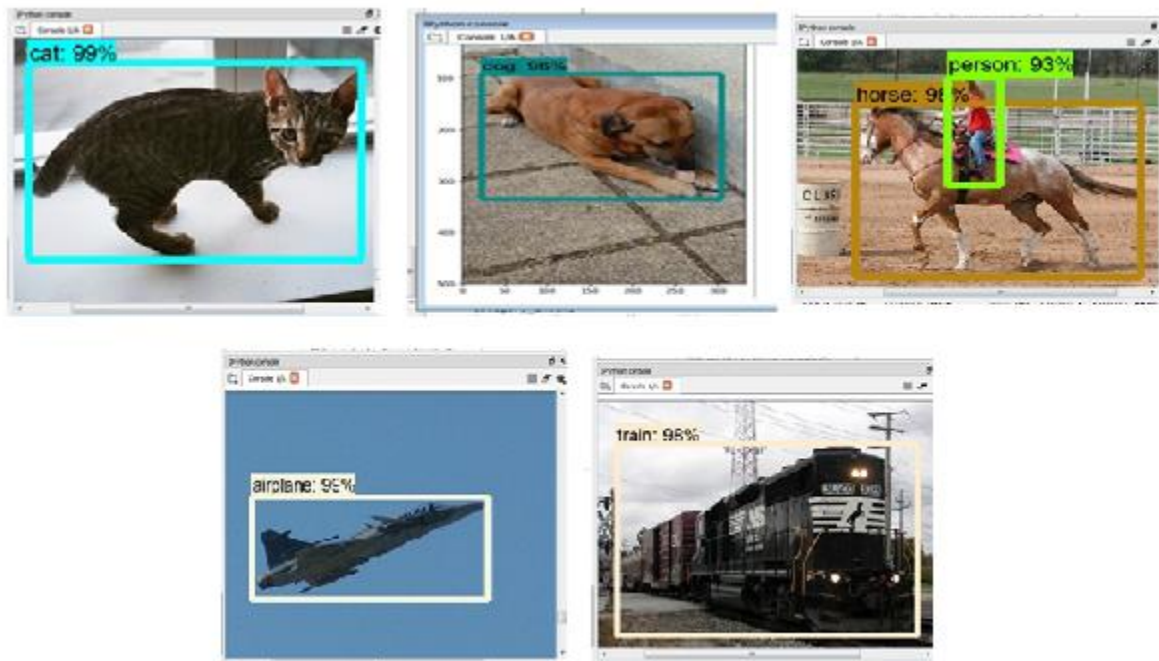


Figure 2 Processed Images for Best Result Five Classes

III. Conclusion and Future work

Conclusion

This project's primary contribution is identifying the model and combining localization with Softmax classification; it also implements the algorithm using the novel deep learning framework, TensorFlow; future researchers can modify this implementation to conduct additional experiments with different datasets, neural network architecture, or agent architecture. The proposed work uses a model named ODDRL-net, which contains three convolutions and two fully connected layers; the convolution layer used for feature extraction and object identification is done with deep reinforcement learning; and a softmax classifier is used to define the class label.

Future work

Several recommendations for advancing this project to the next level are given following the optimal performance of the aforementioned model and establishing the project's full potential. Although the project's breadth prevented me from implementing and carrying out further tests, it is anticipated that this improvement might greatly increase effectiveness and efficacy because there are numerous photographs and sizable datasets, and several experiments can be carried out with varying thresholds.

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