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Recognition of Locust Based on Improved ResNet

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Abstract: A dozen species of locusts (Orthoptera: Acrididae) are a major threat to food security worldwide. Their outbreaks occur on every continent except Antarctica, threatening the livelihood of 10% of the world's population. The locusts are infamous for their voracity, polyphagy, and capacity for long-distance migrations. For effective control, the insects need to be detected on the ground before they start to develop air borne swarms. Detection systems need to determine pest density and location with high speed and accuracy. Location of the swarms on the ground then enables their control by the application of pesticides and bio-pesticides. This work proposes a locust species recognition method based on Resnet50 -convolutional neural network (CNN). We experimentally compared the proposed method with other the state-of-the-art methods on the established dataset. Experimental results showed that accuracy of this method reached higher than the state-of-the-art methods. This method has a good detection effect on the fly species recognition.

INTRODUCTION

Crop pest identification and classification represent one of the major challenges in the agriculture field. Insects cause damage to crops and mainly affect the productivity of crop yield. Classification of insects is a difficult task due to the complex structure and having a high degree of similarity of the appearance between distinct species. It is necessary to recognize and classify insects in the crops at an early stage, especially to prevent the spread of insects, which cause crop diseases by selecting effective pesticides and biological control methods. Traditional manual identification of insects is typically labour-intensive, time-consuming and inefficient. The vision-based computerized system of image processing using machine learning was developed for accurate classification and identification of insects to overcome these problems in agriculture research field

Grasshoppers

Grasshoppers are a group of insects belonging to the suborder Caelifera. They are among what is probably the most ancient living group of chewing herbivorous insects, dating back to the early Triassic around 250 million years ago.
Grasshoppers are typically ground-dwelling insects with powerful hind legs which allow them to escape from threats by leaping vigorously. As hemimetabolous insects, they do not undergo complete metamorphosis; they hatch from an egg into a nymph or "hopper" which undergoes five moults, becoming more similar to the adult insect at each developmental stage. At high population densities and under certain environmental conditions, some grasshopper species can change color and behavior and form swarms. Under these circumstances, they are known as locusts.

Deep Learning

Since the 1950s, a small subset of Artificial Intelligence (AI), often called Machine Learning (ML), has revolutionized several fields in the last few decades. Neural Networks (NN) is a subfield of ML, and it was this subfield that spawned Deep Learning (DL). Since its inception DL has been creating ever larger disruptions, showing outstanding success in almost every application domain. Figure 1 shows the taxonomy of AI. DL which uses either deep architectures of learning or hierarchical learning approaches), is a class of ML developed largely from 2006 onward. Learning is a procedure consisting of estimating the model parameters so that the learned model (algorithm) can perform a specific task.

RELATED WORK

Yiyun Song; et al proposed a pest identification based on the convolutional neural network, this paper collected 71 types of 35,000 images of pests, using the Inception-v3 and Inception-v4 model in GoogLeNet to build pests recognition model.

Duo Long; et al used a video monitoring in greenhouses to obtain crop pictures and identify pests and diseases from crop pictures. The pictures obtained in video monitoring are not necessarily the "real" pictures containing crops.
Reza, M. T et al e propose a noble model that takes advantage of transfer learning and data augmentation to classify insect pest species from image data in the most accurate way. In the proposed model, three different Deep Neural Network (DNN) models were used for image classification: VGG19, Inception v3 and ResNet50.

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Vivek et al proposed a method to identify all the pest that are present in the agriculture field and apply certain measures to prevent them from destroying crops and to make this possible we will be classifying the pest available in a field by using a microprocessor along with infrared camera and normal camera which would be attached to a quadcopter that would fly over the field and identifying the pest.
Fuji Ren et al proposed a new and simple structure based on the original residual block and named as feature reuse residual block which combines feature from the input signal of a residual block with the residual signal. In each feature reuse residual block, it enhances the capacity of representation by learning half and reuse half feature
Souza, W. S et al t presents a novel dataset of fieldbased images for primary and secondary insect pests, with original and augmented images to be used for supervised classification. It also proposes a modification on a residual deep learning model (Inception-V3), called Inception-V3* here, which provides faster learning and better accuracy than the original model.

Roldan-Serrato et al study is to develop and test a recognition system for the Colorado potato beetle. This task is very important for localizing the beetles and reducing the pesticide volume used to protect the harvest. We employ a beetle image dataset that contains 25 images representing different beetle positions and varying numbers of beetles.
Zhichao Shi et al proposes an improved detection neural network architecture based on R-FCN to solve the problem of detection and classification of eight common stored grain insects. In this network, we use the multiscale training strategy with a fully convolutional network to extract more features of the insects and automatically provide the location of potentially stored grain insects through an RPN from the feature map.
Suchang Lim et al developed a classification application that can be used in mobile phones with high automation and portability to solve the above insect classification problems. Experiments were conducted on 30 insect species selected for observable insects irrespective of environmental factors such as habitat and season, and the transform learning were applied to ResNet, which showed excellent performance in ILSVRC to classify forest insect.

Valter A. et al presents a novel approach to the identification of two species of fruit flies as part of a network of intelligent traps designed to monitor these insects population in a plantation. This identification is done essentially by a Convolutional Neural Network (CNN) which learns the characteristics of the insects based on their images made from the adhesive floor of the trap.
Lin Nie et al perform empirical study of the existing state-of-the-art image classification approaches and adopt ResNet as a new baseline. Extensive experiments under empirical settings demonstrate the superiority of the proposed baseline.
Lijin Ren et al proposed a new method based on deep convolution neural network. Firstly, the pest dataset is built by the search engines and manual photographed with image processing algorithm. Then an 11 layers VGG-A neural network is used to recognize common pests in agriculture and forestry.
Liu Liu et al proposes a region-based end-to-end approach named PestNet for large-scale multi-class pest detection and classification based on deep learning. PestNet consists of three major parts.

PROPOSED SYSTEM

The winner of ILSVRC 2015 was the Residual Network architecture, ResNet. Resnet was developed by Kaiming He with the intent of designing ultra-deep networks that did not suffer from the vanishing gradient problem that predecessors had. ResNet is developed with many different numbers of layers; 34, 50,101, 152, and even 1202. The popular ResNet50 contained 49 convolution layers and 1 fully connected layer at the end of the network. The total number of weights and MACs for the whole network are 25.5M and 3.9M respectively. The basic block diagram of the ResNet architecture is shown in Figure 16. ResNet is a traditional feedforward network with a residual connection. The output of a residual layer can be defined based on the outputs of $(l-1)$th which comes from the previous layer defined as xl-1 . $\mathscr{F}($ xl-1) is the output after performing various operations (e.g., convolution with different size of filters, Batch Normalization (BN) followed by an activation function, such as a ReLU on xl-1). The final output of residualthe unit is xl which can be defined with the following equation:xl = $\mathscr{F}($ xl-1) + xl-1. (15)

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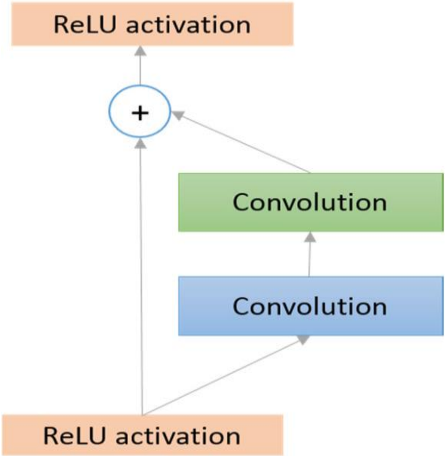

Figure Basic diagram of the Residual block.

The residual network consists of several basic residual blocks. However, the operations in the residual block can be varied depending on the different architecture of residual networks . The wider version of the residual network was proposed by Zagoruvko el at. , another improved residual network approach known as aggregated residual transformation . Recently, some other variants of residual models have been introduced based on the Residual Network architecture. Furthermore, there are several advanced architectures that are combined with Inception and Residual units.

RESULT & DISCUSSION

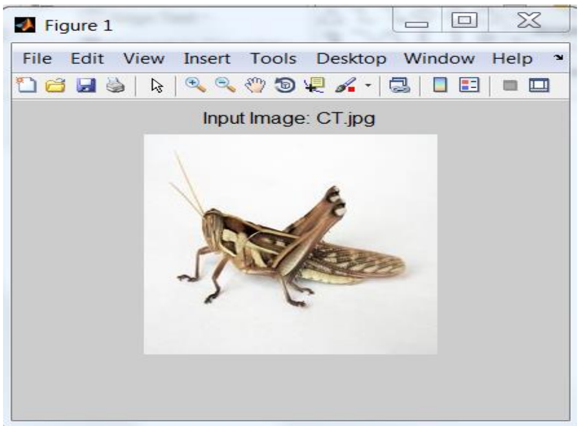

Figure :Input image

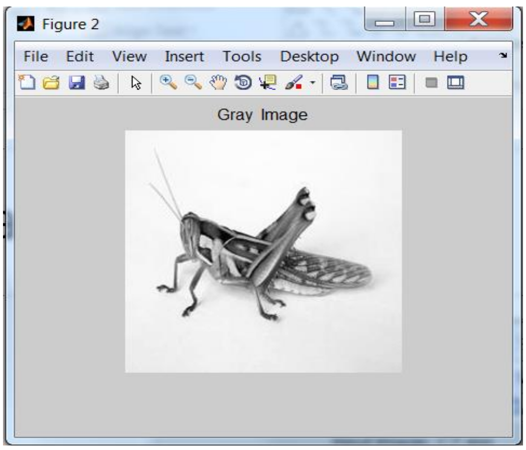

Figure :Gray image

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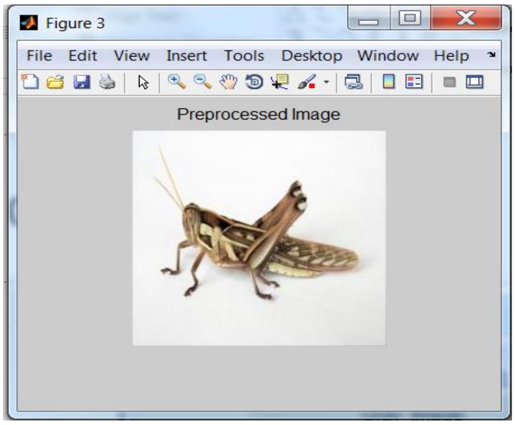

Figure :Preprocessed image

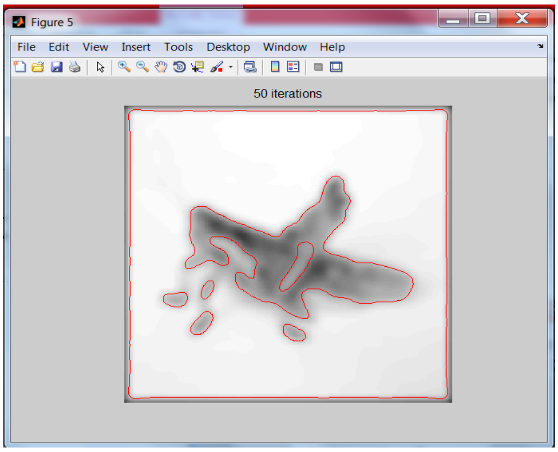

Figure : Feature extraction

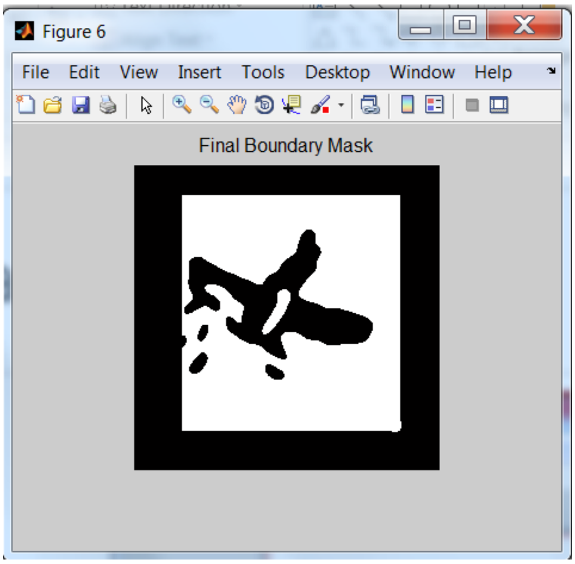

Figure Segmentation

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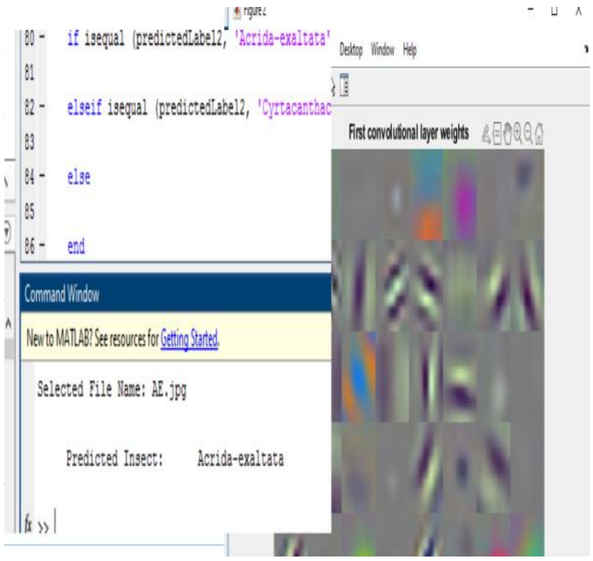

Figure Output classification

CONCLUSION

In this project, we propose a locust recognition method based on improved ResNet, which accurately locates and recognizes flies. We designed the learning structure and introduced a bottom-up path augmentation to improve the low-level features semantic information and the high-level features location ability. The experimental results show that our proposed method have better performance compared with the state-of-the-art methods for fly species recognition. This is of great significance for the species recognition.

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