

# A Framework for Object Detection using Deep-Reinforcement Machine Learning

Saurabh Tiwari, S. Veena Dhari



**Abstract:** Machine learning area enable the utilization of Deep learning algorithm and neural networks (DNNs) with Reinforcement Learning. Reinforcement learning and DL both is region of AI, it's an efficient tool towards structuring artificially intelligent systems and solving sequential deciding problems. Reinforcement learning (RL) deals with the history of moves; Reinforcement learning problems are often resolve by an agent often denoted as (A) it has privilege to make decisions during a situation to optimize a given problem by collective rewards. Ability to structure sizable amount of attributes make deep learning an efficient tool for unstructured data. Comparing multiple deep learning algorithms may be a major issue thanks to the character of the training process and therefore the narrow scope of datasets tested in algorithmic prisons. Our research proposed a framework which exposed that reinforcement learning techniques in combination with Deep learning techniques learn functional representations for sorting problems with high dimensional unprocessed data. The faster RCNN model typically finds objects in faster way saving resources like computation, processing, and storage. But still object detection technique typically require high computation power and large memory and processor building it hard to run on resource constrained devices (RCD) for detecting an object during real time without an efficient and high computing machine.

**Keywords:** AI, Deep RL, Machine Learning, Reinforcement Learning.

## I. INTRODUCTION

Sequential deciding is the fundamental principal of machine learning .for achieving important goals its task of determining actions in terms of order of course from knowledge in a predictive environment. There are huge application related to machine learning like robotics, smart grids, finance, pharmacy and many other fields. Reinforcement learning (RL) proposes a proper framework with its power to have best moves on the basis of history with the basic idea that man made agent can learn by making interaction with environment same as biohazard. when we make use of synthetic agent its expected agent should ready to adapt to certain objectives which will given as cumulative reward ,this type system can handle any sequential problem if we see literature of machine learning. RL has power to execute any type of object detection task sequential decision making problems effectively solved by RL.

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By mixing the capability of reinforcement learning to deep learning sometimes we call it deep RL is useful to sort the problem related to high dimensional state space (Good Fellow et al). Reinforcement learning having ability to deal with different levels of data abstraction in the same way it can solve many complicated task due to early design of RL had a posh (Bellmare 2013 et al.) framework apart of that it fit to resolve many issues. As an example a deep reinforcement learning agent can learn every single policy with high dimensional inputs using end to end RL (Mnih et al 2015). DL has made it likely to extract features of advanced level data which gives a new era for achievements in computer intelligence [11], [16] and speech detection [6], [22]. These are the methods which develop variety of NN design Also we can found several methods which exploited supervised and unsupervised learning like Boltzmann machines, multilayer perceptron, and convolution neural network.

It seems natural to boost whether related techniques could even be helpful for RL with data. In contrast reinforcement learning presents variety of challenges from a Deep Learning perspective. Initially, the bulk successful DL applications so far have essential enormous amounts of hand- labeled training data. Reinforcement learning techniques conversely capable to review with any noisy and sparse reward signals this way it can proves its potential.

The interruption between actions and resulting rewards, which may be thousands of your time steps long, seems mainly intimidating in comparison to the direct association among inputs and targets found in supervised learning. An extra concern is that mainly DL algorithms suppose the info samples to be self-sufficient, while in reinforcement learning one usually encounters sequences of extremely connected states. Also, in RL the info allocation changes because the algorithm learns new behaviors, which may be challenging for DL methods that suppose a preset original distribution.

In this paper we demonstrate that an earlier Neural net can overcome these challenges to review booming control policies from raw images data in RL environments. The network is skilled with a alternative of the planned learning algorithm, with stochastic gradient decline to revise the weights. Our objective is to get a specific neural network instrument that's capable to effectively study to image as several of the pictures as likely. Professionally training deep neural networks on extremely huge data sets involve the bulk methods skilled direct from unprocessed inputs stochastic gradient search mostly relied by Computer apparition and speech recognition.

If we train neural network with sufficient data than it's easy to find improved representation compared to handcrafted features [9] getting efficient results encourage move towards RL.

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Objective is to implement a deep RL algorithm to a NN and processed training data for recognition. RL has gain the maximum power and popularity due to its success in solving sequential decision making problems.

There are several work related to this work which are the combination of RL with deep learning technique(LeCun Et al 2015,GoodFellow et al 2016) mixture called deep RL which often used to sort out problems related to high dimensional state space. In literature there are many techniques which having noble design with the choices of different features(Bell mare 2013,munos 2002). Also to find data at different abstraction level reinforcement learning can be a great tool because its results on lower prior knowledge. A deep reinforcement learning agent able to learn successfully from visual perceptual inputs made from any images many pixels (Mnih et al 2015) .if we talk about breakthrough in computer vision and artificial intelligence RL has ability to extract high level features from data [11, 16] and speech recognition [6,7].there are many methods which gives variety of NN architectures also as convolution NN ,multilayer perceptron, ,recurrent NN also they have used many flavors of supervised and unsupervised learning. With data it seems that we can combine multiple techniques with RL to boost the model.

RL algorithms conversely capable to review from a scalar reward signal that's repeatedly delayed, sparse and noisy. The information samples should be self sufficient for DL in training while in reinforcement learning we have to travel connected states and decide the samples on the basis of reward generated. In RL information allocation changes as algorithm go with the new behaviors may be this is a challenge for DL. For developing better application computer vision and artificial intelligence needs heavy training data sets many techniques are based on neural network through feeding sufficient data one can found improved representation than handcrafted features [11]. Our goal is to use RL with shallower model developed as per faster RCNN protocols for better object detection.

Our paper is divided in following sections, Introduction in section I. Backgrounds of the Reinforcement learning Standard Model and Deep Learning defined in Section II. Associated Work done will focus the detailed study about literature in Section III. We have given a brief description of the ODDRL-Net, the training and evaluation of results in Section IV. The conclusions and future aspects are shown clearly for new researcher in Section V.

## II. BACKGROUNDS OF THE REINFORCEMENT LEARNING STANDARD MODEL AND DEEP LEARNING

### A. Deep learning approach

A deep neural network is defined by a sequence of processing layers, in which each layer consists during a nonlinear transformation and in this way play role in NN and therefore the sequence of those transformations results in learning different levels of abstraction as move to next layers done we get successively filtered information. First, we will explain a really simple neural network with single connected hidden layer (see Fig 1) for easy understanding of deep learning approach.

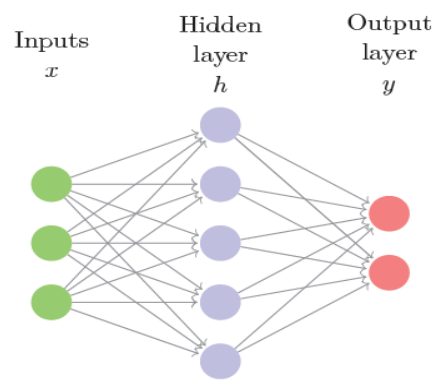


Fig. 1 Deep Learning Standard Diagram

The first layer is used to give the input values  $x$ , within the sort of a column vector of size  $n_x$ . The values of subsequent hidden layer are a change of those values by a non-linear parametric function, which may be a matrix operation by  $Z1$  of size  $n_h \times n_x$ , and a bias term  $b1$  of size  $n_h$ , define by a non-linear transformation....

$$h = Y(Z1 \cdot x + b1)$$

Where  $Y$  is that the activation functions. Activation function defines output of that node. This activation function makes the transformation at each layer non-linear, which finally provides the meaningful duty of neural network.

### B. Reinforcement learning model

The main components of reinforcement learning model are policy, reward signal, value function and model [9], [10]. The policy ( $\pi$ ) is the way that the agent (something that perceives and acts in an environment [1]) will behave under certain circumstances. Simply the policy maps states into actions. It can be a lookup table, a function, or it may involve a search process. Finding the optimal policy is the core goal of RL process [9],[10]. The reward signal ( $R$ ) indicates how well and bad is an event and it defines the goal of the problem where the agent purpose is to capitalize on the total received reward [4]. Accordingly, the reward is the main factor for updating the policy. Reward may be immediate or delayed, for delayed signals the agent need to determine which actions are more relevant to a delayed reward [9], [10]. The value function is a prediction of the whole future rewards, it is used to assess the states and select between actions consequently [9], [10].

The state-value function  $V(s)$  is the supervised return starting from a state ( $s$ ) [9], [10].

$$V(s) = E(G_t / S_t = S) \dots\dots\dots(1)$$

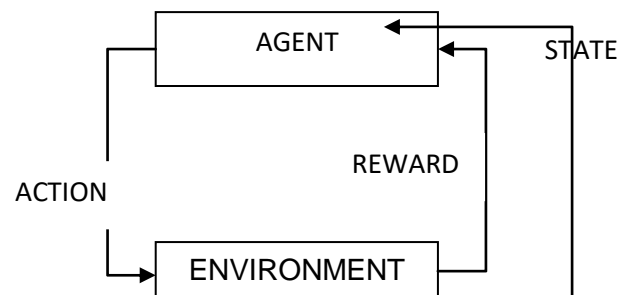


Fig. 2 Reinforcement Learning standard diagram

Where the return  $G_t$  is the total rewards  $R$  from time-step  $t$ . it is the sum of the immediate reward and discounted future reward [9], [10].

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots$$

$$= \sum_{m=0}^{\infty} \gamma^m R_{t+m+1} \quad (2)$$

The discount  $\gamma$  shows the degradation factor of future rewards when they are evaluated at present,  $\gamma$  ranges between 0 and 1. However, the use of discount is sometimes controversial. The action-value function  $q(s,a)$  is estimated output when running from state ( $s$ ) and taking an action ( $a$ ) Equation 3 shows the mathematical foundation [9], [10].

$$q(s, a) = \mathbb{E}(G_t | S_t = s, A_t = a) \quad (3)$$

$$= \mathbb{E}\left(R_{t+1} + \sum_{m=1}^{\infty} \gamma^m R_{t+m+1} \mid S_t = s, A_t = a\right)$$

The model of the environment allows predictions to be made about the behavior of the environment. However, Model is an optional element of RL techniques that use models and planning are called model-based methods. On the other side are model free methods where the agent does not have a model for the environment. Model-free methods are explicitly trial-and error learners [9], [10].

Several works are done using RL algorithms. Many researchers make use of algorithm based on RL and provide the solution with baseline implementation. For evaluating reinforcement Learning evaluation metrics are proposed by many researcher (2011 Winston et al).arcade learning Environment revisit by(2017, machado et al.) for proposing better evaluation methods. We know that accuracy is depends on how to achieve metrics for learning algorithm if you say model is giving satisfying accuracy score it means algorithm is working fine but if it's may give you poor results when evaluated for logarithmic loss or any other metrics so as far as algorithm is concerned depends on many metrics.

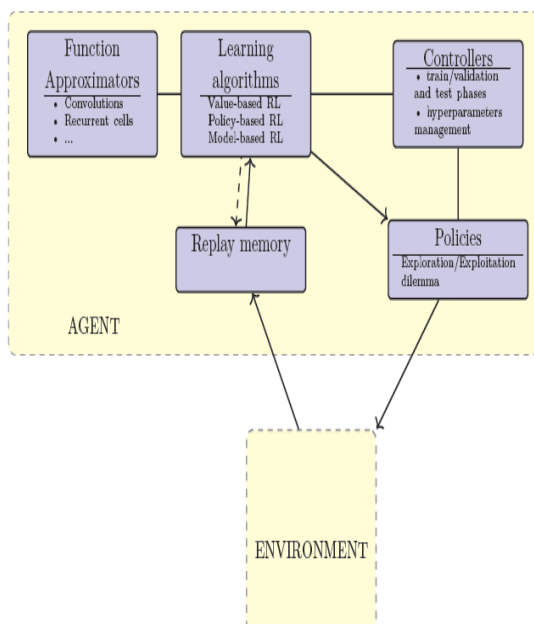


Fig. 3 General frame of deep RL methods

A general framework of the various elements which will be found in most deep RL algorithms is provided in above figure.

### III. SUMMARIZES THE ASSOCIATED WORK DONE

CNN have potential to execute many task related to object recognition using CNN there are many algorithm which gives good results for face ,object and other recognition task. There are many tools developed for helping physically challenged community and many tools are working successful for medical patient as well. Achieving high accuracy and fast training can be done with tensor flow library there exist many models that can use for any object detection .nowadays using CNN the system is competent to convert details of image into words with this information that image can be used anywhere if required face book uses this technique for converting images into audible text. The work given in [22] detect visitor in Singapore images. With convolution layers, three fully-connected layers, 650000 neurons and 60 million parameters Alex-Net model giving best results.

In literature R-CNN is one best approach like by researchers due to its successful results to perform object detection within the image. Because of slow detection and high computational cost there always scope to find better technique for detection. Within the results complementary information of color and edge detection used by hybrid region proposal methods enhance rate of recall which boost system efficiency. Another approach which combines the power of neural network with features extractors improves training time as well.

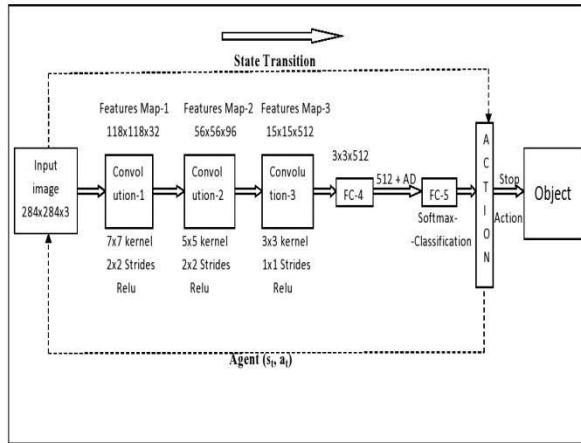
Another approach given by Alex et al uses sliding window which moves over image to find object window from background. Segmentation strategy works to reduce amount of windows which considered for execution.

Faster RCNN is another improved model over RCNN that uses a selective search technique which computed based on output feature map in the previous step then it uses ROI for predefined output, finally two output vector produced which use for object prediction. The main focus to use faster RCNN over RCNN is to reduce time taken in detection of objects and detection speed enhancement it providing the feature required. The problem with RCNN that it takes much time to train object detector also it's not easy to implement RCNN in real time, often the algorithm used is selective search which is fixed and no learning is done which leads to partial correct region proposals sometimes.

There exist more techniques which changes color of first dataset and in this way it also going to change internal details of image. The faster RCNN provide the better RPN (region proposal network) to reduce the training and testing time. Playing Atari game which reaches human level performance [28] an action value extracted by deep neural network given, Playing GO and beat the world level professional silver et al uses policy network and 3 value network. Also there exist various methods of object detection having efficient techniques and procedures.

## IV. PROPOSED OBJECT DETECTION DEEP RL- NETWORK (ODDRL-NET)

In our proposed model aim to urge high speed detection which will detect objects with better evaluation cycle, the ODDRL-NET uses a simplistic faster RCNN model and by performing only one undergoes the image. In literature there are many technique that are using many convolution layers for features map generation normally 20-30 comparative to these ODDRL-net is using only 05 layers .in this model we are using hard and fix size mask which extract faster detection over features map. These following steps are wont to perform the proposed ODDRL-Net model.



**Fig 4 proposed ODDRL-Net model**

### First Step: Fetch and preprocess the dataset

We take the gathering of images which is captured for test having one or more different types of object situated at different distance and angles. These images having content which manually segmented also classified for better result with the help of suitable software. Before using these images it must be necessary to reduce computational cost so they provide better and fast test. They divided in training and testing set the images which used for testing must used in training so they can easily recognize by model. Neural networks having great power of transformation with this ability they can detect an object in different situation the process involved to create artificial data during this work it involved adding noise, translating, rotating scaling within the image for better recognition also brightness, contrast, cropping as required operation performed .training the model with these kind of images ensures and simplify the features of every class and can make possible to recognize under any condition. We used 20,000 images for this test.

### Second Step: The implementation for a single image

As early we have resized our image to mxn during the training phase further for reducing computation cost it will resized A X B, so system resources must be fully utilized.

In training and testing phase we put dimension as input vector, as every pixel behaves like a neuron in beginning layer minimizing computation of image also reduce amount of neurons and cycle. After this process image is taken by ODDRL-net that outputs class

extraction and confidence values for every found region after this bounding boxes are generated over the image for matching size regions may resized. As we know that an output of layer we get as feature map, FM will not be as actual image size but with overlapping region and ratio can predict output. Each connected layer will remove some neurons and connections for next layer with temporally dropout, this can enhance the prediction rate and capability of neural network. When detection is done the regions are checked for low confidence detection and removal with high confidence region will be overlapped and they will belong to equivalent class, these classes will merge and give set of bounding boxes. Once process completes a replacement picture is found with detected object.

### Third Step: Training and Testing dataset

The images are preprocessed for training purpose than dataset is prepared. Now we have to make region in images that should have object inside we can use label image software to generate xml file after that we create map for training using CSV file. The CSV file contains map of objects in region and the model is trained to separate objects. The model is implemented in tensor flow using python 3.5 Anaconda.

The accuracy is the factor which tells model detect object efficiently or not so ALEXANET, A deep model [29] needs 11 GB memory of GPU building it very hard to work with most of GPU. Now its big challenge for ODDRL to work with less memory requirement so it can be used in any type of resource constrained devices for this we divide the training in three phases.

Also input images are 20000 for both testing and training so as to scale back the quantity of GPU memory required.

In first phase we input image to convolutional layer which generates feature maps again with 1x1 strides,3x3 kernel and RELU we generates next feature map than for region proposal we go with reinforcement learning as the good history provide ROI than after stretching image in its actual size we get bounding boxes for object prediction. With these efficient training ODDRL-NET can be a most efficient model which can be used in any kind of microcontroller devices with minimum resource requirement.

### Fourth Step: Result Calculation of dataset

The results are dependent on model with factor high accuracy and detection, better detection we can say having better results.....

*classification Accuracy is calculated as*

$$CA = \frac{\text{True Positive val} + \text{TrueNegative val}}{\text{Positive val} + \text{Negative val}}$$

The output is measured by calculation of comparison of bounding box generated by proposed ODDRL-net and manually created models.

For this purpose IoU intersection over union is used. We can give it by following equation...

$$IoU(X, Y) = \frac{|X \cap Y|}{|X \cup Y|} \quad \text{With } 0 \leq IoU(X, Y) \leq 1$$

Where X and Y bounding boxes extracted and recognize by the faster RCNN. Pixel wise similarity can be defined by the IoU. Size and positioning of region which having bounding box are the point which is the most important point for model point of view which uses first pass for object recognition if an object belongs to right class it will consider as positive and there must be bounding box ratio at least 60%, for a given class Z, IoU will define as IoUz are calculated as shown in equation..

$$IoUz(Z) = \frac{\sum_{ybox=0}^{yboxes-1} IoU(ybox, ground truth)}{ybox}$$

Here Y is the recognize bounding boxes for all dataset pictures often showed by following equation,

$$Score = \frac{IoU \times Accuracy}{Execution Time}$$

In order to execute the ODDRL-Net all operation related to training were executed on laptop having GHz i7- 8550 U Intel Core processor, 8 GB DDR4 RAM, 500 GB drive, and windows 10. The model implemented using Anaconda 3.5 python Tensor Flow for easy operation on devices with different architectures also.

### Fifth Step: Results Analysis

Training the network from images that are not forwarded by pretraining step causes bad results and inconsistent data and it's very hard to detect many classes of object hence moved to low accuracy. For training entire network pretraining is necessary step. The results are obtained in this section with pretrained network. With retraining within identical measures experienced by ODDRL-net having the ability making it to properly classify objects within the training dataset.

Irrespective to work given in literature many models employing convolution on feature map again and again intended to enhanced detection ODDRL-NET uses a hard and fast window over the input image generated by reinforcement learning it having many advantage like fast detection accuracy is more maintained by RF elements and hence evaluation time is decreased this will going to improve image average evaluation time (IAET).also ODDRL-NET is uses the region proposal method to find the ROI for classification there exist many techniques but we have taken reinforcement learning based classification which improves data accuracy by moving agent for collecting rewards. Finally the test shows the efficient working and results as seen in fig 5 using feature map with 3x3 kernel, 1x1strides and Relu make the features of image filtered and within the range provides the amount of space required .SVM classifier used by first RCNN[31] after training this work requires over 2 GB space for storing different classes. Often storing space depends on number of

classes in image and dataset, ODDRL Net is shallower and uses less parameter compared to other it also dataset independent with regard to file size also typical time taken comparative to fast RCNN is less than 3.5 times. In graph we showed that SIAET, storage dataset space required these are the main factor which plays in role of detection. We need to find an architecture which we can implement on any other device so must assure that we have to work with minimum resources to maximum gain ODDRL-net is fulfilling all needs....

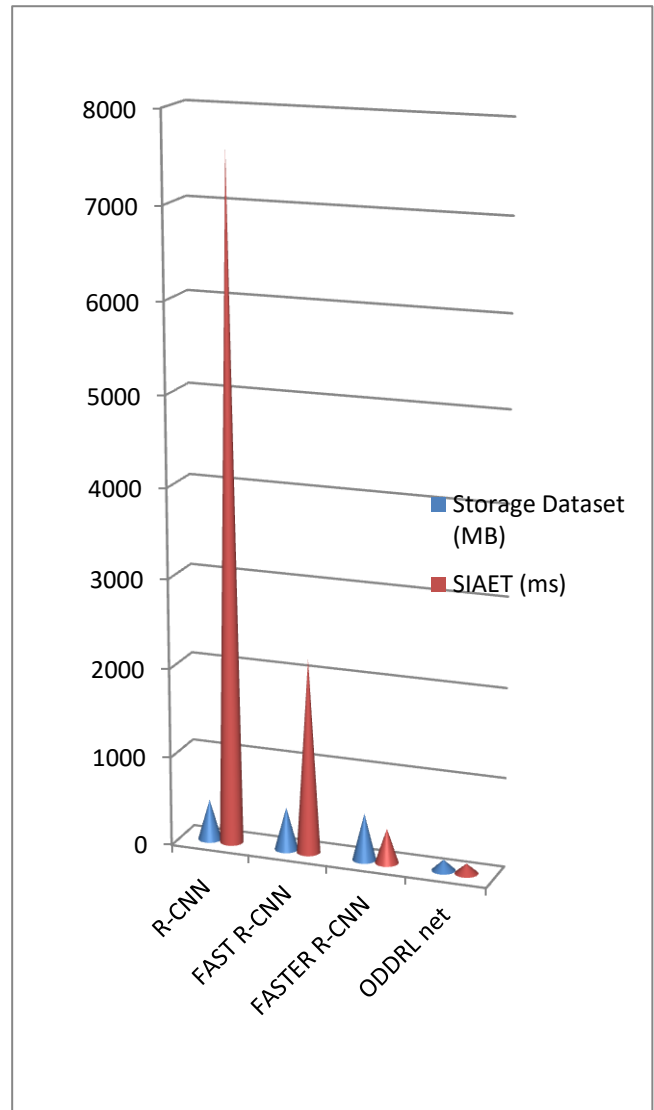


Fig 5 Result Analysis with ODDRL-Net

### V. CONCLUSIONS AND FUTURE WORK

Deep learning models are needs of nowadays with machine learning you can make life very simple and can build any application very easily object recognition is the application which can be used in population count easy identification of objects in industry and used to serve important purpose.

With deep learning it's very easy to extract complex data automatically. We have used reinforcement learning for research that work on positive history and that move makes it very strong for detection.

# A Framework for Object Detection using Deep-Reinforcement Machine Learning

Hierarchical feature extraction is important part of deep architecture which makes deep learning priceless tools for classification. When we want to combine deep learning features with reinforcement learning there are several unexplored point comes in studies. We know that robotics is an area where many work is waiting to be done also the capability of machine learning proved that its only tool which can resolve these kind of problem. Proposed ODDRL-NET is capable of quick identification of objects with minimum passes and by evaluating each region of image once. Due to its low computational cost its saves hardware resources as well as energy and execution time. The technology is improving day by day future work can find the position of bounding box and region of interest with more accuracy without affecting performance of recognition.

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