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INSECT PESTS RECOGNITION BASED ON DEEP TRANSFER LEARNING MODELS

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ABSTRACT

Agriculture is one of the most important sources for human food throughout the history of humankind. In many countries, agriculture is the foundation of its economy, and more than 90% of its population deriving their livelihoods from it. Insect pests are one of the main factors affecting agricultural crop production. With the advances of computer algorithms and artificial intelligence, accurate and speedy recognition of insect pests in early stages may help in avoiding economic losses in short and long term. In this paper, an insect pest recognition based on deep transfer learning models will be presented. The IP102 insect pest dataset was selected in this research. The IP102 dataset consists of 27500 images and contains 102 classes of insect pests, it is considered one the biggest dataset for insect pest and was launched in 2019. Through the paper, AlexNet, GoogleNet, and SqueezNet were the selected deep transfer learning models. Those models were selected based on their small number of layers on their architectures, which will reflect in reducing the complexity of the models and the consumed memory and time. Data augmentation techniques were used to render the models more robust and to overcome the overfitting problem by increasing the dataset images up to 4 times than original images. The testing accuracy and performance metrics, such as the precision, recall, and F1 score, were calculated to prove the robustness of the selected models. The AlexNet model achieved the highest testing accuracy at 89.33%. In addition, it has a minimum number of layers, which decreases the training time and computational complexity. Moreover, the choice of data augmentation techniques played an important role in achieving better results. Finally, A comparison results were carried out at the end of the research with related work which used the same dataset IP102. The presented work achieved a superior result than the related work in terms of testing accuracy, precision, recall, and F1 score.

Keywords: *Agriculture, Insect Pest, Transfer Learning, Convolutional Neural Network, Image Processing, Machine Learning*

1. INTRODUCTION

Agriculture drives any economic system for any given country [1] [2]. Agriculture is the first people activity that helped humanity to advance and develop. Today, the most critical activities worldwide are farming and food industry, due to the increasing population and the increasing growth of their needs for food in order for their life to continue [3][4]. Agriculture not only providing food and raw material but also provides employment opportunities to very large percentage of the population [5][6].

Insect pests have always been considered a serious challenge that affects crop production. The major impact of insect pests is reducing the food available to peoples by ultimately decreasing crop production. This can result an unsuitable and inappropriate food to peoples or lead to starvation in some regions [7]. Detecting of insect pests plays a critical role in agricultural pest forecasting. Agricultural experts usually detect insect pests manually. For farmers this manual technique needs a high cost [8][9]. Therefore, it is necessary to find an efficient and rapid technique for automatic insect pests' classification and detection.

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1.1 Deep learning

Traditional image processing techniques provided reasonable outcomes and performance regarding insect pest detection using insect images. As deep learning has revolutionized the area of computer vision specifically image classification and object detection and recognition. Deep learning (DL) is the latest technology that brought a big improvement in the area of artificial intelligent and machine learning in general [10] [11] [12]. Today, DL is now used at large scale in the agriculture domain. Providing a good large dataset to a deep learning system yielded promising outcomes in various applications that comprise the base for automating agricultural aspects and using agro robots [13] [14] [15]. Besides their use in insect pest recognition, deep convolutional neural networks are also used in other areas in the application of image processing and computer vision in agriculture [16][17].

1.2 Convolution Neural Networks

Convolution Neural Network (CNN) is a kind of deep artificial neural network that is commonly used in analyzing images. It learns features that are related spatially by treating an image as a volume. CNN has some specialized layers that transform the volume of image in different ways. A convolutional layer does much of the computation for classifying an image. There is a sequence of kernels that slide or convolve, over an image volume within a convolutional layer. One of important benefits of CNNs is that when CNN's training increases, these kernels can identify textures, shapes, colors, and other features in the image [18] [19][20].

In the following years, various advances in deep convolutional neural networks further increased the accuracy rate on the image detection/classification competition tasks. CNN pre-trained models introduced significant improvements in succeeding in the annual challenges of ImageNet Large Scale Visual Recognition Competition (ILSVRC). Many pre-trained models were introduced like AlexNet [19], VGG-16, VGG-19 [21], GoogleNet [22], ResNet [23], Xception [24], Inception-V3 [25] and DenseNet [26].

1.3 Transfer Learning Models

In 2012 [19], Alex Krizhevsky designed a new CNN model called AlexNet. The AlexNet network achieved a top-5 error of 15.3 in the ILSVRC Competition. AlexNet contained 8 layers; the first 5 were convolutional layers, some of them followed by max-pooling layers, and the last 3 layers were fully connected layers. In 2016 [27], researchers at DeepScale designed a new CNN model called SqueezeNet. In implementing SqueezeNet, the authors' goal was to create a smaller CNN with fewer parameters that can more easily fit into computer memory. With SqueezeNet, the authors achieve a 50× reduction in model size (5MB) compared to AlexNet (240MB) of parameters, while meeting or exceeding the top-1 accuracy of AlexNet.

In 2015, Christian Szegedy et al. [22] design a new CNN model called GoogleNet that achieves the new state of the art for classification and detection in ILSVRC14. GoogLeNet or Inception v1 is a transfer learning CNN that is 22 layers deep. The main idea behind the GoogLeNet is the inception layer. The inception layer is a combination 1×1 Convolutional (Conv) layer, 3×3 Conv layer and 5×5 Conv layer concatenated into a single output vector.

This paper presents a deep learning system to recognize and detect insect pests. It is divided into five sections. Section 2 presents related work and determines the scope of this works. Section 3 discusses dataset used in our model. Section 4 introduces our outcomes and discussion of the paper. Finally, section 5 provides conclusions and directions for further research.

2. RELATED WORKS

This section conducts the related works on the latest academic researches for applying machine learning and deep learning in the field of insect pest recognition. Most of the related works on insect pest detection can be described by traditional machine learning techniques. For example, In paper [28], Larios et al. proposed automated rapid-throughput taxonomic detection of stonefly larvae. The automated detection based on the SIFT feature learning method. The outcomes show that the combination of all classifiers gives 82% accuracy for 4 classes. Zhu and Zhang [29] introduced an insect detection system by analyzing color image histogram and Gray-Level Co-occurrence Matrices of wing insect images. The outcome accuracy of proposed model is 71.1%. Faithpraise et al. [30] introduced insect pest recognition systems based on combination of k-means cluster and correspondence filters. The experimental outcomes show that the proposed method is useful, which can exact various shapes, sizes, positions, and orientations in insect pest images.

Cheng et al. [31] introduced a pest identification system via deep residual learning in complex farmland background. The accuracy of the proposed system ResNet-101 has much higher than that of support vector machine and backpropagation neural network. For 10 classes of insect pest images with complex farmland background a 98.67% of classification accuracy was achieved. Alfarisy et al. [32] design a new method for paddy pests detection based on deep learning. They collect 4,511 images from search engines fed to CaffeNet and AlexNet model and then processed with Caffe framework. The transfer method classified 3 classes, 9 classes paddy insect pests, and 4 classes paddy diseases with accuracy 87%. Xia et al. [33] proposed a transfer learning model based on VGG19 model to detect and classify insect pests. The dataset expanded to 4800 images that contain 24 insect pest species collected from Xie's [34] data set. Experimental outcomes show that their method achieves a heightened accuracy of 89.22%.

In 2019, He et al. [35] proposed a real-time model for detection of Oilseed Rape pests. The authors created an oilseed rape pest dataset that contains 12 typical insect pests. They used five deferent architectures of deep learning. The experimental result on mobile shows that mean average precision (mAP) was 77.14% using data augmentation and added a dropout layer. In 2019, Dawei et al. [36] introduced a deep learning system based on transfer learning for pest insect detection. The system based on AlexNet pre-train model to classify ten types of insect pests. The proposed system achieves an accuracy of 93.84%.

In 2019, Wu et al. [37] proposed a new dataset benchmark for insect pest called IP102. The dataset contains more than 75, 000 images belonging to 102 categories of insect pest. In addition, they introduced a baseline experiment using handcrafted feature methods and deep feature methods that handle the pest insect images. The best accuracy achieved by authors is 49.5% via ResNet. Experimental results show that IP102 dataset has the challenges of classification and imbalance of dataset.

After surveying different related work papers that have used deep learning especially in classifying insect pests, it has been found that deep learning has brought tremendous development. It was also shown that using existing state of the art deep learning models along with pre-train models lead to better outcomes and higher detections accuracy. In this paper, we tried to develop an effective pre-train learning model to deal with insect pest images. Through the pre-train learning model, end-to-end training of insect pest images can be achieved, thus greatly simplifying the training process. The proposed transfer model with augmentation techniques was evaluated on IP102 [37] dataset introduced by Wu et al in 2019.

3. DATASET

This research used a large scale dataset IP102 [37] for insect pest recognition. Specifically, it contains more than 75,000 images belonging to 102 categories, which exhibit a natural long-tailed distribution. The dataset was annotated by agricultural experts there are 8 kinds of crops damaged by insect pests. The crops rice, corn, wheat, beet, alfalfa, Vitis, citrus, and mango. Table 1 presents the number of insect pest categories under every crop type, and the number of images inside every crop type. Figure 1 illustrates samples of images from IP102 dataset.

4. PROPOSED MODELS

The proposed models used in this research relied on the deep transfer learning CNN architectures to transfer the learning weights to reduce the training time, mathematical calculations and the consumption of the available hardware resources. There are a number of studies in [38][39][40][41] that have attempted to build their own architecture, but those architectures are problem-specific and do not fit the data presented in this paper. The deep transfer learning CNN models investigated in this research are AlexNet [19], SqueezeNet [42], and GoogleNet [22] The mentioned CNN models have only a few layers when compared to large CNN models, such as Xception, DenseNet, and InceptionResNet, which consist of 71, 201 and 164 layers, respectively. The choice of these models reduces the training time and the complexity of the calculations especially with a large number of images in the IP102 dataset. Table 2 presents the number of layers of the CNN models used in this work.

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Table 1: The number of inset pest categories and images for every crop type in the IP102 dataset.

Crop Type	Rice	Corn	Wheat	Beet	Alfalfa	Vitis	Citrus	Mango
Number of Categories	14	13	9	8	13	16	19	10
Number of Images	8417	14004	3418	4420	10390	17551	7273	9738

Figure 1: Images samples from the IP102 dataset [32].

Table 2. Number of layers for the different CNN models

Model	**AlexNet**	**SqueezeNet**	**GoogleNet**
Number of Layers	**8**	18	22

The previous CNN models were customized in the last fully connected layer to match the number of classes of the IP102 dataset, which contains 102 classes, as illustrated in Figure 2.

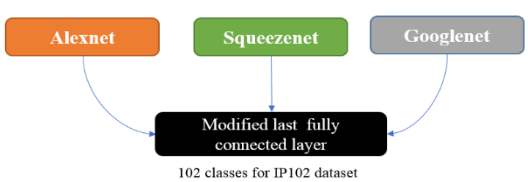

Fig. 2. Proposed model's customization for insect pest recognition.

4.1 Data Augmentation Techniques

The most well-known technique to overcome overfitting is to increase the number of images used for training by applying label-preserving transformations [43]. In addition, data augmentation schemes are applied to the training set to render the resulting model more invariant for any kind of transformation and noise. The augmentation techniques used in this research are

- Reflection around the X-axis.
- Reflection around the Y-axis.
- Reflection around the X-Y axis.

The adopted augmentation techniques have increased the number of images by a factor of 4 times compared with the original dataset. The dataset increased to 300844 images used in the training and testing phases. This increase will lead to a significant improvement in the CNN testing accuracy, as will be discussed in the following section. Additionally, this approach will render the proposed methods immune to memorizing the data and more robust and accountable for the testing phase.

5. EXPERIMENTAL RESULTS

The proposed architecture was developed using a software package (MATLAB). The implementation was a central processing unit (CPU) specific. All experiments were performed on a computer server with an Intel Xeon E5-2620 processor (2 GHz), 96 GB of RAM.

5.1 Testing accuracy and performance evaluation

Evaluate the testing accuracy and the performance of the proposed models is an important step in this research to validate the presented work. The testing accuracy is calculated according to equation (1). The most common performance measures in the field of DL are precision, recall, and F1 score [44], which are presented from equation (2) to equation (4), respectively.

$$\text{Testing Accuracy} = \frac{(\text{TN+TP})}{(\text{TN+TP+FN+FP})} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP+FP})} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP+FN})} \quad (3)$$

$$\text{F1 Score} = 2.\frac{\text{Precision.Recall}}{(\text{Precision+Recall})} \quad (4)$$

where TP is the count of true positive samples, TN is the count of true negative samples, FP is the count of false-positive samples, and FN is the count of false-negative samples from a confusion matrix.

To calculate the pervious performance metrics and testing accuracy, the confusion matrix is required to be calculated first. Due to large number of classes in this research which reached 102 class, it will be very difficult to illustrate all confusion matrix elements which may reach 10404 cells. An alternative method is presented using visualization toolbox of Matlab. Figure 3 presents the confusion matrix visualization for Alextnet.

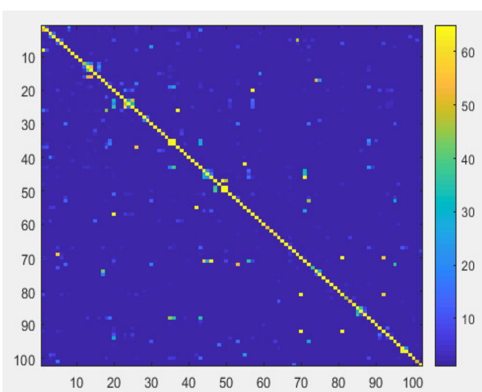

Figure 3: Visualization of a confusion matrix for Alexnet.

Table 3 presents the performance metrics for the different proposed CNN models. The table illustrates that the AlexNet model achieved the highest percentage for the testing accuracy, recall, and F1 score metrics, while GoogleNet achieved the highest percentage for the precision metric.

According to the achieved results for both testing accuracy and the performance metrics, AlexNet is the most appropriate CNN model for the IP102 dataset for insect pest recognition with a testing accuracy of 89.33%. Moreover, GoogleNet also achieved a competitive result, as illustrated in Tables 3.

Table 3. Testing accuracy and performance metrics for the different CNN models

Metric/Model	Squeeze Net	GoogleNet	AlexNet
Testing Accuracy	67.51%	88.80%	89.33%
Precision	66.22%	86.75%	86.38%
Recall	59.97%	85.26%	86.79%
F1 Score	62.94%	86.00%	86.58%

Another measure of performance is the progress of validation accuracy through the training phase. The progress of validation accuracy shows the improvement of the leaning process. Figure 4 presents the progress of the validation accuracy through the training process present in the black circles, while Figure 5 illustrates samples of testing accuracy using the Alexnet where the insect pest class is presented by a number between 1 to 102.

5.2 Comparison with related work

Table 5 presents a comparative result with the related work in [37], it is clearly shown that the adopted augmentation techniques in this research led to a significant improvement in testing accuracy and F1 score. The augmentation techniques helped to increase the number of images from 75211 to 300844 images which reflect on the achieved results. The Alexnet with augmentation presented in this research achieved the highest accuracy and F1 score with 89.33% and 86.58% respectively.

Table 4. The comparative result with related work.

Related Work	Model	Augmentation	Accuracy	F1 Score
[37]	AlexNet	No	41.8%	34.1%
	GoogleNet	No	43.5%	32.7%
	Vgg	No	48.2%	38.7%
	Resnet	No	49.2%	40.1%
Presented Work	SqueezNet	Yes	67.51%	62.94 %
	AlexNet	Yes	89.33%	86.58 %
	GoogleNet	Yes	88.80%	86.00 %

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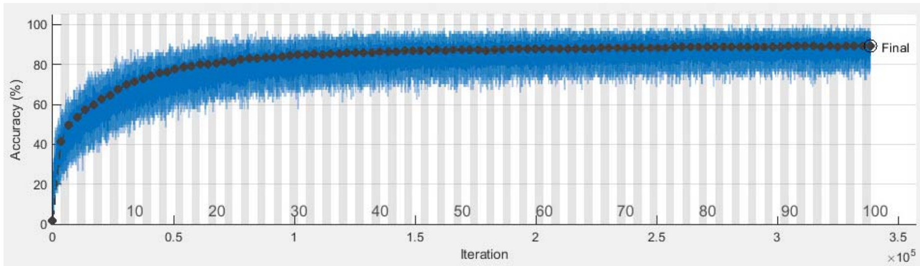

Fig. 4. The progress of validation accuracy through the training phase

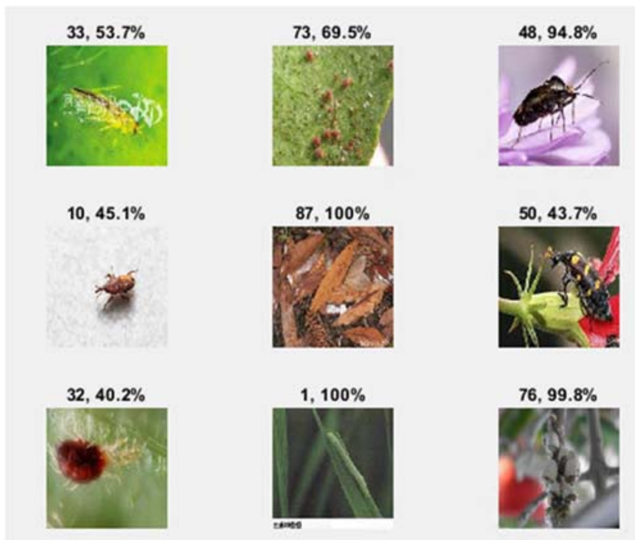

Fig. 5. Samples of testing classification accuracy using AlexNet.

6. CONCLUSION AND FUTURE WORKS

Agriculture energies any economic system for any country. Agriculture is the first people activity that helped humanity to advance and develop. It is not only providing food and raw material but also provides employment opportunities to very large percentage of the population, Insect pests have always been considered a serious challenge that affects crop production negatively. With the advances of computer algorithms and artificial intelligence, accurate and speedy recognition of insect pests in early stages may help in avoiding economic losses in short and long term. In this paper, an insect pest recognition based on deep transfer learning models was presented. The IP102 insect pest dataset was selected in this research. The IP102 dataset consists of 27500 images and contains 102 classes of insect pests. Through the paper, AlexNet, GoogleNet, and SqueezNet were the selected deep transfer learning models. Data augmentation techniques were used to render the models more robust and to overcome the overfitting problem by increasing the dataset images up to 4 times than original images. The AlexNet model achieved the highest testing accuracy at 89.33%. In addition, it has a minimum number of layers, which decreased the training time and computational complexity. Moreover, the choice of data augmentation techniques played an important rule in achieving better results. Finally, A comparison results were carried out at the end of the research with related work which used the same dataset IP102. The presented work achieved a superior result than the related work in terms of testing accuracy, precision, recall, and F1 score. One of the potential future works is applying new architectures of deep neural networks such as Generative Adversarial Neural Networks. GAN will be used before the proposed models. It will help in generating new images from the trained images, which will reflect on the accuracy of the proposed models. Additionally, to expand the current work is to use large deep learning architecture such as Xception, DenseNet, and InceptionResNet

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