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Rice false smut detection based on faster R-CNN

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Article Info	ABSTRACT
	Rice false smut is one of the most dangerous diseases in rice at the ripening phase caused by Ustilaginoidea Virens. It is one of the most important grain diseases in rice production worldwide. Its epidemics not only lead to yield loss but also reduce grain quality because of multiple mycotoxins generated by the causative pathogen. The pathogen infects developing spikelets and specifically converts individual grain into rice false smut ball. Rice false smut balls seem to be randomly formed in some grains on a panicle of a plant in the paddy field. In this study, we suggest a novel approach for the detection of rice false smut based on faster R-CNN. The process of faster R-CNN comprises regional proposal generation and object detection. The both tasks are done in same convolutional network. Because of such design it is faster for object detection. The faster R-CNN is able to detect the RFS using rectangular labelling from on-field images. The proposed approach is the initial steps to make a prototype for the automatic detection of RFS.

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1. INTRODUCTION

Rice (*Oryza sativa L.*) is the primary food crop and consume as a staple food in Asia, Africa, South America, and to some extent in the United States [1]. More than 90% of the world's rice is developed and expanded in Asia, where 60% of the total populace lives [2]. The production of rice is reduced mostly due to pest attacks and diseases. Among many diseases, RFS is one of the most harmful diseases. The RFS is caused by *Ustilaginoidea virens* and also known as pseudo-smut, or green smut. Earlier RFS is treated as a minor disease, but now it has been seen in many regions of the world [3-4]. It is a significant decimating fungal infection causing yield losses from 1.01 to 10.91% [5]. The RFS disease incidence has been recorded in India with the highest infection rate, i.e. 85% in Tamil Nadu [6-7].

In recent years, with the application of computer vision and machine learning [8-11], there has been an incredible advancement in disease diagnosis of crops such as detection, identification and quantification of various diseases. In most of the cases, SVM [12-13], K-Nearest neighbours (KNN) [14-15] and Discriminant analysis [16] are used for disease identification purposes. Many researchers reported automated rice disease diagnosis methods based on digital image processing technique [17], SVM [18], pattern recognition [19] and computer vision [20]. The research is not only for rice disease classification but also for other crops such as wheat [21], maize [22], cotton [23] and tomato [24] etc. Although, machine learning techniques have made great accomplishment in image identification, it has some limitations: restricted data handing capability, the requirement of segmentation & feature extraction [25]. The diseased region segmentation is not always an easy task for all agricultural images [26]. Therefore, traditional machine learning techniques face difficulty in the classification of agriculturally diseased images with adequate results. In past few years, the CNN is applied in various fields such as object detection [27-31], image classification [32-34] and video

classification [35]. In the last couple of years, many pieces of research have been conducted for the diagnosis of plant diseases based on CNN [35-39]. The objective of this study is to detect RFS based on faster R-CNN using on-field images of rice so that precaution can be taken.

2. RESEARCH METHOD

The methodology for the detection of RFS is detailed in the following subsections.

2.1. Collection of rice false smut images

The rice false smut images are collected from rice field with 48 Megapixel smartphone camera in natural daylight. The images captured with special care to blur the background by adjusting its secondary camera meant for focusing. Here we have collected 50 numbers of images only and use rotation (90 degrees, 180 degrees and 270 degrees) to increase the number of datasets. All the images are resized to a standard dimension, i.e. 227×227×3.

2.2. Image labelling

The images are labelled with the fitting of the false smut affected region within the rectangular box. This labelling is done using image labeller app of Matlab 2019a. The defined rectangular regions of interest (ROI) labels are exported to the workspace of the main train algorithm in tabular form. The table contains the path of the images and its ROI label. The ROI label contains the four vertices of the rectangle, which encloses the false smut region.

2.3. Train faster R-CNN

The combination of feature extraction network and subsequent two sub-networks are called a regional proposal network (RPN). The RPN is used to train for the generation of proposals. The actual class of each proposal is predicted by the second sub-network. Here, the feature extraction is done by resnet50. Adjust the negative overlap range and positive overlap range to train the detector to ensure training samples are tightly overlapped with ground truth. The model of faster R-CNN is shown in Figure 1. The training parameters are detailed in Table 1.

Table 1. Detail of training parameter

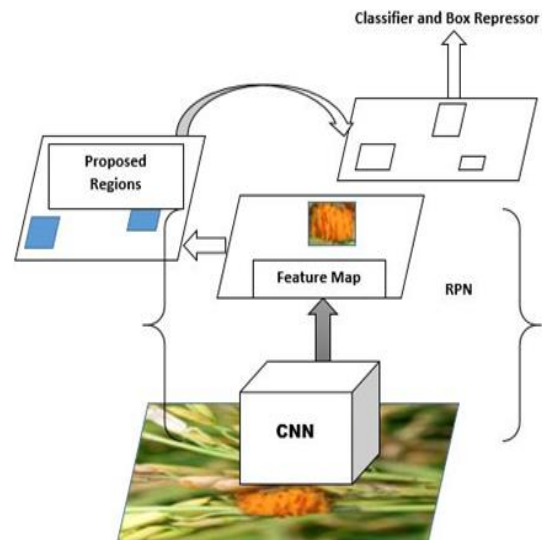|	
Minibatch size	1
Validation frequency	30
Maximum epoch	5
Initial learning rate	0.001
Learning method	Stochastic gradient descent (SGDM)

Figure 1. Faster R-CNN model for detection of RFS

2.4. Detection of rice false smut

After completion of detector training, the panicle images are fed for testing. The testing process is done using three different appearances of panicle image, i.e. immature healthy panicle, matured healthy panicle, and false smut affected panicle. The three different appearances of panicles are shown in Figure 2.
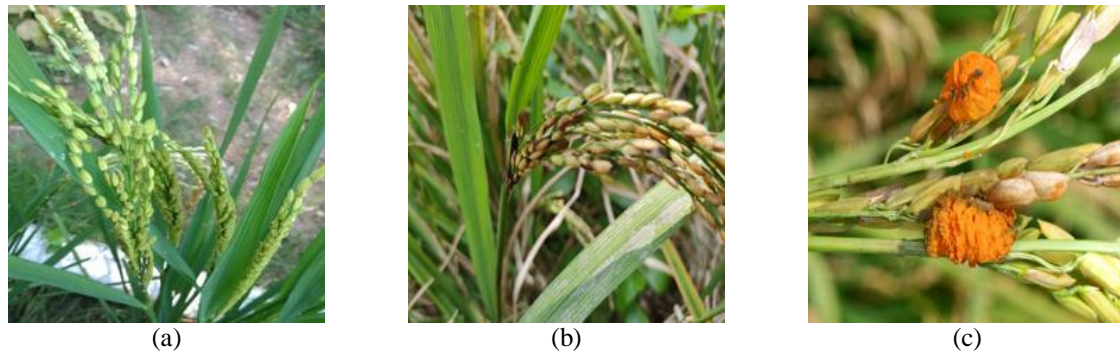
(a)   (b)   (c)

Figure 2. The different appearances of panicles (a) immature healthy panicle, (b) mature healthy panicle (c) false smut affected panicle

The detector of R-CNN returns the bounding box of the region affected by RFS with its score. If the summation of the score value is less or equal to zero, the panicle is healthy. If the summation of the score value is more than zero, the panicle is affected by false smut, and the affected region is enclosed by a rectangular bounding box.

3. RESULTS AND DISCUSSION

In this study, we detected the RFS using faster R-CNN. The experimental studies were implemented using the MATLAB 2019a deep learning toolbox. All applications were run on a laptop, i.e. Acer Predator Helios 300 Core i5 8th Gen - (8 GB/1 TB HDD/128 GB SSD/Windows 10 Home/4 GB Graphics) and equipped with NVIDIA GeForce GTX 1050Ti. The proposed method is examined using three appearances of panicles.

The first CNN provides the feature maps to the RPN. To make the region proposals, 3×3 filters slide over the feature map using a pre-trained network like resnet50. The output of resnet50 feeds to the fully connected layer to predict the boundary box and objectness score. The objectness ensures the presence of the object within the box and the regressor measures its score. Figure 3 shows the bounding box enclosing the false smut affected region with their scores. The RPN makes multiple guesses for a single location in the feature map, leading to multiple proposals for single objects, as in Figure 4(b). In contrast, the Faster R-CNN does not predict the random proposals, and makes a resemblance with the reference bounding box (called, Anchors) which makes way for successful detection. Again, for a single object, multiple numbers of Anchors are available with different shapes (one centred) which makes confusion to the detector to predict the proposals. The main reason for such a phenomenon may be, not to make bounding box proposals for each false smut affected region, like those shown in Figure 4 (a, c & d). The different situation of anchors and proposals is illustrating in Figure 5.
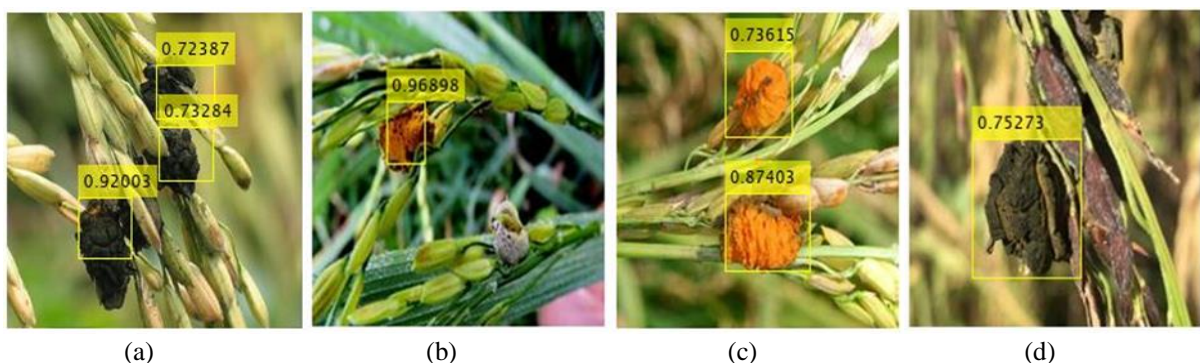

(a)   (b)   (c)   (d)

Figure 3. Successful detection of rice false smut with their score

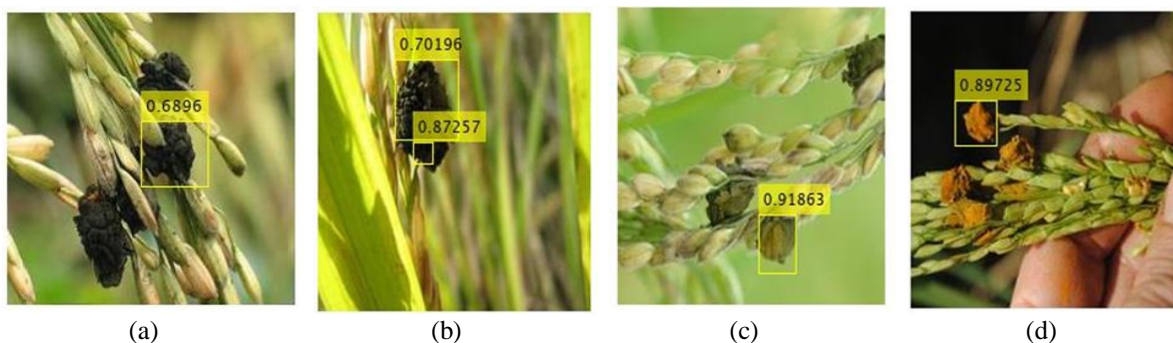(a)   (b)   (c)   (d)

Figure 4. Ineffectual detection of rice false smut
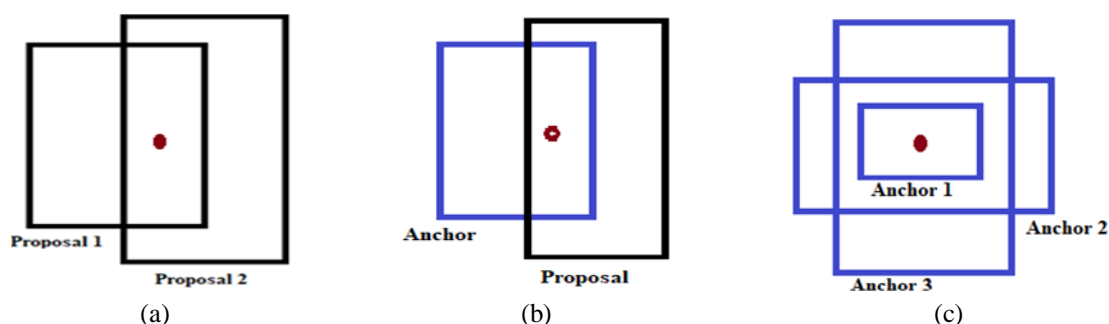

(a)   (b)   (c)

Figure 5. Different situation of anchors and proposals

The three main reasons for ineffectual detection are: (1) for one object location, multiple numbers of proposals are made, as shown in Figure 5 (a). (2) The shape of the proposal does not resemble with the Anchor, as shown in Figure 5(b). (3) The multiple numbers of Anchors are available for one object location, shown in Figure 5 (c). In the case of RFS detection, the ineffectual detection occurs due to touching and/ or overlapping of the false smut affected regions. The similar shape of bounding box labelling is made for different object locations leading to confusion to the detector.

4.   CONCLUSION

This study proposes a method to detect rice false smut using on-field images. The faster R-CNN successfully detects the RFS, but in some cases, it leads to ineffectual detection. Therefore, the method of RFS detection needs to further improvement, even if false smut regions appear in complicated visual situations. Even if its limitation, this method is helpful to make a prototype for detection of rice false smut. In addition, this one is the first method for detection of rice false smut using computer intelligence instead of phytological diagnosis in state-of-art.

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