International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 7 July 2021, pp: 2991-2994 www.ijaem.net ISSN: 2395-5252

Object Detection Deep Learning

G.Adithya, C.Muneeswari, G.Venkatesh, T.Venkata Sainath, R.E.Yasodha, Dr.R.Gomalavalli

Department of Electronics & Communication Engineering Siddharth Institute of Engineering & Technology Puttur,India

Submitted: 10-07-2021 Revised: 23-07-2021 Accepted: 26-07-2021

ABSTRACT—Object detection is a vast, vibrant and complex area of computer vision. If there is a single object to be detected in an image, it is known as Image Localization and If there are multiple objects in an image, then it is Object Detection. This detects the semantic objects of a class in digital images and videos. The applications of real time object detection include tracking objects, video surveillance, pedestrian detection, people counting, self-driving cars, face detection, ball tracking in sports and many more. Convolution Neural Networks is a representative tool of Deep learning to detect objects using OpenCV(Open source Computer Vision), which is a library of programming functions mainly aimed at real time computer vision.

Keywords— Convolution neural network, deep learning, image edge detection.

I. INTRODUCTION

Object detection and tracking has become a major part in today's technology. Object detection is the process of finding the instances of real-world objects such as faces, bicycles, buildings and many real time objects. Object detection is the task of detecting the object and drawing a bounding box around them i.e., localizing them[1]. Object detection has already been the remarkable research direction and the focus in the computer vision which can be applied in the automatic car, robotics, video surveillance and pedestrian detection. The exposure of deep learning technology has changed the traditional ways of object identification and object detection. The deep neural network has the vigorous feature depiction capacity in image processing and is usually used as the feature extraction module in object detection[`2].

Therefore, the deep learning technology is of significant prospect in the object detection. The deep learning is an artificial intelligence function that imitates the workings of the human brain in processing data and creating patterns for decision making it is a subset of machine learning in artificial intelligence which has networks capable of learning from unsupervised data[3].

Improving object detection with deep convolution networks via Bayesian optimization and structured prediction[4]. According to Y. Zhang, K. Sohn, R. Villegas, G. Pan, and H. Lee, Object detection systems based on the profoundly convolutional neural network (CNN) have recently made groundbreaking progress on many benchmarks for object detection. Although the characteristics learned from these high-capacity neural networks are egalitarian for categorization[5], a major source of detection error is still inaccurate localization. Built on highcapacity CNN architectures, we answer the position problem by 1) using Bayesian optimization search algorithm which sequentially proposes candidate regions for an object bounding box, and 2) training the CNN with a formal loss that specifically penalizes the inaccuracy of the position[6]

Object detection via a multi region and semantic segmentation aware CNN model. According to S.gidares and n.komodakis.we proposed a method for object detection that relies on a profoundly convolution neural network(CNN) of multi region that also encodes semantic segmentation aware features. The resulting CNN based representation attempts to capture a diverse collection of discriminative appearance variables and exhibits sensitivity to localiazation which is important for the precise location of objects[7].By implementing it on an iterative localiazation system that alternates between scoring a box proposal and refining its position with a deep CNN regression model.we leverage the above mentioned properties of our recognisation model. Thanks to the efficient use of our modules. We are detecting objects with very high precision in localization[8].

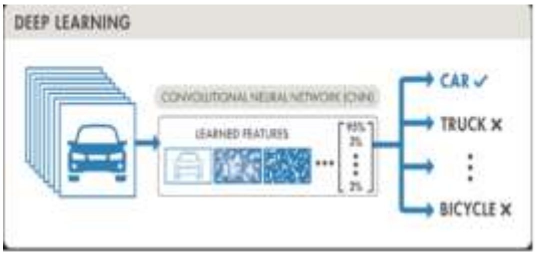
Sub category aware convolution neural networks for object proposals and detection. According to p.druzhkov and v.kustikova. in methods of detection of artifacts based on CNN, area proposal becomes a bottle neck when artifacts show large variance in size, occlusion ,or truncation. Moreover

,these methods concentrate primarily on 2D object detection and cannot estimate accurate object properties.In this paper, we suggest sub category aware CNN further detection of objects[9]. We implement a new area proposal network using sub category information to direct the proposal generation process.and a new detection network for joined identification and classification of sub categories .we achieved object detection using deep learning department of ece, sietk Page 3 state-of- the –art efficiency on both detection and post estimation on widely used bench marks by using sub categories related to object pose [10].

Face detection using deep learning: An improved faster RCNN approach. According to X. Sun. P. Wu. and S. C. Hoi., via tuned several key hyper- parameters in the faster RCNN architecture, where they have found that among others, the most crucial one seems to be the member of anchors in the RPN parts[11]. Traditional faster RCNN uses 9 anchors , which sometimes fails to recall small objects. For face detection tasks however ,small faces tend to be fairly common, especially in the case of unclear face detection. Therefore, instead of using the default of setting. We add a size group of 64x64. Thus, increasing the number of anchors to 12 and proposed a new method for face detection using deep learning techniques. we extended the state-of –the-arts faster RCNN framework for generic object detection and proprosed several effective strategies are improving the faster Rcnn algorithm for resolving face detection tasks. Including feature concatenation. Multi scaled training ,hard negative mining , and configuration of anchor sizes for RPN[4].

II. RELATED WORK

Block Diagram:



The CNN model is a single class label and hence this approach will not work if more than one class labels are present in the image. We need to try a different approach if we want to localize the presence of an object in the bounding box.

Single Shot MultiBox Detector:

• Single Shot: this means that the tasks of object localization and classification are done in a single forward pass of the network

• MultiBox: this is the name of a technique for bounding box regression developed by Szegedy et al. (we will briefly cover it shortly) • Detector: The network is an object detector that also classifies those detected objects

• Object Detection With Deep Learning : The resulting architecture (check MultiBox architecture diagram above again for reference) contains 11 priors per feature map cell (8x8, 6x6, 4x4, 3x3, 2x2) and only one on the 1x1 feature map, resulting in a total of 1420 priors per image, thus enabling robust coverage of input images at multiple scales, to detect objects of various sizes. At the end, MultiBox only retains the top K predictions that have minimized both location (LOC) and confidence (CONF) losses.

Python : Python is a powerful scripting language and is very useful for solving statistical problems involving machine learning algorithms. It has various utility functions which help in preprocessing. Processing is fast and it is supported on almost all platforms. Integration with C++ and other image libraries is very easy, and it has inbuilt functions and libraries to store and manipulate data of all types. It provides the pandas and numpy framework which helps in manipulation of data as per our need. A good feature set can be created using the numpy arrays which can have n-dimensional data.

Keras : Keras is an open-source library that provides a Python interface for artificial neural networks. Keras acts as an interface for the Tensor Flow library. Keras contains numerous implementations of commonly used neural-network building blocks such as layers, objectives, activation functions, optimizers, and a host of tools to make working with image and text data easier to simplify the coding necessary for writing deep neural network code.

Tensorflow : Tensor Flow is a python library for fast numerical computing created and released by Google. It is a foundation library that can be used to create Deep Learning models directly or by using wrapper libraries that simplify the architecture of the Tensorflow[12].

Google Collaboratory : • As a programmer, you can perform the following using Google Collaboratory • Write and execute code in Python • Document your code that supports mathematical equations • Create/Upload/Share notebooks • Import/Save notebooks from/to Google Drive • Import/Publish notebooks from GitHub • Import external datasets e.g. from Kaggle[13] • Integrate PyTorch,TensorFlow, Keras, OpenCV • Free Cloud service with free GPU.

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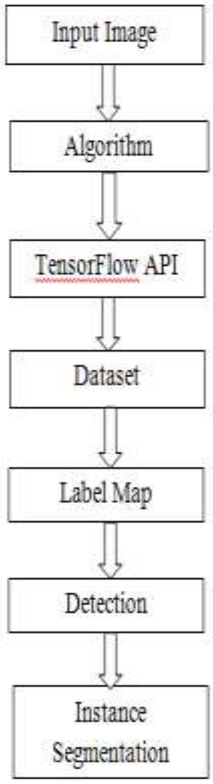
Jupyter Notebook : The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modelling, data visualization, machine learning, and much more.

Anaconda: Anaconda is a distribution of the Python and R programming languages for scientific computing (data science, machine learning applications, large-scale data processing, predictive analytics, etc.), that aims to simplify package management and deployment [14]. The distribution includes data-science packages suitable for Windows, Linux, and macOS. It is developed and maintained by Anaconda, Inc., which was founded by Peter Wang and Travis Oliphant in 2012.As an Anaconda, Inc. product, it is also known as Anaconda.

SSD Improvements:

Back onto SSD, a number of tweaks were added to make this network even more capable of localizing and classifying objects. Fixed Priors: unlike MultiBox, every feature map cell is associated with a set of default bounding boxes of different dimensions and aspect ratios. These priors are manually (but carefully) chosen, whereas in MultiBox, they were chosen because their IoU with respect to the ground truth was over 0.5[15]. This in theory should allow SSD to generalize for any type of input, without requiring a pre-training phase for prior generation. For instance, assuming we have configured 2 diagonally opposed points (x1, y1) and (x2, y2) for each b default bounding boxes per feature map cell , and c classes to classify, on a given feature map of size f = m * n, SSD would compute f * b * (4 + c) values for this feature map.

III. FLOWCHART



IV. RESULT

Object detection as the term suggests is the procedure to detect the objects in realworld. For example, dog, car, humans, birds etc. In this process we can detect the presence ofobject in the image.

Another great thing that can be done with it is that detection of multiple objects is asingle frame can be done easily.

For example, the below image SSD model has detected laptop in one image and number of persons in one image.

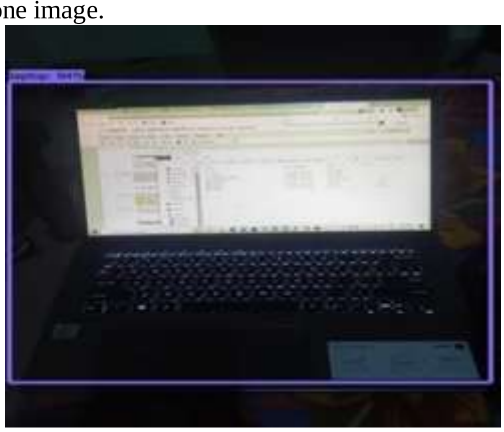


Fig: Detecting a Laptop

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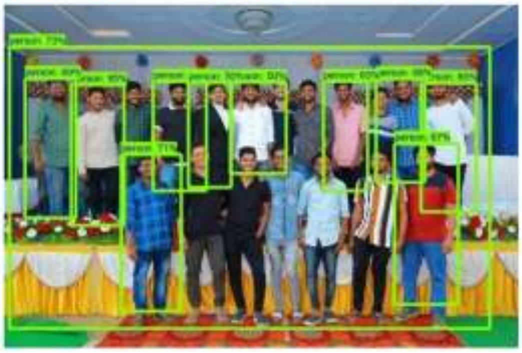

Fig: Detecting persons in the image

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