Convolutional neural network based encoder-decoder for efficient real-time object detection

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Article Info

Article history:

Received Feb 27, 2024
Revised Nov 26, 2024
Accepted Jan 27, 2025

Keywords:

Convolutional neural networks
Deep learning
Encoder-decoder
Mean average precision
MS-COCO dataset
Object detection

ABSTRACT

Convolutional neural networks (CNN) are applied to a variety of computer vision problems, such as object recognition, image classification, semantic segmentation, and many others. One of the most important and difficult issues in computer vision, object detection, has attracted a lot of attention lately. Object detection validating the occurrence of the object in the picture or video and then properly locating it for recognition. However, under certain circumstances, such as when an item has issues like occlusion, distortion, or small size, there may still be subpar detection performance. This work aims to propose an efficient deep learning model with CNN and encoder decoder for efficient object detection. The proposed model is experimented on Microsoft Common Objects in Context (MS-COCO) dataset and achieved mean average precision (mAP) of about 54.1% and accuracy of 99%. The investigational outcomes amply showed that the suggested mechanism could achieve a high detection efficiency compared with the existing techniques and needed little computational resources.

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1. INTRODUCTION

More than 90% of human understanding is visual, and various imaging equipment are frequently used in fields that are directly related to human activity and living [1]. The processing of photos and other information has been successfully adopted in various industries to the ongoing growth of machine learning algorithms. The primary research challenge in computer vision, object detection, has drawn increasing attention from academics. The object discovery typically contains two stages: first, looking for the item in the image; second, employing bounding boxes to find the object. Convolutional neural networks (CNN) has become highly effective at object detection in recent years [2]–[5], region based convolutional neural network (R-CNN) [6], YOLO [7], the spatial pyramid pooling network (SPP) [8], and Fast R-CNN [9] object detection techniques that are used in this field of study. Due to computational hardware and data availability, traditional object detection algorithms have significant drawbacks [10]. Conversely, with the development of artificial intelligence (AI) and processing power in recent years, the entire process can now be automated with little to no human involvement. The primary distinction is that traditional object detection techniques rely on human experience standards and expert judgement to extract features, whereas AI uses a sophisticated neural network that can be trained to routinely identify powerful and judicial features.

In particular, encoder-decoder models based on fully convolutional networks (FCNs) have significantly enhanced performance, such as semantic segmentation [11], [12], edge recognition [13] object exposure [14], and crowd counting [15]. Essentially, the trend of popular object identification techniques are operate within the encoder-decoder framework. For the detection task, some researchers created structures based on the encoder-decoder paradigm and attained cutting-edge performance [16]. With regard to benchmark datasets, CNN-based encoder-decoder models are particularly crucial for continuously improving detection performance [17]. Convolution is done by the encoder, whereas deconvolution, un-pooling, and up-sampling are done by the decoder to forecast pixel-wise class labels. The up-sampling decode that corresponds the low-resolution encoder feature maps, is the important feature. This architecture employs the encoder's pooling indicators to up-sample to map pixel-wise categorization while also significantly reducing the number of trainable parameters. This paper is structured as follows.

The goal of object detection, which is typically done with photos or videos, is to find borders as well as to show the object's range and location. The next step is to classify the object's category and to provide the categorization likelihood. This task is more difficult than simple picture classification because the positions of many items must be determined from the image or video. CNNs have been used for the detection and classification of objects with success [18]. Current models include ways to categorise either a full input window for each scene for a bounding box of several objects. Semantic segmentation has had a breakthrough thanks to FCN. It has provided a potent method for boosting the effectiveness of CNNs by providing inputs of any size [19]. The encoder-decoder-based concept that presented by [20]. It suggested for feature learning that is unsupervised; then, neural networks backed by encoder-decoders have emerged as a potential replacement for further aids. An intriguing pedestrian collision alert system for advanced driver assistance systems was suggested in [21]. However, it is only capable of detecting and warning pedestrians. Facial feature localization [22] extracted information from input strings that could only be one dimension using the Viterbi decoding technique. Support vector machine (SVM)-based predictive modeling [23] utilised the similar concept to expand SVM outcomes using two-dimensional maps.

As an attention generating module that learns to specifically attend to significant locations for every pixel by employing bidirectional long short-term memory (Bi-LSTM) module within the feature maps, paediatric intensive care audit network (PiCANet) was proposed in [24]. For C-elegans tissues with FCN inference, coarse multi-class segmentation CNN with FCN architecture. In order to forecast pixel-level labels and to improve the label map using conditional random field (CRF), network achieves denser score maps using FCN architecture. One of the current major trends in CNN architecture design is the incorporation of encoder and decoder to improve performance. Apart from these object detection models; several detection algorithms are implemented on hardware platforms to improve the detection performance.

Pyramid scene analysis network (PSPNet) is yet another effective CNN architecture that was just released. It is intended for prediction jobs at the pixel level. The global pyramid pooling structure that combined global and local hints that produce the results builds the pixel-level features for effective segmentation. Due to the PSPNet architecture's extreme complexity, training and testing processes need for a sizable amount of processing power and graphics processing units (GPU) capabilities. The concept of panoptic segmentation (PS) was recently introduced in a study about pixel-wise segmentation. To complete a broad segmentation task, PS combines segmenting instances and segmentation based on semantics. Comparatively speaking, it performs well when compared to previous visual geometry group (VGG) based networks, although size is the design's main flaw.

The prophet algorithm, K-means clustering, and seasonal autoregressive integrated moving-average methods act a task in enhancing the cloud infrastructures. Also, it grouping servers into clusters with similar utilization patterns. K-means clustering enhances the resource allocation efficiency [25]. Internet of things (IoT)-driven image recognition system utilizing CNNs to notice and quantify microplastics [26]. The data collected by sensors is forward to a centralized monitoring system that decides whether or not an alarm activated in the event if the situation diverge from their ideal state [27]. K-nearest neighbor (KNN) and SVM algorithm forms a precise arrangement model to utilize the important data expectation exactness [28]. SVM with recurrent neural networks are powerful classification that makes it feasible to classify patients' risks and predict how they will react to therapy [29]. Cloud computing grants the seizure prediction system to improve accessible and scalable [30] and it examines the feature selection developed in for improving accuracy [31]. Hybrid machine learning techniques like SVM with CNN algorithm to anticipates Alzheimer's sickness [32].

2. PROPOSED DEEP LEARNING MODEL

The proposed architecture is a pixel-wise model that built on two decoupled FCNs for encoding as well as decoding as explained in Figure 1. The previously described encoder is built using the first 16 convolutional layers of VGG-19 network, then a batch normalised (BN) layer, function of activation, pooling layer, as well as dropout units. The decoder network is composed of layers for upsampling, deconvolution, activation, batch normalisation, dropout, and a multi-class classification. Every decoder is matched to a pooling unit of an encoder in the system's overall encoder-decoder interface. Consequently, the decoder CNN has 16 de-convolution layers. To probabilities of output class meant to each individual pixel individually, the decoder sends its computations to softmax classifier.

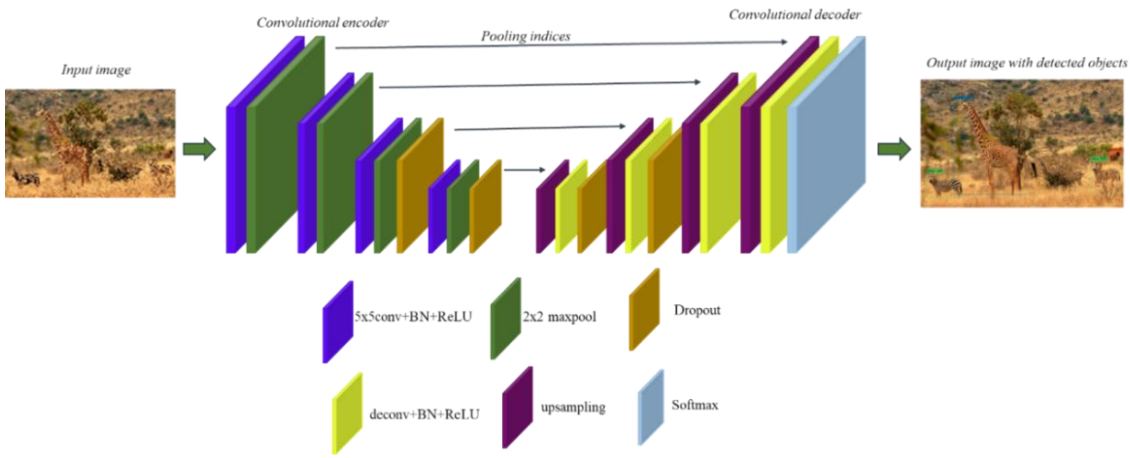

Figure 1. Proposed architecture for real-time object detection

The key benefits of our suggested decoupled architecture are its simple training with various environmental factors and ease of customization. For pixel-wise classification, the encoder creates low-resolution feature maps, which the decoder up-samples through convolutioning the trainable filters to yield intense feature maps [33]. The fundamental component of the suggested method is the decoding procedure, which provides several useful advantages in terms of improving boundary delineation and reduction. Also much improved is the ability to provide training by lowering the amount of trainable attributes. It offers a simple training, which trains both the encoder as well as decoder at the same time.

With an input image, the network begins training and acts during the network to the top layers. Adopting convolution with a prearranged set of filter banks to fabricate feature maps, the batch normalisation process is fulfilled by the encoder. Afterwards, activations are accomplished by rectified linear units (ReLUs). The max-pooling function is then fulfilled with a window size of 2x2 and a tread of 1. This outcomes in a two-fold subsampling of the last image. Multiple pooling layers able to increase translation invariance for effective categorization jobs, but the feature maps' spatial resolution is unnecessarily reduced.

Therefore, prior to the sub-sampling function, the boundary information needs to be recorded and stored in the encoder feature maps. However, it is not practical to save the entire encoder feature maps because to memory limitations. The best option is keep the max-pooling indicators in storage. For each 2x2 pooling window, two bits are used to memorise the positions of each max-pooling feature-map. Having a lot of feature maps on hand is a really effective solution. With this approach, the encoder can store data much more efficiently and fully connected layers can be dropped.

3. RESULTS AND DISCUSSION

The MS-COCO dataset that consist of 91 item with 2.5 million labelled examples in 328k images, is used to train the proposed object detection algorithm. On a single 12 GB NVIDIA Tesla K40c GPU, the suggested network was trained. The network is trained until the accuracy as well as loss do not significantly grow or decrease and the loss has converged. The whole network is established and trained utilizing the Caffe Berkeley Vision Library. Caffe provides a flexibility while it relates creating network layers as well as training the network to meet the suggested specifications. Thus, once converges, it is trained, and no considerable reduce in training loss is seen. The entire results are then evaluated, examined, and subsequently contrasted with the specified benchmark results.The dataset is divide by training and testing. Here, 90% is allotted for training and 10% is allotted for testing.

Many weights are 0 because training models frequently use the ReLU activation function. In this work, it was found that after creating the sparsity model, the gradient vanished during training with ReLU6. This is as a result of the mask excluding 50% of the weights from the gradient update. As indicated in Table 1, the public dataset MS-COCO evaluated and contrasted with the earlier techniques. In this work, there are 5 k and 118 k photos are utilised for testing and training the model, respectively. To ensure that the suggested method works, the outcomes of each trial were examined. For all classes, average precision (AP) is typically determined, and its middling is known as the mean average precision (mAP). Additionally, for AP75 candidate images, regions with above 75% accuracy are counted, and the AP50 designates the 50% area properly. Figure 2 shows the multi-object detection results received via training model on MS-COCO dataset.

Figure 2. Screenshot formulti-object detection of complex scenes using proposed model trained on MS-COCO dataset

For complex scenes, the proposed CNN based encoder decoder model achieved better detection performance. The detection results include various objects such as horse, potted plant and person as shown in Figure 3. For this detection, floating point operations per second (FLOPs) is about 128.46 with model size is 134.22 MB. Figure 3 illustrates the detection of multiple objects on MS-COCO dataset using proposed model. There are various objects are detected from sample complex images in MS-COCO dataset.

Figure 3. Results for object detection of complex scenes using proposed model trained on MS-COCO dataset

The proposed model achieved mAP of 54.1% at 327 FPS as shown in Table 1. With the help of this investigation, the model's performance in real-time was guaranteed. MS-COCO dataset contains the FPS value is 327, the percentage of mAP value is 54.1%, AP50 value is 77.2% and AP75 value is 69.3%. Table 2 demonstrates the comparative results of proposed model with existing approaches. Figure 4 explains the execution analysis of single-shot detector (SSD), YOLOv3, EfficientDet, YOLOv4 tiny, RetinaNet, and proposed CNN-based encoder decoder model for object detection. Compare to all other models, the proposed model has provided better results.

Table 1. Results for proposed object detection model

Dataset	FPS	mAP (%)	AP50 (%)	AP75 (%)
MS-COCO	327	54.1	77.2	69.3

Table 2. Comparison of proposed CNN-based object detection model with existing algorithms

Model	Architecture	AP75 (%)	AP50 (%)	mAP (%)	FPS
SSD	VGG	30.3	48.5	28.8	36
YOLOv3	Darknet-53	34.3	58	33	66
EfficientDet	EfficientNet	35.8	52.2	33.8	16
YOLOv4 tiny	CSPNet-15	20	40	22	330
RetinaNet	ResNet101	36.8	53.1	34.4	11
Proposed	VGG-19	69.3	77.2	54.1	327

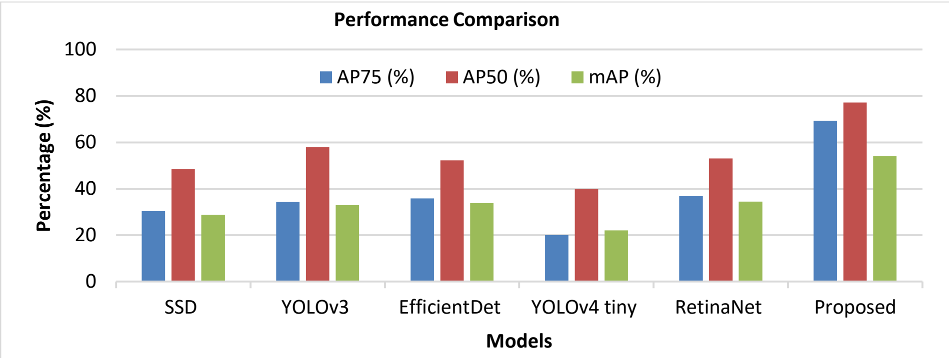

Figure 4. Performance analysis of existing approaches with proposed detection model

The outcomes of every experimentation are examined to confirm the efficiency of the proposed method. For assessment, AP is utilized, that concerns to the region under the precision-recall curve. Usually, AP is computed for all classes, and its average is determined as the mAP. In addition, the AP50 denotes to the 50% region correctly detected in comparison to the ground truth, and for AP75 candidate images over 75% parts are considered. This study assured the operation of the model for real-time applications with a good recognition accurateness.

4. CONCLUSION

We have noticed that recent efforts on object detection using CNN-based encoder-decoder models have addressed salient object detection (SOD) as a classification task at the pixel level. The proposed method was demonstrated through experimental findings on the open-source MS-COCO 2017 dataset to be capable of good detection accuracy and quick execution. The objective of this work going forward is to significantly enhance multiple object detection for high quality images without sacrificing prediction speed. It employs the unique technique of pooling indices as well, which uses fewer processing parameters and speeds up inference.With a mAP of 54.1 and 327 FPS, the suggested network model is highly suited for multiple object identification. To sum up, the model's ease of training and the proposed method's low computational resource requirements are its key features. As a result, the suggested approach is practical for many real-time applications and offers a more economical alternative. Overall, the suggested method results in a system for cutting-edge auto driving systems that is more affordable and more effective.

FUNDING INFORMATION

Funding information is not available.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interest relevant to this paper.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [NM]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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