

IMPROVED OBJECT DETECTION WITH NEURAL NETWORK - SURVEY

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ABSTRACT

*Object detection is a computer technology related to computer vision and image processing that deals with detecting instances of semantic objects of a certain class (such as humans, buildings, or cars) in digital images and videos. In Image Processing two methods are used CLASSIFICATION and DETECTION. CNN is a one type of Feature Extraction but it is used for detect multiple shape and object. CNN is used as a classification. In this paper we focuses on convolution neural networks and Deep Pyramid technique allowing further insights into their internal operation. After giving a brief introduction to neural networks and its layers, we review supervised training of neural networks in detail. The second section introduces the different types of layers present in recent convolutional neural networks. Based on these basic building blocks, we discuss the architecture of the convolutional neural network. In the third section we focuses on the deep pyramid technique. In **DeepPyramid**, or **pyramid representation**, is a type of multi-scale signal representation developed by the computer vision, image processing and signal processing communities, in which a signal or an image is subject to repeated smoothing and sub sampling.*

Keywords :- Object detection, Pre-processing, Feature Extraction, Convolutional Neural network, Deep Pyramid, Classification

1. INTRODUCTION:

In image processing the object detection is generated large amount of data and class of the image in multiple level .In this survey used of CNN technique to detect the right portion of the object that the input comes. CNN have associated terminology and a set of concepts that is unique to them, and that sets them apart from other types of neural network architecture. CNN are usually applied to image data. Every image is a matrix of pixel values. The range of value that can be encoded in each pixel depends upon its bit size. CNN is biologically-inspired models[7]. The most popular application for CNNs in the recent times has been image analysis[8]. DEEP PYRAMID is the technique to shows the support of the CNN that uses to generated the double accuracy of the object. In future predicted that by use of this two technique image detection has clear to detect the object.

2. SYSTEM MODEL:

Object Detection is the process of selecting, exploring and classify large amounts of images in order to discover unknown techniques or relationships which provides a clear and useful result to the image providers.

2.1 Object Detection with neural network involves the following Steps:

1. Input Image: The first step is to identify image.
2. Pre-Processing: Its processes the input image to produce output that used as input to another image also.
3. Feature Extraction: The purpose of this step is to detect and select the important data of the image and its done with DEEP PYRAMID method.
4. Classification: In used of the CNN the important part is detected and the other chunk of data is deleted. For next step the detect part is classify its class by the classification step.
5. Object Detection: Based on the results of the CNN technique, an analysis is conducted to determine the image detection from the analysis and create a detection of the image and the final image part is detected.

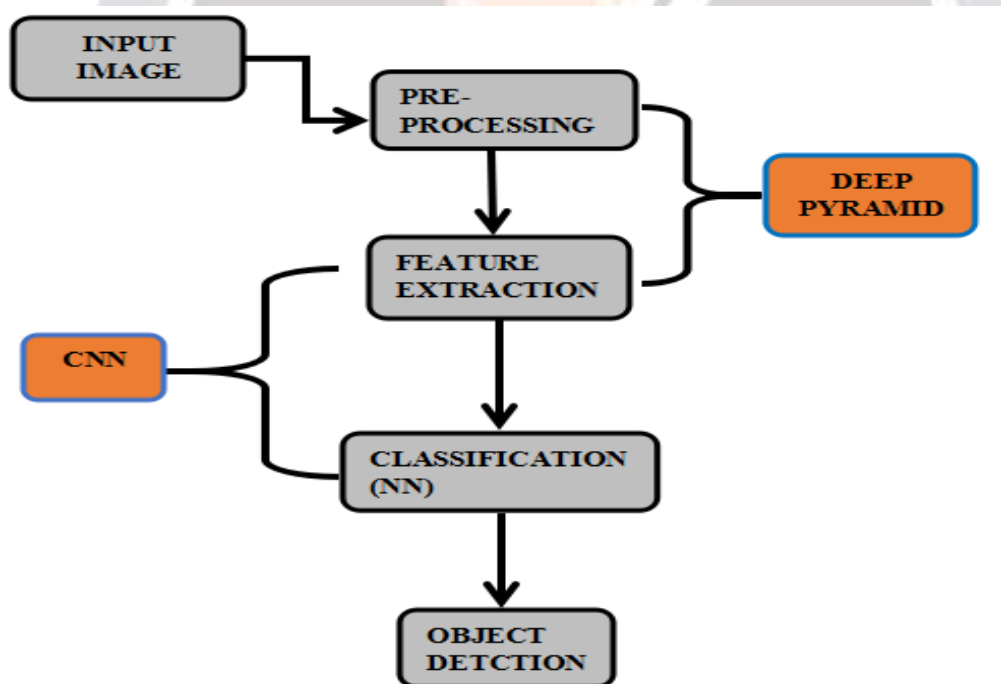


Fig -1: Object Detection with Neural Network Process

3. RELATED BACKGROUND:

3.1 Convolutional Neural Network(CNN):

In Image Processing Object Detection is most important. There are many techniques in object detection like SVM, HOG and many more. But CNN is the best in performance and time in multiple ways.

There are two types of Image Processing Techniques:

Classification: It don't know the object but it knows the class of the object.

Detection: It detect the object in the image.(ex. dog , people)

CNN is one type of machine learning algorithm.CNN is also called as CONVOLUTIONAL NEURAL NETWORK (ConvNet).In machine learning algorithm there is always usefull Feature Extraction.It is a techniques to use to take only important data (color, texture , shape) from the image. Sometimes it is difficult to generate Feature Extraction in a huge dataset like multiple images. So by that I would like to use CNN in object detection.CNN is a one type of Feature Extraction but it is used for detect multiple shape and object. CNN is used as a classification.In the object detection if we used the CNN so anyone else like HOG,SVM and many more algorithm is not need to generate and it also increase the performance of the process.Convolutional networks were inspired by biological processes.

In CNN it takes chunks of data and then detect the image. And generated the nodes in 3D forms.In CNN using deep pyramid. It is use in CNN as a layer like HOG,SVM. But not a Feature Extraction. Deep Pyramid is mostly used to capable the CNN in multiple nodes. In Feature Extraction it used to generated separately in system but this is good to generated CNN. CNN have three important layers:(1) Convolution layer, (2) Pooling layer and (3) Fully-connected layer.

3.2 Deep Pyramid:

Pyramid, or pyramid representation, is a type of multi-scale signal representation developed by the computer vision, image processing and signal processing communities, in which a signal or an image is subject to repeated smoothing and sub sampling. Pyramid representation is a predecessor to scale-space representation and multiresolution analysis. Sometimes Feature Extraction do not used in multiple image detection So the main advantage of Deep Pyramid is that it is like Feature Extraction but it is used in CNN in all bid and small data types and images.

Rectifier Linear Unit: $F(x)=\max(0,x)$

Sigmoid Linear Unit: $S(t) = \frac{1}{1+e^{-t}}$.

Convolution Formulas

4. PREDICTION OF OBJECT DETECTION:

In this paper, Multi-resolution image features may be approximated via extrapolation from nearby scales, rather than being computed explicitly. This fundamental insight allows us to design object detection algorithms that are as accurate, and considerably faster, than the state-of-the-art.

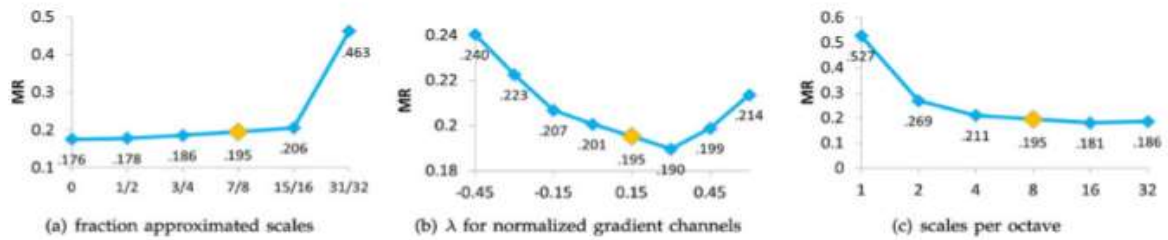


Fig: Fractions scale

Our results are not restricted to object detection nor to visual recognition. The foundations we have developed should readily apply to other computer vision tasks where a fine-grained scale sampling of features is necessary as the image processing front end[1]. In this survey, We have presented a framework for detecting multipleobject instances in images which is similar to the traditionalHough transform.

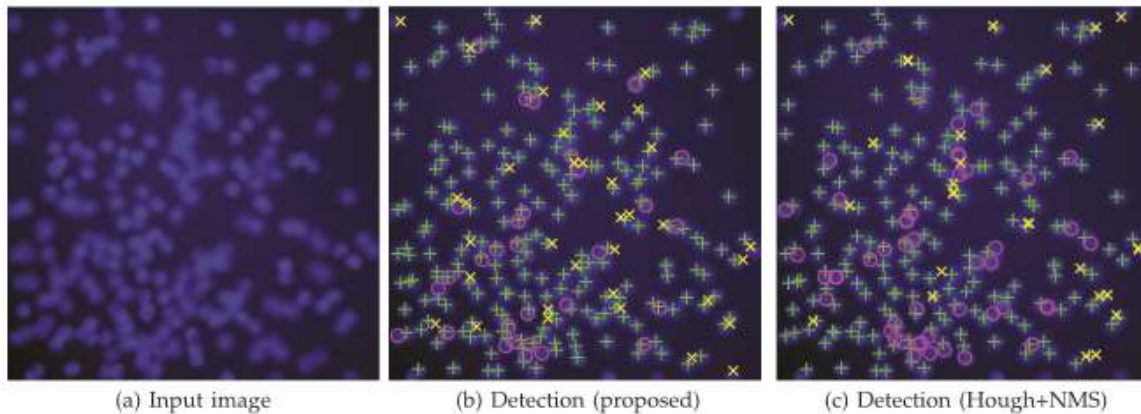


Fig. 9 HBM Process

This is investigated in our follow upwork [6], where we consider a multilayer graphical modelfor the parsing of animage ofaman-made environment.The model [6] includes layers for 1) estimation of straightlines based on edge pixels (this layer corresponds to themodel derived and evaluated in this paper), 2) grouping ofthe detected lines in parallel line families, 3) the estimationof the horizon and the zenith of the scene[2]. In this survey, We investigate the problem of incorporating color for objectdetection. Most state-of-the-art object detectors rely onshape while ignoring color. Recent approaches to augmentingintensity-based detectors with color often provide inferiorresults for object categories with varying importance ofcolor and shape. We propose the use of color attributes as anexplicit color representation for object detectionFinally, we introduce a new dataset of cartoon characterswhere color plays an important role[3]. In this paper,In this paper we have presented the Shape BoltzmannMachine, a strong generative model of object shape. TheSBM is based on the general DBM architecture, a form ofundirected graphical model that makes heavy use of latentvariables to model high-order dependencies between theobserved variables. We believe that the combination of (a)carefully chosen connectivity and capacity constraints, alongwith (b) a hierarchical architecture, and (c) a training procedurethat allows for the joint

optimization of the full model, is key to the success of the SBM.

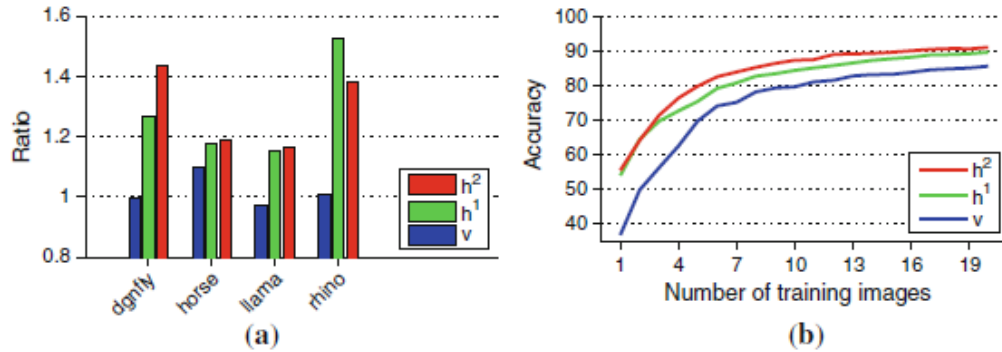


Fig: (a)The ratio of interand intra-class distances, (b) GLM classification

Overall we believe that by integrating powerful component models like the SBM into comprehensive generative models of images, performance in many computer vision tasks can be improved. We believe this to be a very promising direction of research [4]. In this surveying, in recent years, object detection performance had stagnated. The best performing systems were complex ensembles combining multiple low-level image features with high-level context from object detectors and scene classifiers. This paper presents a simple and scalable object detection algorithm that gives more than a 50% relative improvement over the best previous result on PASCAL VOC 2012.

Segmentation accuracy (%) on VOC 2011 test. We compare against two strong baselines: the "Regions and Parts" (R&P) method of [68] and the second-order pooling (O₂P) method of [59]. Without any fine-tuning, our CNN achieves top segmentation performance, outperforming R&P and roughly matching O₂P. These experiments use TorontoNet without fine-tuning.

VOC 2011 test	bg	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mean
R&P [68]	83.4	46.8	18.9	36.6	31.2	42.7	57.3	47.4	44.1	8.1	39.4	36.1	36.3	49.5	48.3	50.7	26.3	47.2	22.1	42.0	43.2	40.8
O ₂ P [59]	85.4	69.7	22.3	45.2	44.4	46.9	66.7	57.8	56.2	13.5	46.1	32.3	41.2	59.1	55.3	51.0	36.2	50.4	27.8	46.9	44.6	47.6
ours (full+fg R-CNN f _{C0})	84.2	66.9	23.7	58.3	37.4	55.4	73.3	58.7	56.5	9.7	45.5	29.5	49.3	40.1	57.8	53.9	33.8	60.7	22.7	47.1	41.3	47.9

Table: Segmentation Accuracy(%)

We achieved this performance through two insights. The first is to apply high-capacity convolutional networks to bottom-up region proposals in order to localize and segment objects. The second is a paradigm for training large CNNs when labeled training data are scarce [5]. By this, in this survey paper we predict that the accuracy (%) of the object is increased with the use of the CNN and DEEP PYRAMID technique.

5. CONCLUSION:

In image processing many techniques are used to detect the object perfectly. In R-CNN technique used of classical tools from computer vision and deep learning. And also the 62% of object is detected clear. In this future prediction shows the use of DEEP PYRAMID used in CNN layer to generate the multipleshape and object of live things and also the detection of invisible object. But in CNN algorithm for object detection due to some limitations of CNN algorithm we used DEEP PYRAMID layered as synchronization with CNN used to generate the perfect window size of data and pixel. And also % of accuracy is increased in the CNN compared to R-CNN. So by this predicted that the CNN is usefull and better than R-CNN. In future predection we predict the increase % of accuracy of object detection in CNN using DEEP PYRAMID method.

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