Component Detection with Deep Learning: A Review

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ABSTRACT

Object detection is a computerized technology-related technique in Computer vision and image processing. It is a technique that allows us to identify and locate objects in an image or video. With the help of this technology, the identification and localization of objects or any component can be simplified, object detection can be used to count objects in a scene and determine their precise locations, all while accurately labeling them. Object detection algorithms typically leverage machine learning or deep learning to produce meaningful results. The goal of object detection is to replicate this intelligence using a computer. Object detection can be done more accurately using certain algorithms. OpenCV which is a python library that functions mainly on computer vision, Yolo is the most efficient real-time algorithm which is used to effectively detect an object. In deep learning, CNN Tensorflow Keras is the algorithms used to accurately locate and identify objects.

Keywords— computer vision, OpenCv, Tensorflow, Keras, yolo, CNN.

I. INTRODUCTION

Object detection is a technique that allows to identify and locate objects present either in the real world or in an image or video where the object can be anything such as humans, machines, etc. It provides various features to identify objects, humans can easily recognize any object without any efforts in the real world by themselves but for machines, it cannot be possible to recognize objects or things. Object detection is totally linked to other computer vision techniques such as image recognition and image segmentation. It helps us to understand and analyze things in images or videos. It is mostly used in image annotations, activity recognition, face detection, face recognition, image retrieval, security surveillance, machine inspection, automated vehicle systems, etc. It is also used in tracking things, for example, tracking movements of a person, etc. Basically, it deals with finding and locating specific objects, the process of locating moving objects using the camera in video sequences over time is known as object tracking, the main aim of object tracking is to relate target objects in consecutive video frames. Object tracking requires features of objects or the shape of the object and location. To detect or locate the moving object in the frame.

II. LITERATURE SURVEY

This section of the literature survey eventually reveals some facts based on thoughtful analysis of many authors work as follows.

OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks[1]

Localization/Detection pipeline Figure no.(1)[1]

Inspired via way of means of the early fulfillment of AlexNet within the 2012 ImageNet competition, wherein CNN—primarily based totally characteristic extraction defeated all home made characteristic extractors, OverFeat fast delivered CNN lower back into the item detection place as well. The concept may be very straightforward: if we will classify one picture the usage of CNN, what approximately greedily scrolling thru the complete picture with one of a kind sizes of windows, and try and regress and classify them one- via way of means of one the usage of a CNN? This leverages the energy of CNN for characteristic extraction and category, and additionally bypassed the tough area notion trouble via way of means of pre-described sliding windows. Also, for the reason that a close-by convolution kernel can percentage a part of the computation result, it isn't always important to compute convolutions for the overlapping place, as a result lowering value a lot. OverFeat is a pioneer within the one-degree item detector. It attempted to mix characteristic extraction, vicinity regression, and area category within the equal
CNN. Unfortunately, this sort of one-degree method additionally suffers from fantastically poorer accuracy because of much less previous information used. Thus, OverFeat did not lead a hype for one-degree detector research, till a far extra stylish answer popping out 2 years later.

Region-based Convolutional Networks for Accurate Object Detection and Segmentation[2]

Also proposed in 2013, R-CNN is a chunk past due as compared with OverFeat. However, this vicinity-primarily based totally method sooner or later caused a huge wave of item detection studies with its two-level framework, i.e, vicinity notion level, and vicinity type and refinement level.

In the above diagram, R-CNN first extracts capacity areas of the hobby from an enter photograph with the aid of using the usage of of a way referred to as selective seek. Selective seek doesn’t actually try and recognize the foreground item, instead, it businesses comparable pixels with the aid of using counting on a heuristic: comparable pixels normally belong to the equal item. Therefore, the consequences of selective seek have a completely excessive opportunity to incorporate something meaningful. Next, R-CNN warps those place proposals into fixed-length pics with a few paddings and feeds those pics into the second level of the community for extra fine-grained recognition. Unlike the one’s vintage techniques the usage of of selective seek, R-CNN changed HOG with a CNN to extract functions from all place proposals in its 2d level. One caveat of this technique is that many place proposals aren’t absolutely a complete item, so R-CNN desires to now no longer handiest discover ways to classify the proper classes, however additionally discover ways to reject the poor ones. To remedy this problem, R-CNN dealt with all place proposals with a ≥ 0.5IoU overlap with a ground-reality field as positive, and the relaxation as negatives.

Region notion from selective seek incredibly relies upon the similarity assumption, so it could handiest offer a difficult estimate of location. To in addition enhance localization accuracy, R-CNN borrowed a concept from “Deep Neural Networks for Object Detection” (aka DetectorNet) and added an extra bounding field regression to expect the middle coordinates, width, and peak of a field. This regressor is broadly used withinside the destiny item detectors.

However, a -level detector like R-CNN suffers from massive issues: 1) It’s now no longer absolutely convolutional due to the fact selective seek isn’t E2E trainable. 2) place notion level is normally very sluggish in comparison with different one-level detectors like OverFeat, and going for walks on every place notion one by one makes it even slower. Later, we can see how R-CNN evolve through the years to cope with those issues.

-Fast R-CNN[3]

Also, this research described that CNN suffer from massive latency, and that CNN evolved through the years to cope with those issues. CNN is used to recognize the foreground item, but doesn’t absolutely try and recognize the foreground item, using a way referred to as selective seek. Selective seek businesses comparable pixels with the aid of using counting on a heuristic. Selective seek is a concept that was previously used in the detection component make Fast R-CNN a famous preference withinside the enterprise as well.


As we brought above, in early 2015, Ross Girshick proposed an progressed model of R-CNN referred to as Fast R-CNN with the aid of using the usage of of a shared characteristic extractor for...
proposed regions. Just some months later, Ross and his crew got here again with any other development again. This new community Faster R-CNN isn’t best quicker than preceding variations however additionally marks a milestone for item detection with a deep gaining knowledge of method.

With Fast R-CNN, the simplest non-convolutional piece of the community is the selectively seek location thought. As of 2015, researchers began out to recognize that the deep neural community is so magical, that it could analyze something given sufficient data. So, is it viable to additionally teach a neural community to thought regions, in preference to counting on heuristic and homemade methods like selective seek? Faster R-CNN observed this path and thinking, and efficiently created the Region Proposal Network (RPN). To honestly put, RPN is a CNN that takes a photo as entering and outputs a hard and fast of square item proposals, every with an objectiveness score. The paper used VGG at the beginning however different spine networks which include ResNet grow to be extra big later. To generate location proposals, a 3x3 sliding window is carried out over the CNN function map output to generate 2 scores (foreground and background) and four coordinates for every location. In practice, this sliding window is carried out with a 3x3 convolution kernel with a 1x1 convolution kernel. Although the sliding window has a hard and fast size, our items may also seem on unique scales. Therefore, Faster R-CNN brought a way referred to as anchor field. Anchor containers are pre-described earlier containers with unique element ratios and sizes however proportion the equal significant location. In Faster R-CNN there are k=nine anchors for every sliding window location, which covers three-element ratios for three scales every. These repeated anchor containers over unique scales carry first-class translation-invariance and scale-invariance functions to the community whilst sharing outputs of the equal function map. Note that the bounding field regression may be computed from those anchor fields in preference to the entire photo.

So far, we mentioned the brand new Region Proposal Network to update the vintage selective seek area proposal. To make the very last detection, Faster R-CNN makes use of the equal detection head from Fast R-CNN to do type and fine-grained localization. Do you recollect that Fast R-CNN additionally makes use of a shared CNN characteristic extractor? Now that RPN itself is likewise a characteristic extraction CNN, we will simply proportion it with a detection head just like the diagram above. This sharing layout doesn’t deliver a few hassles though.

If we educate RPN and Fast R-CNN detector together, we are able to deal with RPN proposals as a steady enter of ROI pooling, and unavoidably forget about the gradients of RPN’s bounding container proposals. One stroll round is referred to as opportunity education in which you educate RPN and Fast R-CNN in turns. And later in a paper “Instance-conscious semantic segmentation through multi-undertaking community cascades”, we will see that the ROI pooling layer also can be made differentiable w.r.t. the container coordinates proposals.


While the R-CNN collection began out a huge hype over-degree item detection withinside the studies community, its complex implementation delivered many complications for engineers who preserve it. Does item detection want to be so cumbersome? If we’re inclined to sacrifice a chunk of accuracy, are we able to alternate for a whole lot quicker speed? With those questions, Joseph Redmon submitted a community known as YOLO to arxiv.org handiest 4 days after Faster R-CNN’s submission and subsequently delivered recognition again to one-degree item detection years after OverFeat’s debut.
Unlike R-CNN, YOLO determined to address location concept and location class collectively withinside the equal CNN. In different words, it treats item detection as a regression hassle, as opposed to a class hassles counting on location proposals. The trendy concept is to cut up the entry into an SxS grid and having every mobileular immediately regress the bounding field area and the self-assurance rating if the item middle falls into that mobileular. Because items may also have distinctive sizes, there might be a couple of bounding field regressor in keeping with mobileular. During training, the regressor with the best IOU might be assigned to evaluate with the ground-fact label, so regressors on the equal area will discover ways to deal with distinctive scales over time. In the meantime, every mobileular may also are expecting C magnificence probabilities, conditioned at the grid mobileular containing an item (excessive self-assurance rating). This method is later defined as dense predictions due to the fact YOLO attempted to are expecting lessons and bounding containers for all viable places in an image. In contrast, R-CNN is based on location proposals to filter history regions, therefore the very last predictions are tons extra sparse.

-SSD: Single Shot MultiBox Detector[5]

YOLO v1 established the potentials of one-degree detection, however, the overall performance hole from two-degree detection remains noticeable. In YOLO v1, a couple of items may be assigned to the equal grid cell. This became a huge mission whilst detecting small items, and has become an essential hassle to remedy as a way to enhance a one-degree detector’s overall performance to be on par with two-degree detectors. SSD is any such challenger and assaults this hassle from 3 angles.

SSD went down in this avenue similarly via way of means of aggregating multi-scale capabilities earlier than detection. This is a totally not unusual place technique to choose up fine-grained neighborhood capabilities whilst keeping coarse international capabilities in CNN. For example, FCN, the pioneer of CNN semantic segmentation, additionally merged capabilities from a couple of degrees to refine the segmentation boundary. Besides, multi-scale characteristic aggregation may be without problems accomplished on all, not unusual place class networks, so it’s very handy to switch out the spine with every other network.

First, the anchor container approach from Faster R-CNN can alleviate this problem. Objects withinside the equal place generally include one-of-a-kind factor ratios to be visible. Introducing anchor containers now no longer most effective improved the quantity of the item to locate for every cell, however additionally helped the community to higher differentiate overlapping small gadgets with this factor ratio assumption.

-Feature Pyramid Networks for Object Detection[7][19]

With the release of Faster-RCNN, YOLO, and SSD in 2015, it looks like the overall shape of an item detector is determined. Researchers begin to examine enhancing every person a part of those networks. Feature Pyramid Networks is an try and enhance the detection head through the usage of functions from extraordinary layers to shape a function pyramid. This function pyramid concept isn’t very novel in pc imaginative and prescient research. Back then while functions are nevertheless...
manually designed, a function pyramid is already a completely powerful manner to apprehend styles at extraordinary scales. Using the Feature Pyramid in deep mastering is likewise now no longer a brand new concept: SSPNet, FCN, and SSD all tested the advantage of aggregating multiple-layer functions earlier than classification. However, the way to percentage the function pyramid among RPN and the region-primarily based totally detector remains but to be determined.

First, to rebuild RPN with an FPN shape just like the diagram above, we want to have an area inspiration walking on more than one extraordinary scale of characteristic output. Also, we most effectively want three anchors with extraordinary issue ratios according to the region now due to the fact items with extraordinary sizes could be taken care of with the aid of using extraordinary tiers of the characteristic pyramid. Next, to apply an FPN shape within the Fast R-CNN detector, we additionally want to conform it to locate on more than one scale of characteristic maps as well. Since area proposals may have extraordinary scales too, we ought to use them within the corresponding stage of FPN as well. In short, if Faster R-CNN is a couple of RPN and area-primarily based totally detector walking on one scale, FPN converts it into more than one parallel branch walking on extraordinary scales and collects the very last effects from all branches within the end.

-YOLO9000: Better, Faster, Stronger[9]

While Kaiming He, Ross Girshick, and their group hold enhancing their -level R-CNN detectors, Joseph Redmon, on the alternative hand, became additionally busy enhancing his one-level YOLO detector. The preliminary model of YOLO suffers from many shortcomings; predictions primarily based totally on a rough grid added decrease localization accuracy, scale-agnostic regressors in line with grid mobileular additionally made it hard to apprehend small packed objects. Fortunately, we noticed too many wonderful improvements in 2015 in lots of laptop imaginative and prescient areas. YOLO v2 simply desires to discover a manner to combine all of them to grow to be better, faster, and stronger. Here are a few highlights of the modifications:

- YOLO v2 introduced Batch Normalization layers from a paper called “Batch Normalization: Accelerating Deep Network Training through Reducing Internal Covariate Shift”.

- Just like SSD, YOLO v2 additionally added Faster R-CNN’s concept of anchor bins for bounding container regression. But YOLO v2 did a few customizations for its anchor bins. Instead of predicting offsets to anchor bins, YOLOv2 constraints the item middle regression tx and ty inside the accountable grid mobileular to stabilize early education. Also, anchors sizes are decided with the aid of using a K-way clustering of the goal dataset to higher align with item shapes.

- A new spine community known as Darknet is used for characteristic extraction. This is stimulated with the aid of using “Network in Network” and GooLeNet’s bottleneck structure.

- To enhance the detection of small objects, YOLO v2 delivered a passthrough layer to merge functions from an early layer. This element may be visible as a simplified model of SSD.

- Last however now no longer least, Joseph found out that enter decision is a silver bullet for small item detection. It now no longer simplest doubled the enter for the spine to 448x448 from 224x224 however additionally invented a multi-scale education schema, which entails one-of-a-kind enter resolutions at one-of-a-kind durations of education.

Note that YOLO v2 additionally experimented with a model that’s skilled on 9000 magnificence hierarchical datasets, which additionally represents an early trial of multi-label type in an item detector.

-Focal Loss for Dense Object Detection[8]

To apprehend why one-degree detectors are generally now no longer as exact as two-degree detectors, RetinaNet investigated...
the foreground-heritage elegance imbalance difficulty from a one-degree detector’s dense predictions. Take YOLO as an instance, it attempted to expect instructions and bounding containers for all feasible places within the meantime, so a maximum of the outputs is matched to terrible elegance all through training. SSD addressed this difficulty via way of means online tough instance mining. YOLO used an objectiveness rating to implicitly educate a foreground classifier within the early degree of training. RetinaNet thinks they each didn’t get the important thing to the problem, so it invented a brand new loss feature referred to as Focal Loss to assist the community study what’s important.

\[
FL(p_i) = -\alpha(1 - p_i)^\gamma \log(p_i).
\]

Focal Loss Definition

| Figure no.(11)|[8] |

Focal Loss brought a strength \(\gamma\) (they name it focusing parameter) to Cross-Entropy loss. Naturally, because the self-belief rating turns higher, the loss fee becomes a lot decrease than an everyday Cross-Entropy. The \(\alpha\) parameter is used to stability this sort of focusing effect.

This concept is so easy that even a number one college pupil can understand. So too in addition to justify their work, they tailored the FPN version they formerly proposed and created a brand new one-level detector known as RetinaNet. It consists of a ResNet spine, an FPN detection neck to channel capabilities at extraordinary scales, and subnets for type and field regression as detection head. Similar to SSD and YOLO v3, RetinaNet makes use of anchor bins to cowl objectives of numerous scales and component ratios.

A little bit of a digression, RetinaNet used the COCO accuracy from a ResNeXt-one zero one and 800 enter decision version to comparison YOLO v2, which handiest has a light-weighted Darknet-19 spine and 448 enter decision. This insincerity indicates the team’s emphasis on getting higher benchmark results, as opposed to fixing sensible trouble like a speed-accuracy trade-off. And it is probably a part of the cause that RetinaNet didn’t take off after its release.

YOLO v3 is the closing model of the reputable YOLO series. Following YOLO v2’s tradition, YOLO v3 borrowed greater thoughts from preceding studies and was given a very effective one-level detector like a monster. YOLO v3 balanced the velocity, accuracy, and implementation complexity quite well. And it was given honestly famous within the enterprise due to its speedy velocity and easy components. If you're interested, I wrote a completely distinctive rationalization of ways YOLO v3 works in my preceding article “Dive Really Deep into YOLO v3: A Beginner’s Guide”.


Simply put, YOLO v3’s achievement comes from its extra effective spine function extractor and a RetinaNet-like detection head with an FPN neck. The new spine community Darknet-fifty three leveraged ResNet’s pass connections to gain an accuracy that’s on par with ResNet-50 however a whole lot faster. Also, YOLO v3 ditched v2’s skip thru layers and completely embraced FPN’s multi-scale predictions design. Since then, YOLO v3 eventually reversed people’s influence of its bad overall performance whilst handling small objects.

Besides, there are some laugh records approximately YOLO v3. It dissed the COCO mAP 0.5:0. ninety-five metric, and additionally proven the uselessness of Focal Loss whilst the use of a conditioned dense prediction. The creator Joseph even determined to end the entire laptop imaginative and prescient studies 12 months later, due to his subject of navy usage.

III. PROPOSED ARCHITECTURE
In the above figure the Object detection algorithms use features which can be extracted to recognize a particular object. This model is not at all complex, it is easy to implement. Here, object detection is a single regression problem which detects directly from bounding box coordinates and class probability. Every object has its own class such as all circles are round, which are used while recognizing the objects.

- **Preprocessing**
  Preprocessing is the lowest level of abstraction. This process improves the image intensity by suppressing the features which we don’t want for further processing. It resizes the image size to 448*448 and also normalizes the contrast and brightness effects. The image is also cropped and resized by which we can perform feature extraction easily. The input images are pre-processed and very easily normalize the contrasts and brightness. Preprocessing step can be done by subtracting the mean of image intensities and divide by the standard deviation. New brightness value can be found by using the neighborhood of a pixel in the input image. The fig 2 below shows the pre-processing of image.

- **FEATURE EXTRACTION**
  Its main motive is to simplify the image by considering only the information which we want i.e. important information and leaving out the extra information which is not necessary for recognition. It uses the method of edge detection which can only keep the essential information. It represents the reduced part of the required image as a feature vector. This approach is mostly used when the size of image is very large. Hence, by this process, image recognition becomes simplified. It starts from the already measured data and features which provides some kind of information facilitating the further steps.
DETECTION IN IMAGES

The n number of different components of object detection are integrated into a single neural network, which uses certain features from the whole image to predict a bounding box. The bounding boxes for other classes are also predicted at the same time. Hence the neural network analyses the full image and also the different objects in the image.

Object Recognition

Object recognition is a computer vision technique for identifying objects in images or videos. Object recognition is a key output of deep learning and machine learning algorithms. When humans look at a photograph or watch a video, we can readily spot people, objects, scenes, and visual details.

IV. CONCLUSION

Deep Learning based Object Detection has been a research hotspot in recent years. This paper provides a detailed review of deep learning-based object detection frameworks. The need for object detection systems is gaining more importance. Object Detection algorithms typically leverage machine learning or deep learning to produce accurate results. Some algorithms are used to detect objects such as OpenCV is the huge open-source library for computer vision, machine learning, and image processing and now it plays a major role in real-time operation which is very important in today’s system by using it one can process images and videos to identify objects and instances. YOLO (You Only Look Once) is one of the most effective object detection algorithms Yolo uses totally different approach for object detection process frames at the rate of 45 fps (larger network) to 150 fps (smaller network) which is better than the real-time network is able to generalize the image better. Also, CNN (Convolutional Neural Network) algorithm is used for more accuracy in the detection of objects. It consists of several different layers such as the input layer, at least one hidden layer. They are best used in object detection for recognizing patterns.

By using this thesis and based on experimental results we are able to detect object more precisely and identify the objects individually with the exact location of an object.

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