Instance segmentation based precise object detection in UAV Images using Mask R-CNN

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Abstract

Object detection plays a vital role in remote-sensing datasets which trains the image or things and helps in classifying the images into their classes. Instance segmentation is the avant-garde technique used for object detection in Deep Learning. There are many instance segmentation models which can produce significant results. Object detection, segmentation, and RGB analysis in images taken from Unmanned Aerial Vehicles (UAV) are difficult with the desired level of performance. Instance segmentation is a powerful method that extracts each object and its location with the predicted label for pixels in the input image. In this paper, a study has been carried out on the implementation of Mask R-CNN for instance segmentation with different optimization algorithms to obtain a more accurate result for UAV images. The training has been carried out with Mask R-CNN for object detection using ResNet50 and ResNet101 as the backbone. After extensive experiments, it has been observed that the optimization algorithm plays a vital role in the overall computational process and can improve the accuracy level with a reduction in the training/validation loss. The experiment has been conducted on publicly available UAV datasets. The paper further presents the results in terms of different performance parameters

Keywords: Deep learning, Instance Segmentation, Mask R-CNN, UAV Images, Optimization algorithm.

1. Introduction

Deep learning is part of machine learning (ML), which includes many patterns and libraries to implement advanced learning patterns. The results of the deep learning algorithms in computer vision and image processing applications are different models available which develop different image segmentation approaches in the future (He K, Gkioxari G, Dollar P, Girshick R, et al., 2020). The main segmentation process is to reduce the complexity of the image, which is

one of the techniques applied in deep learning. Built-in hierarchical architecture of a deep learning algorithm called Artificial Neural Network (ANN) explores and ensures those who can learn results independently from data. The image segmentation model can be applied in different applications like medical images, UAV images, self-driving cars images, satellite image and fire detection images etc. (Begum, S. R., Datta, S. Y. & Manoj, M. S. V. et al., 2021). The object detection, tracking, and recognition module used images from shading and creates deep learning through image segmentation. This module needs to segment the pixels of the object to the front. Instance segmentation is done through these processes including both object Detection and Segmentation.

The models generated through deep learning for computer vision can achieve meaningful breakthroughs in various fields (Fengbao Yang Yingjie Liu and Peng Hu., 2017) (Lucas Prado Osco, José Marcato Junior, et al.,2021) UAV images are usually within a range of tens to hundreds of meters, bringing large scenes to imagestaken. In the UAV image, most of the things are prone tobe misclassified due to their unclear position and relativelysmaller size compared to that in general terrestrial images. Object recognition in aerial images makes it difficult to annotateobjects and boxes. However, the images are easy to see, but there are many, not just small ones, these investigations are oneof the key discoveries that undermine today's discipline. ThePipeline of the R-CNN model that attempts to solve the disclosureproblem i.e., object detection for UAV images and variousdeep learning techniques can also be used to increase theexposure in various real-time applications like weed control,traffic counting, agriculture, robotics, autonomous vehicle, etc.The object detection issues limit the expressiveness of Future Pyramid Networks (FPNs). In other words, self-markingfrom the pyramid layer is still not enough to effectively detectsmall objects. To solve this issue, the Mask R-CNN modelextracts the features from different layers (Padmalaya Nayak and Ravalisri Vasam et al., 2019). To achieve the best efficiency, Mask R-CNN uses a simplenetwork structure in the entire network. It is a highly simple andfully convolution network selected on the mask head. The aimis to minimize the processing cost while maintaining theinstance segmentation accuracy (Cong Lin and Shijie Zhang et al.,2021). The key points of this work are as follows:

1. Implementation of Mask R-CNN Model with different optimization algorithms for UAV images.
2. Training and validation of the Mask R-CNN model witha backbone of ResNet50 and ResNet101 enumerate environment.
3. Fine-tuning of the R-CNN network's parameters to improve the accuracy.

The paper is formulated as follows: Section II gives the views on the work related to object detection and Mask R-CNN model implementation with ResNet50and ResNet101 backbone. Section III tests and validates the model with UAV image datasets. Results and discussion of the experiment are represented in Section IV. Finally, section V presents the conclusion of experiment and the future research work.

2. Materials and Methods

2.1 Related works

Deep learning models are modern techniques that areused for object detection (Pathak, Ajeet & Pandey, Manjusha & Rautaray, Siddharth. et al.,2018). It supports the advanced technique used for analysis, which is captured by UAV, and compares the results with different convolution layers for object detection (Chenfan Sun, Wei Zhan, et al., 2020). The FPN is used to extract the feature from Convolutional Networks by detecting the more common features with specific classes and it produces more accuracy for real-time images i.e. drone images (Vaddi, Subrahmanyam & Kim, Dongyoun et al., 2021).To explain the data transfer to the next layers, various types of activation functions and their importance in deep learning (Sharma and Siddharth et al., 2020). Theoretical concepts and characters are used for ReLU activation neural network's function and the results shown are obtained throughthe lens of spline theory (R. Parhi and R. D. Nowak et al., 2020). Existing work (Olgac, A & Karlik, Bekir et al., 2011) compares the back-propagation algorithms of neural networks and the process of different activation indeep learning. Proposed (Konstantin Eckle, Johannes Schmidt Hieber (2019) (Zhang, Yiqing, et al., 2020). The inequality in data binding and risk of fitting neural networks through statistical representations and the results shows that deep networks perform better in terms of feature extraction. In the Mask R-CNN structure, the scale-invariant fully convolution network ignoreslocal data differences between fields of interest of different sizes. Large-scale images do not focus on the size of the image compared to small-scale images in semantic information. So, the network model does not work while comparing the pixels at the object edge and it can misclassify (Renu Khandelwal, 2019). The CNN-based model can be applied in emerging remote sensing applications. It will give a high-accuracy output (Chen and Leiyu et al.,2021). To explore the Convolutional neural network (CNN) architecture for segmentation, classification, and image detection, the functionality of layers will give significant results. (Muhammad Asif Saleem and Norhalina Senanet al., 2022).

2.2 Methods

Drone-based image dataset is downloaded from the public domain (https://github.com/VisDrone/VisDrone-Dataset). The downloaded dataset consists of 2500 UAV acquired images. after proceeding to the data annotation process once the annotation was completed. The following input are setup to the Mask R-CNN model for training with ResNet50 and ResNet101 backbone. The mask R-CNN model is fine-tuned with certain parameters. i.e optimization algorithm and it is passed on the testing process ends with final results.

Pipeline of mask R-CNN model Fig.1. consists of the following

- Data preparation
- Image Annotations
- Select the Base model
- Backbone Selection
- Activation Function Selection
- Optimizer algorithm
- Train the model
- Test the model

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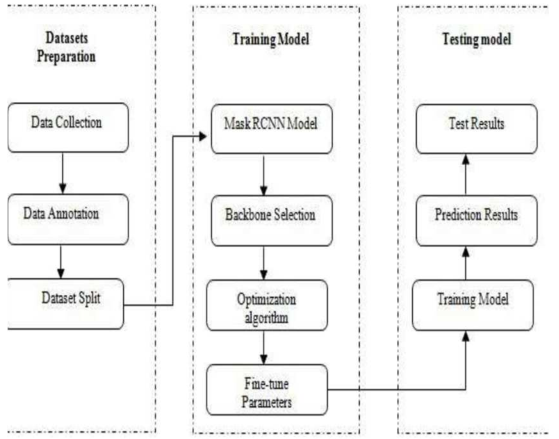


Fig. 1. Pipeline of Mask R-CNN

2.3 Datasets preparation

The datasets consist of 2500 UAV-acquired images. The test dataset consists of 2000 images, taken by various drone cameras, covering a wide range, including location, environment, and objects.

2.4 Datasets Specifications

COCO dataset can be used in huge volumes of datasets for object detection and instance segmentation with more than 85 classes like car, person, and bye cycle, etc., It includes all images with more than 85 objects. Initially were applied the pre-train process to extract features in the COCO dataset with all categories. Objects are labeled (Car) and instance segmentation has been done.

2.5 Image Annotation

The images are collected and have to be annotated. Afterthe annotation, a mask indicates the corresponding objects for the model to identify and train. This process has to be done through the Labelme annotation software tool used to annotate

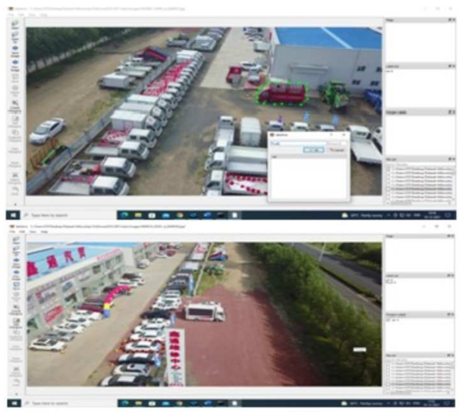


Fig. 2. Annotation of images

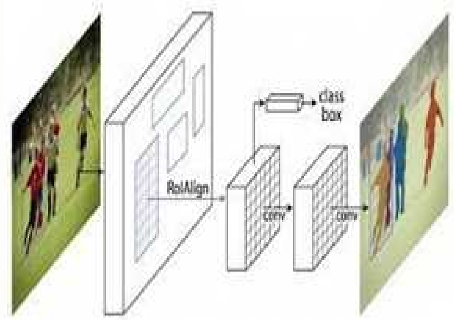
theimages Fig.2. There is a free tool and provides an option whichcreates polygons and a mask for an object. One image contains more than one desired object in a variety of classes. Once the annotation process has completed, it may generate a jsonfile to store a mask which coordinate and class name may be given for all the annotated images.

2.6 Model Training

If the annotation process is successfully completed, combine the entire json file into one json file for the given input to the model and the training process. Use Python programming for the translation process. The dataset along with the entire json file have to be uploaded to the NVIDIA GPU V100 environment. The model was trained which supports instance segmentation (S. L. Ullo et *al*., 2021). The mask R-CNN model is trained with actual LR 0.001 with 500 epochs and 2 imagesper GPU. The original weight is “COCO” such as the updated instance model weight (Jaikumar, Punitha, and Vandaele et al., 2021).

2.7 Mask Region-Based Convolutional Neural Network

Fig. 3. Mask R-CNN Architecture (Kaiming He et al., 2016)



Mask R-CNN is a Convolutional Neural Network (CNN), which is the most advanced in image segmentation and instance segmentation. Mask R-CNN Model is located at thetop of Faster R-CNN, Region-Based Convolutional Neural Network Concepts. Mask R-CNN is a deep learning model which includes both object detection and instance segmentation. Mask R-CNN may identify objects at the pixel level. The objective is to identify objects in real-time images using models implemented are mask R-CNN. Mask R-CNN is a two-step process. Region Proposal Network (RPN) is created andidentifies the objects in an input image which is called step 1. In the second step, these inputs are used to predict a class of objects and build a boundary box around a detected object. The boundary box is refined and masked to the pixel level for input in the first step. Both functions have been executed and connected to the backbone.

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The main advantage of Mask R- CNN Fig.3 includes pixel-wise adjustment, which is lost in a piece of the Faster R-CNN model (K. He, G. Gkioxari, P. Dollár, etc.,2017).

Step 1: Extraction of features from input images using feature extractor

Step 2: RPN uses the feature maps and return the predicted values

Step 3: ROI is to align and extract features with the input images

Step 4: ROI Align layer process

Step 5: Bounding box with prediction classes

Step 6: Mask prediction

Fig. 4. Steps for detecting objects in Mask R-CNN

The main advantage of mask R-CNN is Instance Segmentation. Mask R-CNN is built on Faster R-CNN as shown in Fig.4. It is image pixel-wise segmentation (Kaiming He et al. 2016).

2.8 ResNet50 Backbone

Developing (Dalal AL-Alimi et al., 2020) the ResNet50 (Residual Neural Network) models are based on deep architectures that have shown good convergence behaviors and compelling accuracy. The ResNet50 (Residual Neural Network) has been used to resolve the vanishing gradient problem compare to other activation functions i.e. sigmoid and tangent activation functions. The network usually has a very deep gradient signal, which quickly approaches zero, making the decline unbearably slow. During gradient descent, moves the last layer back to the first layer. This process is multiplied by the matrix weights at any level, so the gradient can exponentially decrease to zero. ResNet," shortcut" or" skip connection" solves Fig.5 the escalation problem directly in the upper level and adds a link to the next level. ResNet blocks placed on top of each other can form a very high network. ResNet blocks with "shortcuts" are also one of the easiest blocks to learn identity functions.It is understood that one may stack on additional ResNet blocks with little risk of harming training set performance the ResNet learning process has been represented and defined in the following equation (1)

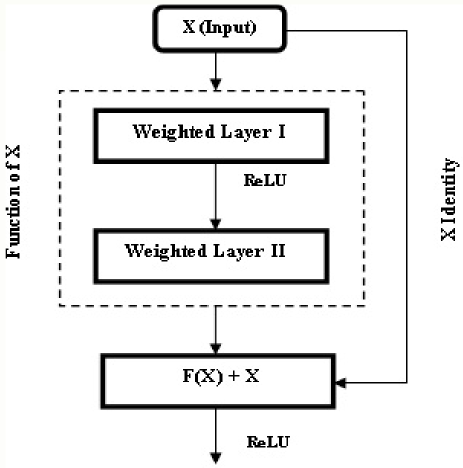

Fig. 5. Skip Connection

$$OutputY(i+1) = f(X) * W \quad (1)$$

When outputting Y(i+1), input X, Wi are the parameters of the convolutional learning layer, and f(X)*Wi is assigned to the residual that we have learned. The identity block is the standard block used in ResNet, and this corresponds to the case where the activation input has the same function as the activation output. ResNet architecture intends to pass the gradient values through the skip connection to the upper layers in the model exits from the last layer to the first layer. The ResNet50 contains five convolutional layers: c1x, c2x, c3x, c4x, and c5x with 1 polling layer and average pooling layers.

The user loaded the image to the convolution layer with 64 filters and a kernel size of 7*7*3 along with a max pooling layer with stride 2. The Max pooling layer executes on the feature map and reduces the image size to the maximum image size. Noise value may be added into the main path ResNet layer in which they perform the convolutions layer size and kernel size 7*7*3 while changing the dimension set 64,128,256,512 every 2convolutions layer skip connection occurs; the input and output remain unchanged. When dimensions change, automatically convolution layer of the block has been added to skip the connection process. The ResNet layer reached i.e. Average polling is completed the feature map gives the output after obtaining the feature map and then passed to ANN.

This process is called forwarded propagation. Loss value is calculated at the output layer which is calculated by exiting weighted value to update the proposed model. It will improve the performance and accuracy value.

3. Implementation

The Experiment was successfully executed and each input image is adjusted to 800 x 1024 using the

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zero padding input images Fig.6. Zero padding helps match the size and size of each input environment. The initial size was 2 images per GPU each image had an ROI of 200 which was investigated on a 2 GPU dataset with 300 iterations and 500 epochs. The RPN is supplied to the two networks. One creates a detection limit and a boundary regressor box for each object found, and the other gets a mask to detect the same object.

The output of instance segmentation is calculated with mAP scores. It is measured through the classification of objects. The accuracy is calculating the confusion matrix to the whole dataset first to get the TP-True Positive, FP-False Positive, TN- True Negative, FN - False Negative values. Some other models are noticed and almost all the available solutions are out there for the calculation of the confusion matrix, the only outputs are the TP, FP, and FN values. Instances of the segment generate a collection of local masks that map each object found in the image. The method of estimating the quality of an instance of segmentation is very similar to object detection, except that IoU can calculate masks instead of bounding boxes.

3.1 Calculate the loss value

The loss value of Mask R-CNN includes damage caused by RPN and damage caused by classification, positioning, and segmentation

$$ML(RPN) = RPN - CL + RPN - BBL \qquad (2)$$

Where Mask Loss, RPN-LL is Class Loss and RPN-BBL Boundary Box loss

$$ML(RPN) = RPN - CL + RPN - BBL \qquad (3)$$

$$Loss = L - RPN + L - Mask\ R - CNN \qquad (4)$$

So, the optimizer is to minimize the loss value

4. Results and Discussions

The performance of the proposed method was analyzed using mAP and IOU values. By predicting bounding boxes in the input image to determine whether the above boxes and the actual boxes overlap. The result can be calculated by dividing the overlap integral by the total area of each bounding box, otherwise, the intersection value may be divided by the union Intersection over Union (IoU). The exact results may be the prediction i.e., the bounding box will have an IoU. The representation ofaccurate prediction of a bounding box, IoU value is greater than 0.5.

- Precision is measured by the accuracy of predictions
- The recall is measured by positives findings

The mathematical representation of the following Precision, Recall, and F1 Score

$$Precision = TP/(TP + FP) \qquad (5)$$

$$Recall = TP/(TP + FN) \qquad (6)$$

$$F1 = 2\,(Precision.\ recall)/(Precision + Recall) \qquad (7)$$

Equation (5) refers to the percentage of predicted bounding boxes at position (IoU Greater than 0.5) to the link abovefrom all bounding boxes ending in the image Equation (6) is the percentage of the correct end boundary box (IoU less than 0.5)from all objects in the image. If you want to improve accuracyby using more images to make predictions, the recall will be better, but when false positives start to occur, the accuracy willbe reduced or unstable. The average or average accuracy ofall images (APs) is called average accuracy or mAP.

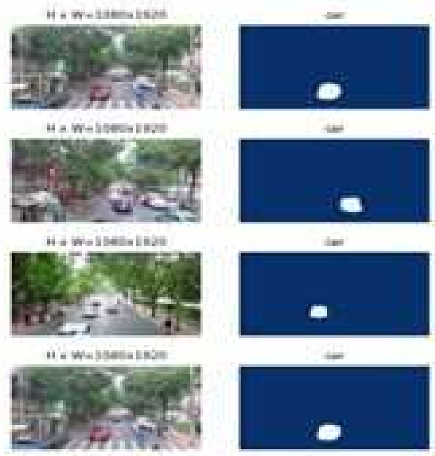

Fig. 6. Input images and Boundary box around images

The mask R-CNN model is to fine-tune with a few parameters in the configuration part i.e., threshold value. It also used different optimization algorithms like SGD and Adam. Initially, the SGD optimizer algorithm is working better and improving the accuracy while minimizing the loss ratio (Mahmoud, Amira, and Mohamed, Sayed et al., 2020) compared to the Adam optimizer. In the above experiments, the dataset of 100, 250, 500, 1000, and 1500 images were used in Fig.7 and Fig.8. The tests are according to the validation dataset of 50, 100, and 250. From the experiment, an average value has been calculated. The dataset trained for 500 epochs as loss is decreased by using the SGD optimizer algorithm and results are stable at the point. The results are compared to the existing model.

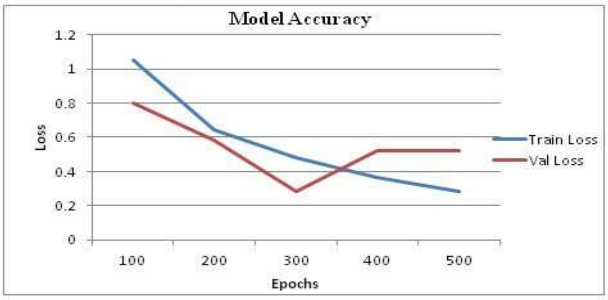

Fig. 7. Accuracy obtained for 1000 images-SGD Optimizer

Fig. 8. Result of Mask R-CNN-SGD Optimizer

along with pixels accuracy which can further implemented the results shows that AP Scores 88-92 results for 1000 images. The analysis of the obtained results during training, testing and actual validation has proved the role of optimizer in deciding the accuracy of the instance segmentation and object detection in UAV images. Implementation can be further improved by real-time UAV images and videos with huge dataset size, as observed there is better accuracy while increasing the dataset size which also helps to increase the accuracy, number of class and its counting values.

For the datasets with 1000 images, the results are in Fig. 9 and Fig. 10 for bounding box scores slightly decreases and mask segmentation value are reduced due to Adam optimizer being used, with ROI values of 200 which needs to be increased. The model trained with different learning rates and weights is collected from the “COCO dataset” model. It will support the new updated weight values with fewer epochs. While increasing the 1000 to 1500 images dataset is trained with an optimizer algorithm with other parameters. The proposed model can be trained well and improved the results. The proposed model improves the accuracy with a minimum computation process.

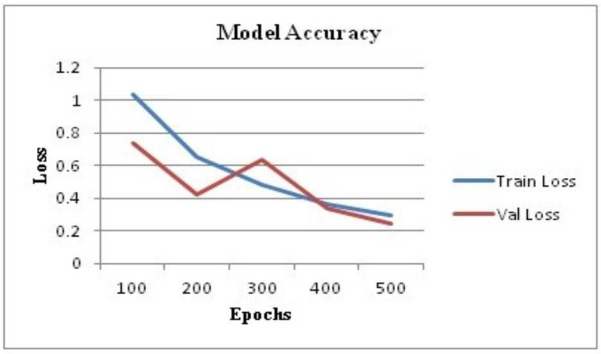

Fig. 9. Accuracy obtained for 1000 images-Adam Optimizer

Fig. 10. Result of Mask R-CNN-Adam Optimizer

5. Conclusion and future work

Mask RCNN is better, for instance, segmentation by identifying each pixel of every object in the input image with a bounding box. Mask R-CNN model with backbone ResNet50 and ResNet101 applied for UAV image dataset. The training was executed into ROI values along with SGD and Adam optimizer algorithms with different dataset sizes. The results show the mask created all over the car along with pixel accuracy which can be further implemented the results shows that AP Scores 88-92 results for 1000 images. The analysis of the obtained results during training, testing, and actual validation has proved the role of the optimizer in deciding the accuracy of the instance segmentation and object detection in UAV images. Implementation can be further improved by real-time UAV images and videos with huge dataset size, as observed there is better accuracy while increasing the dataset size which also helps to increase the accuracy, number of class and its counting values.

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