A PRE-TRAINED DEEP CONVOLUTIONAL NEURAL NETWORK FOR THE DETECTION OF TUNGRO IN RICE PLANTS

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ABSTRACT

This paper presents a computer vision application of transfer learning in the detection of 'Tungro' among rice plants, using pre-trained deep convolutional neural networks. An AlexNet network, consisting of 5 convolution layers and 3 fully connected layers of neurons, was customized and fine-tuned to accommodate as inputs, images of rice plants representing two (2) classes: those afflicted with Tungro, and those that are healthy. The fine-tuned network was trained on five hundred twenty (520) images of rice plants, three hundred sixty-eight (368) of which belong to the group without infestation, and one hundred fifty-two (152) are infested with Tungro. Both the training and testing dataset-mages were captured from rice fields around the district and validated by technicians in the field of agriculture. Applying stochastic gradient descent as the learning algorithm, the two-class classifier achieved a very high accuracy of 98.17% at mini batch size of twenty (20) and learning rate of 0.0001.

KEYWORDS

Deep Learning, Transfer Learning, AlexNet, Convolutional Neural Network

1 INTRODUCTION

1.1 Machine Learning

Advances in computer processing power have revolutionized not only the scope of its applications but as well as its capability to process large amounts of data. What were once constrained to a few layers of neurons, neural networks can now span several layers each comprising thousands of computational neurons, largely due to significant improvements in computing hardware. With this structure, neural networks have evolved into more powerful computational tools closely mimicking human intelligence.

One of the hottest applications of machine learning nowadays is on computer vision and object recognition in general and in plant health monitoring in particular as can be found in [1], [2] and in [3]. Neural networks and deep learning currently provide the best solutions to many problems in image recognition, speech recognition, and natural language processing [4]. Many researchers around the world continue to exploit this computational power in almost every problem domain.

1.2 The Rice Problem Domain

Rice, also known as Oryza Sativa, is one of the most important plants with over half the world population depending on it for food. It is primarily grown in Asia and in the Philippines for instance, rice is a major staple food for millions of Filipinos. As the Department of Agriculture puts it, "an average Filipino diet is based on rice. It provides half of our calorie requirements and one-third of our protein intake [5]. Rice accounts for 20% of food expenditures for average households, which increases to 30% for households belonging to the bottom third of our society."

However, despite numerous programs being orchestrated by the government, the ever growing multiplicity of diseases that affect rice productivity remain a serious issue. Data from the International Rice Research Institute (IRRI) Knowledge Bank show that rice farmers lose an estimated average of 37% of their rice crop to pests and diseases every year [6].

If the onset of a rice infestation is instantly detected, its spread can be prevented by administering timely interventions. But before anything can be done, the immediate detection of the early signs or stages and symptoms of any disease is paramount. As intimated in International Rice Research Institute, “in addition to good crop management, timely and accurate diagnosis can significantly reduce losses.” [6].

1.3 Original Contribution

A number of ideas have been proposed on the use of image processing and computer vision techniques in the identification and detection of plant diseases such as those in [7, 8, 9, 10, 11, 12].

The use of Support Vector Machines (SVM) as a classification algorithm was demonstrated in the work of Singh, et. al. to identify Leaf Blast in rice plants [13]. The authors claim 82% classification rate.

In [12], the image processing algorithm developed was enhanced with an interface for digitally illiterate users, especially farmers to efficiently and effectively retrieve information. This work therefore takes into account some principles of Human-Computer-Interaction (HCI), which is a significant step forward considering that most farmers are alien to the digital world.

Phadikar, et. al. is also a study featuring use of Support Vector Machines [9]. However, the proposed system has two (2) stages: first, detection of disease is accomplished through histogram characterization; and second, either a Bayes’ or SVM algorithm is applied. The system gives 79.5% and 68.1% recognition rates for the Bayes’ and SVM classifiers, respectively.

Aside from those mentioned above, while some researchers have also ventured into the possibility of using shallow, fully-connected networks in identifying rice diseases/infestations, the use of deep convolutional networks for the detection of infestations such as Tungro still remains to be examined. This is the main contribution of this paper.

2 TRANSFER LEARNING

Transfer learning is an approach in Deep Learning where a large, deep neural network previously trained on other datasets is adopted and used in another application. Although designing and training a deep network from scratch remains an interesting alternative, adoption of pre-trained deep networks is an appealing prospect for a number of reasons:

1. “Reinventing the wheel” and training networks from scratch takes time and demands high computing power. A convolution networks the size and topology of AlexNet finished training in 5 to 6 days;

2. Pre-trained networks have been trained over millions of images to classify thousands of object and classes; As such, the weights and biases connecting its neurons have been optimally calculated; and

3. Many successful applications of pre-trained networks can be found in the literature in applications such as speech recognition and object detection.

AlexNet is a deep, convolutional neural network originally designed to classify 1.2 million high-resolution images in the ImageNet Large Scale Visual Resolution Challenge (ILSVRC) in 2010 into 1000 different classes. It has 650,000 neurons in a total of eight (8) hidden layers of neurons.

During training, Alexnet used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers, the network employed “dropout” method that proved to be very effective. In the ILSVRC-2012 competition a variant of AlexNet achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry [14].

The use of Support Vector Machines (SVM) as a classification algorithm was demonstrated in the work of Singh, et. al. to identify Leaf Blast in rice plants. The authors claim 82% classification rate [11].

As shown in Fig.1 below, the first convolutional layer of the AlexNet network uses 96 kernels of size 11 x 11 x 3 to filter the 224×224×3 input image, with a stride of 4 pixels, producing 96 feature maps. The second convolutional layer takes as input the features from the first convolutional layer and filters it with 256 kernels of size 5 × 5 × 48, producing 256 feature maps. The third, fourth, and fifth convolutional layers are connected to one another without any intervening pooling or normalization layers. The third convolutional layer has 384 kernels of size 3 × 3 × 256 connected to the outputs of the second convolutional layer. The fourth convolutional layer has 384 kernels of size 3 × 3 × 192. Both the third and fourth convolutional layers produce 383 feature maps. The fifth convolutional layer has 256 kernels of size 3 × 3 × 192 as filter to the outputs at the 4th convolutional layer, producing 256 feature maps. The first two fully-connected layers have 4096 neurons each while the last fully connected layer has 1000 neurons.

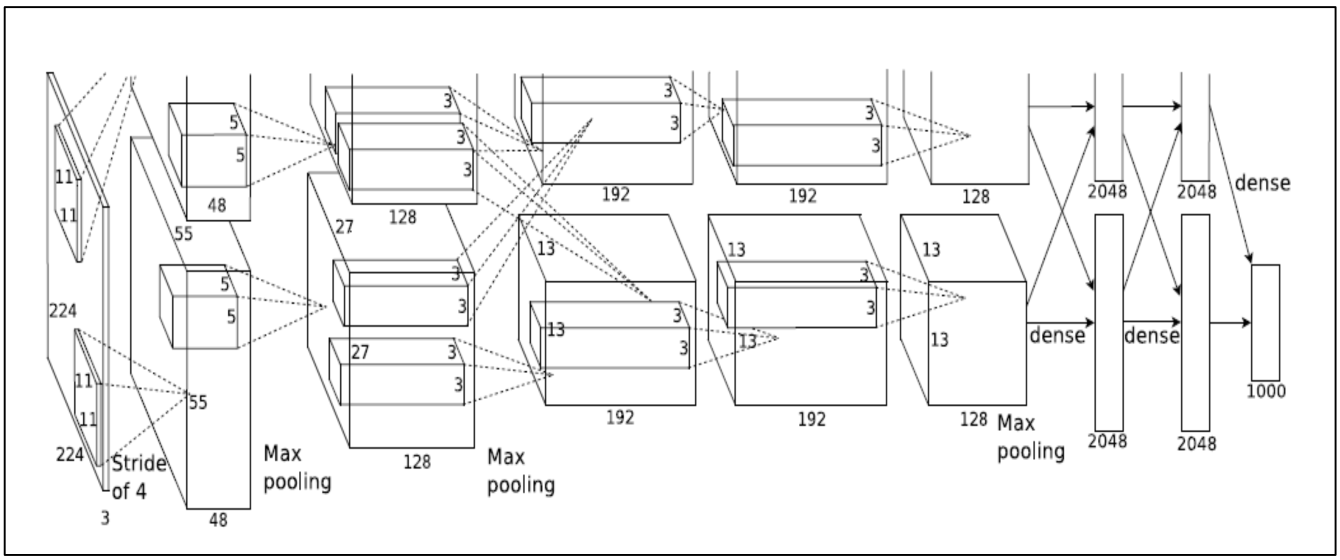


Figure 1. Architecture of AlexNet Deep Convolutional Network [14]

Instead of sigmoid activation functions, AlexNet used Rectified Linear Units (ReLU), and a Softmax function at the output of the last fully connected layer.

3 RICE INFESTATIONS AND DISEASES

A rice infestation, loosely speaking, is the unwarranted presence of damaging species of insects and pests that injures the rice plant and diminishes its ability to produce food. Most of these infestations are readily recognized by their symptoms primarily by visual features on the leaves of the rice plant. Rats, black bugs, leaf folders, and hoppers are just some of the most common species of rice infestations in the Philippines [6].

The concept supporting the application of DIP (Digital Image Processing) in the detection of rice plant infestations, is bolstered by the observation that most of these are manifested in the appearance of the leaves and on the general visual features of the plant. It is therefore not hard to imagine that these visual patterns can be taken collectively to form multivariate basis of identity and traits unique to each type of disease. For instance, Brown Spot, a fungal disease, is characterized by presence of lesions that are initially small, circular, and dark brown to purple-brown, while Bacterial Blight is identified with wilting and yellowing of leaves, which, among older plants, turn yellow to grayish white with black dots due to the growth of various saprophytic fungi [6].

4 METHODS

4.1 Fine-Tuning AlexNet

We first customized AlexNet in order to accommodate our 2-class classification problem. The objective of our proposed system is to classify an input image of rice plant of no a priori class into whether it is infested/ill or not. And since AlexNet was designed to handle 1000 classes, its output layer also has to be retrofitted to handle our 2-class system.

In a 2-class problem, the use of sigmoid as activation functions instead of ReLUs will suffice but we leave these components untouched to avoid unnecessarily modifying the network architecture and evade lengthy fine-tuning. The learning algorithm used was the same with the pre-trained network, Stochastic Gradient Descent, while adopting the mini-batch size of twenty (20), and learning rate of 0.0001.

4.2 Rice Image Datasets

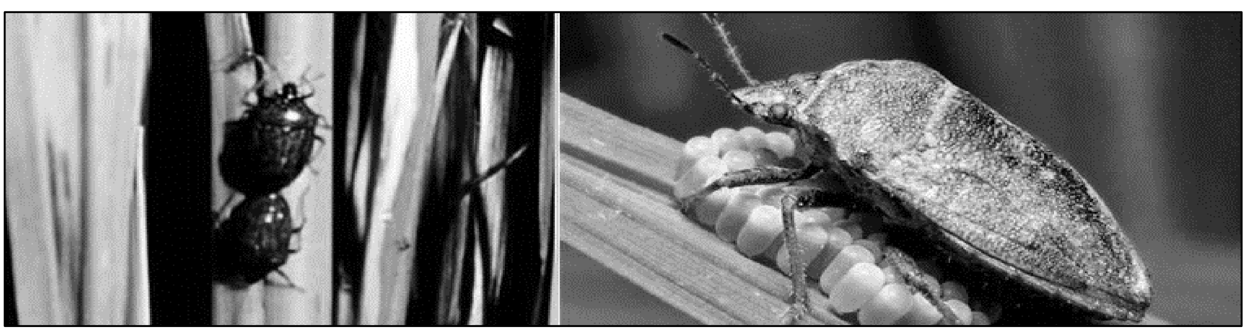
A total of four hundred sixty-eight (468) rice images were captured in rice fields around the district particularly in Goa (Digdigon, Buyo, Matacla, Abucayan, Halawig-gogon, Catagbacan, and Belen), San Jose (Bilog, Pugay, and Dolo), Tigaon (San Rafael, Vinagre, and San Antonio), and Sagnay (Huyon-huyon, and Nato). The images were resized into 227 x 227 resolution in order to fit the input layer of AlexNet.

These images were manually augmented by operations such as cropping and rotations, as well as by downloading public images from [15]. A priori classification was conducted with the assistance of technicians at the Municipal Agriculturist's Office of Goa, Camarines Sur, and the Crop Protection Office of Department of Agriculture, Regional Office V.

Of the total images, 70% or five hundred twenty (520) were used for training and the remaining 30% or two hundred twenty-two (222) were used for testing. There were also unstructured interviews conducted with farmers during the image capture activities.

5 RESULTS

Our unstructured interviews with farmers revealed that the three (3) most common rice plant infestations/diseases in the district are: golden apple snail, Tungro, and black bug. Figure 2 shows sample images of rice plants afflicted with the three (3) most common diseases/pests in the district: black bug, Tungro, and golden apple snail.



(a)

(b) (c)

Figure 2. Images of Rice Plants with Infestations and/or Diseases: (a) Black Bug, (b) Tungro, and (c) Golden Apple Snails. Images were downloaded from [6].

Shown in Table 1 is the summary of performance of the pre-trained network in terms of accuracy under learning rate of 0.0001 and batch size of 20. At the end of the simulation, the algorithm converged into an accuracy of 98.17% using the test images. In other words, the classifier was incorrect in only three (3) of the two hundred twenty-two (222) images tested.

Table 1. Accuracy of the Pre-Trained Classifier by Batch Size and Learning Rate

Epoch	Time Elapsed (s)	Accuracy
1	1.54	65%
2	26.28	90%
4	51.39	100%
6	76.12	95%
8	101.22	95%
10	130.17	100%

Figure 3 shown next is a sample testing image showing a Tungro-infested rice plant. Images when sent as input into the classifier's convolution layers are broken down into features when the filters are activated or applied.

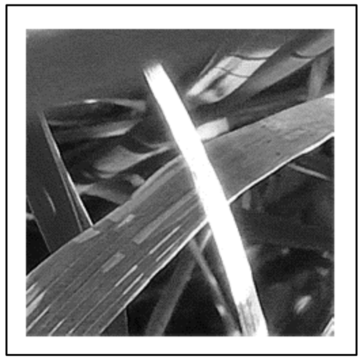


Figure 3.
Sample input image of rice leaves infected with Tungro

For the input image in Figure 3, the corresponding activations of all channels for convolution layer 1 is shown in Figure 4 below. These activations are characterized as feature maps for visual analyses. In Figure 5 is a sample output of the classifier showing correctly classified input images.

Figure 4.
Activations / Feature maps in All Channels of Convolution Layer 1 for the Test Image in Figure 3.

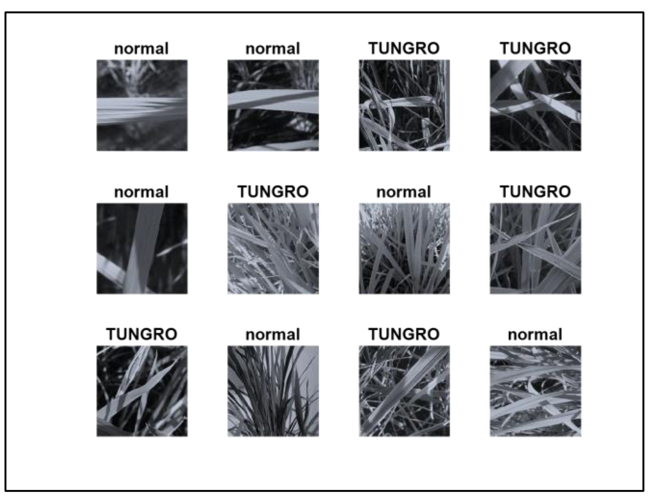


Figure 5.
Sample outputs of the classifier showing detected TUNGRO diseases.

4 CONCLUSION

We developed in this paper a deep convolutional neural network applying the pre-trained weights and biases for classifying rice plants' images into two (2) classes: healthy or Tungro-infested. The dataset of images was comprised of images captured in several rice fields around the district as well as public images from the internet. The images were resized and augmented and divided into training-testing set of 70%-30% ratio.

Stochastic gradient descent was the learning algorithm applied at varying learning rates with fixed batch size of five (5). Using the test data, the algorithm obtained accuracy was 98.17% at learning rate of 0.0001 and batch size of 20.

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