The Study of Locating Diseased Leaves Based on RPN in Complex Environment

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Abstract. Plant disease is one of the major factors threatening the plant growth. In this paper, we utilize the region proposed network (RPN) to detect and locate the plant leaf based on the machine deep learning algorithm. Firstly, the original image needs to be input into convolution neural network (CNN). After several convolution and pooling operations, highly condensed image features can be obtained. Secondly, a reference boundary frame for predicting the position of an object can be obtained by sliding nine boundary frames as sliding windows on the feature map. Two neural networks are input into each boundary box to get the classification result and boundary location. Finally, with the help of non-maximum suppression algorithm (NMS), multiple boundary boxes for the same object are eliminated and only the best boundary boxes are retained. Experiments show that RPN algorithm has better performance on locating the diseased leaves in complex environment, thus reducing the influence of disease on agricultural production. At the same time, it is of great significance in economic development, ecological protection, agricultural production and other fields.

1. Introduction
Plant is the most important resource of food, but the main reason for famine and food safety is plant disease [1]. It’s estimated that the economic loss is up to $20 billion dollars per year all over the world. At the same time, healthy growth of plant ensures the normal operation of farmland ecosystem while plant disease destroy the ecological balance among plants, microorganism and animals. Therefore, the prevention and control of plant disease have significant meaning to the economic development, environmental protection and other fields.

This paper makes use of RPN algorithm to locate the plant leaf and it can better adapt to various complex environment. The rest of paper is structured as follows. Section 2 reviews other scholars’ studies. Section 3 presents the diseased plant leaf position model based on RPN. Experimental study is conducted in Section 4. Section 5 concludes the work and discusses the future research.

2. Literature Review
In complex environment, the most crucial step is how to segment the images while locating and detecting diseased plant leaves. There are many experts making a deep study on it. Early in 2014, H. Ali and M. Sharif apply Delta E color difference algorithm to separate the disease affected area. There are four main methods to perform the image segmentation [3].
Some researchers integrate the region of interest and other methods to segment images. For example, in I-Hsi Kao’s study, they utilized a convolutional autoencoder as background filter to determine the ROI in an image[4]. And Jara and his colleagues employ ROI and polygon region of interest (PROI) in order to make some progress in ROI[5]. Images are denoised and segmented by homomorphic filtering and region of interest (ROI) segmentation in the Zhongqi Lin’s studies[6].

In 2013, Pujari and his co-workers partition images into various regions which have a special meaning and extract the images’ feature[7]. In 2016, Gutte and his colleagues integrate a technique based on color segmentation, threshold and learning based segmentation[8].

However, there is a fact that can’t be ignored. Because of the complexity of color information in complicated environment, some machine vision algorithm based on color, ROI and threshold perform poorly in practice.

3. Modeling

This article uses the plant leaf datasets in complex environment to train the RPN algorithm. Then using boundary regression and neural network and classification neural network can locate and detect the diseased leaves in complex environment.

Firstly, the data must be condensed and the features are extracted from images, that is, convoluting the data. Secondly, condensed image features are computed by inputting the original images into CNN and manipulating many convolutions and pooling operations. Thirdly, a reference boundary frame for predicting the position of an object is obtained by sliding nine boundary frames as sliding windows on the feature map. Fourthly, inputting two neural networks into each boundary box, classification and border positions can be computed. Finally, with the help of RPN algorithm, the results eliminate the multiple boundary of the same object and keep the best boundary boxes. The complete structure of RPN algorithm is shown in Figure 1.

\[
\text{IoU} = \frac{S_1}{S_2}
\]

where \(S_1\) represents the overlap area of predicting boundary box and artificially marked boundary box, and \(S_2\) represents the total area of it. Sigmoid function was employed as loss function.

One boundary box can be represented by four-dimensional variable \((x, y, w, h)\). \((P_x, P_y, P_w, P_h)\) represents the given boundary box, \((G_x, G_y, G_w, G_h)\) represents the target boundary box, and \((\hat{G}_x, \hat{G}_y, \hat{G}_w, \hat{G}_h)\) represents the predicting boundary box. In order to find a mapping relationship \(f\) of boundary regression neural network, 
\[
f(P_x, P_y, P_w, P_h) = (\hat{G}_x, \hat{G}_y, \hat{G}_w, \hat{G}_h)
\]
\((\hat{G}_x, \hat{G}_y, \hat{G}_w, \hat{G}_h) \approx (G_x, G_y, G_w, G_h)\) are defined. The movement of boundary consists of pan and zoom.

The parameter of pan is \((\Delta x, \Delta y)\). Given \(\Delta x = P_x d_x (P)\) and \(\Delta y = P_y d_y (P)\). The formula is shown.

\[
\hat{G}_x = P_x d_w (P) + P_x \\
\hat{G}_y = P_y d_h (P) + P_y
\]

The parameter of zoom is \((S_w, S_h)\). Given \(S_w = \exp (d_w (P))\) and \(S_h = \exp (d_h (P))\). The formula is shown.

\[
\hat{G}_w = P_w \exp (d_w (P)) \\
\hat{G}_h = P_h \exp (d_h (P))
\]

The real learning objectives of boundary regression neural network is represented with \(d(P) = (d_x (P), d_y (P), d_w (P), d_h (P))\), and the real transform parameters between predicting boundary box and artificially marked boundary box is shown as \(t = (t_x, t_y, t_w, t_h)\).

\[
t_x = (G_x - P_x) / P_x \\
t_y = (G_y - P_y) / P_y \\
t_w = \log (G_w / P_w) \\
t_h = \log (G_h / P_h)
\]

The objective function of boundary regression neural network is \(d(P) = w^t P\), where \(w\) represents the learning parameter of boundary regression neural network. The loss function is shown as follows:

\[
\text{Loss} = \sum_{i=1}^{N} (t_i - d_i (P))
\]

4. Experiment Study

4.1. Data acquisition and pre-processing

4.1.1. The acquisition of plant leaf image in complex environment

Firstly, the paper employs Crawler technology and obtains 1000 leaf photos from Chinese Plant Image Library. Aiming at watermarkless shelter, obvious leaves and easy labeling, 189 images are screened out as leaf photos in complex environment.
4.1.2. The acquisition of plant leaf image in complex environment

Labellmg is a visual image annotation software, which can quickly annotate images and generate XML files in PASCAL VOC format. It can directly input target detection neural network as training data. The annotated image is shown in Figure 2. The annotated PASCAL VOC data format code is as follows:

```
<annotation>
  <folder></folder>
  <filename></filename>
  <path></path>
  <source>
    <database></database>
  </source>
  <size>
    <width></width>
    <height></height>
    <depth></depth>
  </size>
  <object>
    <name></name>
    <bndbox>
      <xmin></xmin>
      <ymin></ymin>
      <xmax></xmax>
      <ymax></ymax>
    </bndbox>
  </object>
</annotation>
```

Figure 2. Annotated image.

4.2. Experimental setup in complex environment

RPN algorithm setup includes extracting features in convolution neural network and detecting plant leaf in boundary regression neural network. Different network setup has great influence on model operation effect, model training time. In addition, model training parameter is comprised of gradient descent to optimize parameters and input data parameters, which has an impact on convergence rate of model.

4.2.1. Network Parameter Setup

This article utilizes VGG-16 model to extract features of images. The composition and parameters of the complete VGG-16 model are shown in Table 1.

| Network layer | Number of kernels | Size of kernel | Output shape       | Number of parameter |
|---------------|-------------------|----------------|--------------------|---------------------|
| Convolution   | 64                | (3,3)          | (224,224,64)       | 1728                |
| Convolution   | 64                | (3,3)          | (224,224,64)       | 36864               |
| maxpooling    | /                 | (2,2)          | (112,112,64)       | 0                   |
| Convolution   | 128               | (3,3)          | (112,112,128)      | 73728               |
The parameter setup of classification neural network and boundary regression neural network is shown in Table 2 and Table 3. Anchors in the table represent the candidate boxes generated.

Table 2. Parameter setup of classification neural network.

| Network layer | Number of kernels | Size of kernel | Output shape | Number of parameter |
|---------------|-------------------|----------------|--------------|---------------------|
| Convolution   | 512               | (3,3)          | (14,14,512)  | 2359296             |
| softmax       | anchors * 2       | (1,1)          | /            | /                   |

Table 3. Parameter setup of boundary regression neural network.

| Network layer | Number of kernels | Size of kernel | Output shape | Number of parameter |
|---------------|-------------------|----------------|--------------|---------------------|
| Convolution   | 512               | (3,3)          | (14,14,512)  | 2359296             |
| softmax       | anchors * 4       | (1,1)          | /            | /                   |

4.2.2. Training Parameter Setup and results

Plant leaf dataset in simple background is used to train the RPN algorithm. Parameter setup includes gradient descent optimization parameters to control model convergence, input data parameters to control training dataset, and threshold parameters RPN parameters to control the effect of RPN algorithm. The parameter of RPN is comprised of positive sample judgment threshold, negative sample judgment threshold, NMS threshold. The threshold of positive and negative sample judgment is referred to that if the classification neural network scores the target in the frame more than the threshold of positive sample, it will be judged as the foreground, and if it is lower than the threshold of negative sample, it will be the background. To determine whether the NMS threshold is the same target in different candidate boxes, if the IOU value of the two boxes is higher than the NMS threshold, it is the same target. The parameters setup of model training is presented as follows in Table 4.

Table 4. Parameter setup of model training.

| Parameter category | Name of parameter | Setup of parameter |
|--------------------|-------------------|--------------------|
| Gradient descent   | Learning rate     | 0.001              |
| optimization parameter | Weight decay     | 0.0005             |
|                    | Learning impulse  | 0.9                |
|                    | Decay of learning rate | 0.1          |
| Input data parameters | Picture size     | (224,224)          |
|                     | Batch size        | 256                |
|                     | Iteration times   | 30000              |
| RPN parameter      | Positive Sample Judgment Threshold | 0.7 |
|                    | Negative Sample Judgment Threshold | 0.3 |
|                    | NMS threshold     | 0.7                |
In the process of model training, the loss rate of frame recognition, classification loss rate and total loss rate are shown in Figure 3.

In Figure 3, rpn_loss_box represents the loss value of boundary regression neural network, and rpn_loss_cls represents the loss value of classification neural network. According to Figure 3, we can find that after 30,000 iteration training, the loss value of boundary regression neural network and classification neural network have converged, and the loss value of the model are low. It proves that the model training is completed and the training results are good.

4.3. Results of Plant leaf Detection

The test image is input into VGG-16 model and RPN algorithm, and the results are shown in Figure 4.

With regard to the above images, there is inaccuracy of the frame selection range in FIG. 4 (b) and the blades in FIG. 4 (d) are missing. But RPN algorithm can basically frame the main blade structure, which has better performance than the original model.

Figure 3. Loss rate of training. Figure 4. Results of detection in complex environment.

5. Results and Discussion

The paper employs RPN algorithm to train the dataset of plant leaf in complex environment, and boundary regression neural network and classification neural network are applied to locate the plant leaf in complex environment. The results of experiment show that RPN algorithm performs well in locating the diseased leaves in complex environment.

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