Rice Pest and Disease Detection Using Convolutional Neural Network

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ABSTRACT

Detection of rice pest and diseases, and proper management and control of pest infested rice fields may result to a higher rice crop production. According to the International Rice Research Institute, farmers lose an average of 37% of their rice crops due to pest and diseases, yearly. Using modern technologies, like smart phones, farmers can be aided in detecting and identifying the type of pests and diseases found in their rice fields. This study proposed an application that will help farmers in detecting rice insect pests and diseases using Convolutional Neural Network(CNN) and image processing. It looked into the different pests that attack rice fields; information on how they can be controlled and managed was considered; farmers' knowledge in different rice pests and diseases, and how they control these pests was regarded in this study; the study also looked into the reporting mechanism of farmers to government agencies. Using CNN and image processing, the application that detects rice pests and diseases was developed. The searching and comparison of captured images to a stack of rice pest images was implemented using a model based on CNN. Collected images were pre-processed and were used in training the model. The model was able to achieve a final training accuracy of 90.9 percent. Cross-entropy was low, which implies that the trained model can perform prediction or can classify images with low percentage of error. Through the developed application, farmers were provided with information and procedures on how to control and manage rice pest infestation. Future researchers may look into multiple pest comparison to a stack of images for faster retrieval of information.

CCS Concepts

• **Computing methodologies~Image processing** • Computing methodologies~Supervised learning by classification.

Keywords

Rice pest; rice diseases; machine learning; convolutional neural network.

1. INTRODUCTION

Rice is grown in varying agroecological and socio economic conditions in more than 100 countries [1]. Rice is one of the most important human food crops which occupies one-tenth of the world's arable land [2]. However, there are several diseases that affect plant that could cause devastating economic and ecological losses. Hence, diagnosing disease in an accurate and timely manner is of most importance [3]. Rice insect outbreaks have increased and the insect pest complex has changed in the last four decades [4]. Out of 266 insect species identified in rice ecosystems, 42 species are considered to be pests [5]. Finding out the pest or diseases and percentage of the pest or disease incidence plays an important role in successful cultivation of crops [6].

Rice producing countries have come up with their own programs in increasing rice crop production. In Bangladesh for instance, Green Revolution package was introduced into agriculture system which is promised to increase production of cereal crops, particularly rice [7]. In Thailand, Farmer Field School was established. It is a training program that provides farmers with science-based knowledge in integrated pest management. It significantly affects the farmers in terms of the ability to reduce the use of pesticide while increasing yields [8]. However, as public policy, developing countries have failed to invest in educating farmers on how to deal with variable agro-ecosystems and a changing world [9]. For insect pest control, application of chemical insecticides is still the favorite method for farmers which causes environmental pollution and reduces population of the natural enemies of herbivores [10]. Although, chemical pesticides play crucial roles in the management of crop diseases and pests [11], its disadvantages are also evident in the environment. Knowledge and information are key to correct pest management decisions [12]. The point of Integrated pest management (IPM) is to apply pesticide only when and where it is needed [13]. IPM as a system which provides intensive information for appropriate decision making for field practitioners [12]. Technology can help farmers monitor crops efficiently and potentially detect destructive insects or pest and prevent their relevant disease in early stage [14]. Advance computing technology can help farmer take decision about many aspects of crop development. Suitable diagnosis of crop disease in the field is critical in increasing production [15]. However, in the field of agriculture, there were little application reported in using intelligent materials as compared to other fields such as medical, aerospace, construction, etc. It is still a challenge for the scientific community the improvement and application of pest and disease models to analyze and predict yield losses [16]. In most cases, diagnosis about diseases is performed visually by humans. Trained raters may be efficient in recognizing plant diseases however some associated disadvantages may harm the efforts of recognizing diseases [3].

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Implementation of disease detection application in agricultural sector will help farmers get the information about the diseases of the leafy vegetables and the necessary management techniques that can be used to prevent the diseases without depending on the experts [17]. Computer vision and image processing technology have been widely used in many fields and have many potential applications in modern agriculture [18]. Moreover, the techniques of machine vision are extensively applied to agricultural science and have great perspective especially in the plant protection fields [19]. Moreover, machine vision and digital image processing are extensively applied to agricultural science which leads to crops management [20]. Automatic detection of plant disease takes less time and effort, and more accurate as compared to visual way of detecting [21]. It is important to develop agricultural pest identification system based on computer vision technology to correctly identify and target control measures to prevent damage caused by pests [22]. Automatic technique of plant disease detection reduces large work of monitoring big farms and at early stage symptoms of diseases are detected [21].

Several approaches based on automation and image processing have come to light to address early detection of pest infestation. Most of the algorithms concentrate on pest identification limited to a greenhouse environment [23]. Cheng et.al. suggested a pest identification method that uses deep residual learning to achieve pest identification with complex farmland background [22]. In the study of Kawasaki et. al., a novel plant disease detection system based on convolutional neural network was presented. Using only training images, CNN can achieve high classification performance [24]. In the study of Sladojevic et. al., deep convolutional network was used in the development of plant disease recognition model based on leaf image classification. Convolutional neural networks(CNN) has achieved impressive result in the field of image classification [25]. Yao et. al. proposed in their study a three-layer detection method to detect and identify White-backed planthoppers using image processing. The proposed method was found to be feasible and effective for the identification of different developmental stages of planthoppers on rice plants [26].

In the Philippines, specifically in the Ilocos Region, infestation of pests in rice fields has resulted to decrease in rice yields of farmers. Although, the Department Agriculture Regional Crop Protection Center has exerted its effort to help and educate farmers about rice pests and diseases, the support to farmer is limited to what is being reported to their office. This motivated the researchers to develop an application that can aid farmers identify rice pests and diseases and provide ways of controlling it. The study aims to develop a rice pest and disease detection application using convolutional neural network.

The paradigm shows how the Input-Process-Output variables interact. The conceptualization of this study is presented through a framework in Figure 1.

In the Input variable, the profile of rice pests and diseases in terms of the physical features, the damages it caused to rice plants and how it can be controlled were determined. In the process variable, analyses of rice pests and diseases were made and a model that can detect rice pests and diseases was developed and trained. A system prototype of rice pest and disease detection was the output of this study.

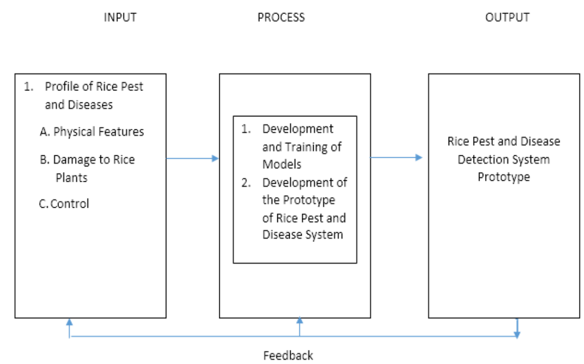

Figure 1. Research Paradigm

2. METHODOLOGY

2.1 Data Collection

In order to gather the necessary data of the different rice pests and diseases, the researchers conducted interviews to the personnel of the Department of Agriculture specifically to the staff of the Regional Crop Protection Center and also studied and analyzed documents related to rice pests and diseases. Images of different rice pests and diseases were collected using available image capture devices such as digital camera and smart phone. After collecting, all images were pre-processed and encoded as part of the dataset.

2.2 Training the Model

The captured and pre-processed rice pest and diseases images form the dataset. The input data was divided into three parts; the training set, validation and test set. For training data, 80 percent of the total images were used. The validation data set used the remaining 20 percent of the images. The test set was composed of separate independent data.

In order to develop the model, the researchers utilized transfer learning. Transfer Learning is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned [27]. In the study of Cruz et. al., it was demonstrated that transfer learning can be used when it is not possible to collect thousands of new images [28]. Transfer learning is the use of already trained deep learner to new problem. In this study, the researchers made used of a model already trained on another problem instead of developing a model from scratch. Using Python and Tensorflow, Google's inception-v3 was re-trained in order to predict different classes of rice pests and diseases. Inception-v3 is trained for the Imagenet Large Visual Recognition Challenge using the data from 2012. The final layer of the model was retrained from scratch using the supplied images.

2.3 System Development

In order to come up with the working prototype, Agile modeling and Extreme Programming was utilized. Agile modeling is a practices-based software process whose scope is to describe how to model and document in an effective and agile manner. At a more detailed level agile modeling is a collection of values, principles, and practices for modeling software that can be applied on a software development project in an effective and light-weight manner [29]. Extreme Programming is one of several popular Agile Processes. It empowers the developers to confidently respond to changing customer requirements, even late in the life cycle [30].

In developing the prototype, the trained model was used as part of the library of the android application. After creating the model, the graph was frozen by converting the variables in the checkpoint file into Const ops that contains the values of the variables. After the graph was frozen, the model was further optimized for inference purposes by removing the graph needed only for training then Tensorflow libraries was compiled before it was added in the android project. The developed android application was tested by feeding images and checked whether the developed applications can accurately detect or classify fed images to the system. The testing process validates the correctness of the trained model.The text should be in two 8.45 cm (3.33") columns with a .83 cm (.33") gutter.

3. RESULTS AND DISCUSSIONS

3.1 Convolutional Neural Network

The model used in detecting rice pests and diseases was based on Convolutional Neural Network(CNN). CNNs are at the core of most state-of-the-art computer vision solutions for a wide variety of tasks [31]. A Convolutional Neural Network (CNN) is comprised of one or more convolutional layers and then followed by one or more fully connected layers as in a standard multilayer neural network.. CNNs are typically comprised of different types of layers, including convolutional, pooling, and fully-connected layers. By stacking many of these layers, CNNs can automatically learn feature representation that is highly discriminative without requiring hand-crafted features [32]. Figure 2 shows the structure of a CNN. It is composed of an Input, Output Layer and multiple hidden layers. The hidden layers can either be a convolution layer, pooling or fully connected layers. The Input layer will hold the raw pixel values of the images while the convolution layer computes the output of neurons that are connected to the local region of the input. The pooling layer will perform a downsampling operation along the spatial dimensions. The fully connected layer will compute the class scores.

The model for detecting rice pests and diseases was based on CNN. Figure 3 shows how the model predicts images, an image must be fed to the classifier as an input then the convolution layer computes the output of the neuron to the logical region of the input. Downsampling of the operation along the spatial dimensions will be performed in the pooling layer. The operation will be repeated depending on the number of layers until it reaches the final layer which is a fully connected layer which will compute the scores of the different classes as basis for making prediction.

Using the images of rice pests and diseases as the training dataset, the researchers were able to retrain the model and produce the results as seen in Figure 4. The figure shows the data of the actual training of the model. It shows the output of the training for every 10 iterations. The display contains information about the training accuracy, validation accuracy and cross-entropy. The training of the dataset was able to achieve a final test accuracy of 90.9%, which is high considering that some classes has limited number of images. This implies that the trained model can perform accurate prediction based on images that will be fed to the system.

As the training of the model progresses, the results were also being documented and is written on a file. Figure 5 shows the accuracy scalar graph of the training as documented using tensorboard. The orange colored line represents the training accuracy while the blue colored line represents the validation accuracy. At about 400 iterations in the training, the model already achieved 100 percent accuracy both for the training and validation data. This implies that the trained model is neither overfitting nor underfitting.

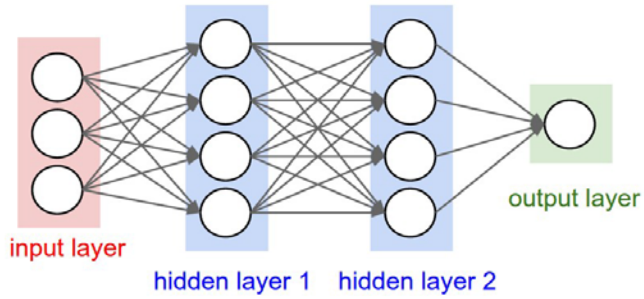

Figure 2. Convolutional Neural Network [33]

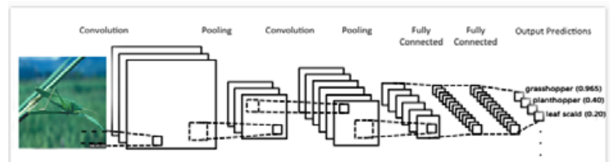

Figure 3. Rice Pest and Disease CNN

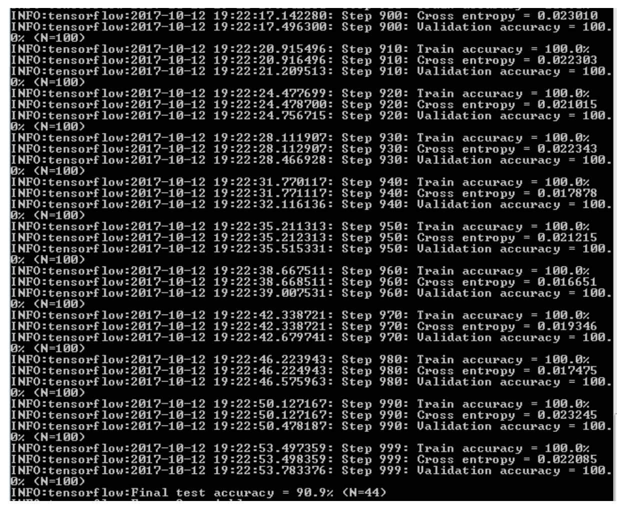

Figure 4. Training Results of the Dataset

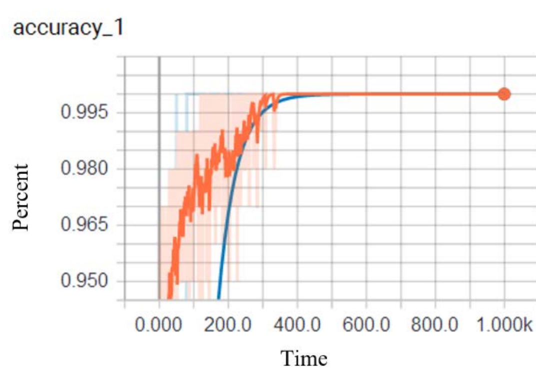

Figure 5. Training and Validation Accuracy Graph

Figure 6 shows the cross-entropy graph of the training. Cross-entropy is used to measure the difference between probability distributions. It measures how far or how wrong your prediction from the true distribution. The orange line represents the cross-entropy of the training data while the blue line represents the validation data. The cross-entropy loss for training and validation is low. This implies that the model can perform prediction with minimal error.

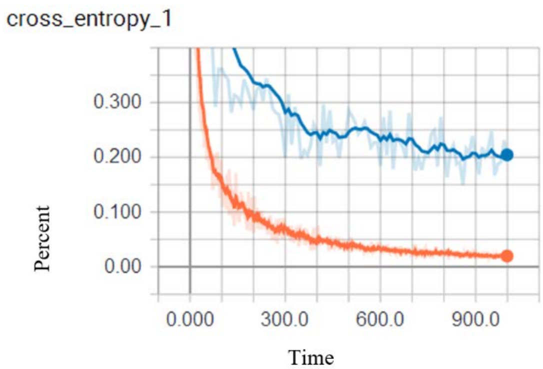

Figure 6. Cross-entropy Graph

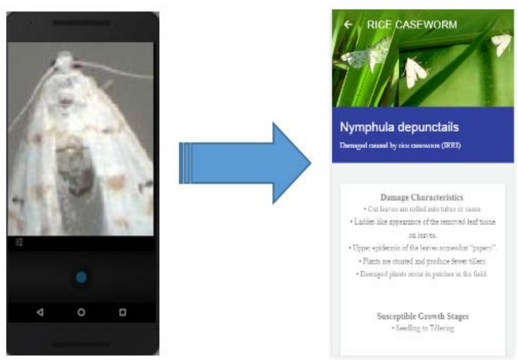

Figure 7. Sample Rice Pest Detection Interface

The trained model was used in developing the android application. It was imported as library to the system. Figure 7 shows a sample screen of the mobile application which displays the information of the pest and information on the possible damages to plants and how it can be controlled. The display will be based on the result of the identification of pest using an image [34] being feed to the trained model. The image will be used as an input to the classifier then will be matched to the rice pest database in order to display the appropriate description.

4. CONCLUSION

In this paper, the researchers were able to develop a rice pests and diseases detection application using convolutional neural network. To accurately predict the pests and diseases in rice, a model was trained using transfer learning. This allows the researchers to train the model much faster rather than building the model from scratch. The trained model has achieved high accuracy with minimal cross-entropy or error in predicting results. Therefore, the model can be used to predict or detect rice pests and diseases with very high accuracy. These developed application can be recommended to farmers with smartphone to aid them in controlling rice pest infestation. These will also help staff of Department of Agriculture to provide assistance to farmers once pests are identified and reported to their office

5. REFERENCES

[1] Rao, A. N., Wani,S. P., Ramesha ,M. S. and Ladha, J. K. 2017. "Rice production systems," Rice Production Worldwide (February 2017), 185-205.

[2] Thorburn, C. 2015. "The rise and demise of integrated pest management in rice in Indonesia," Insects(April 2015), 381–408.

[3] Garcia, J and Barbedo, A.2013. "Digital image processing techniques for detecting, quantifying and classifying plant diseases," Springer Plus, 2 (2013) 660.

[4] Heinrichs, E. A. 2017 Retreived September 2017 from ipmworld: https://ipmworld.umn.edu/heinrichs

[5] Alam, M. Z., Crump,A. R., Haque, M. M., Islam, M. S., Hossain, E., Hasan S. B., Hasan ,S. B. and Hossain, M. S. 2016. "Effects of integrated pest management on pest damage and yield components in a rice agro-ecosystem in the Barisal Region of Bangladesh," Environmental Science (March 2016)

[6] Patil, J. K. and Kumar,R. 2011. "Advances in image processing for detection of plant diseases," Journal of Advanced Bioinformatics Applications and Research, 2(2)(2011) 135-141.

[7] Headey, D. and Hoddinott, J. 2016. "Agriculture, nutrition and the green revolution in Bangladesh". Agricultural Systems 149 (Nov. 2016) 122-131.

[8] Yamsake, S. and Resosudarmo, B. P. 2008. "Does sending farmers back to school have an impact? revisiting the issue," Blackwell Publishing Asia(2008).

[9] Berg H. D., and Jiggins,J. 2007. "Investing in farmers—the impacts of farmer field schools in relation to integrated pest management," World Development, 35(4)(2007) 663-686.

[10] Lou ,Y., Zhang ,G., Zhang, W., Hu, Y., Zhang ,J. 2013. "Biological control of rice insect pests in China," Biological Control, 67(2013) pp. 8-20.

[11] Hong-xing ,X., Ya-jun Y., Yan-hui ,L., Xu-song, Z., Jun-ce ,T. and Feng-xiang, L.2017. "Sustainable management of rice insect pests by non-chemical-insecticide technologies in China," Rice Science, 24(2)(2017) 61-72.

[12] Bajwa ,W. I. and Kogan, M. 2017. "Internet-based IPM informatics and decision Support," Integrated Plant Protection Center (IPPC), Retrieved September 2017 from ipmworld: https://ipmworld.umn.edu/bajwa.

[13] MacRae, I. V. 2017. "IPM World," University of Minnesota, Colorado State University, Retrieved September 2017 from ipmworld : https://ipmworld.umn.edu/macrae-ipm.

[14] Azfar,S., Nadeem ,A., and Basit ,A. 2015. "Pest detection and control techniques using wireless sensor network", Journal of Entomology and Zoology Studies, 3(2)(2015) 92-99.

[15] Revathi, P. and Hemalatha, M. 2012. "Classification of cotton leaf spot diseases using image processing edge detection techniques," Emerging Trends in Science, Engineering and Technology

[16] Donatelli, M., Magarey, R.D., Bregaglio, S., Willocquet L., Whish, J.P.M., and Savary, S. 2017. "Modelling the impacts of pests and diseases on agricultural systems," Agricultural Systems, 155(2017) 213-224.

[17] Hira, J. K. and Din, S. 2015. "Design and development of software for disease detection and management of leafy vegetables," International Journal of Innovative Research in Computer and Communication Engineering, 3(6)(2015) 2320-9798.

[18] Wang ,K., Zhang, S., Wang ,Z., Liu, Z. and Yang,F. 2013. "Mobile smart device-based vegetable disease and insect pest recognition method," Yang Intelligent Automation & Soft Computing, 19(3) (2013).

[19] Phadikar, S. and Sil, J. 2009. "Rice disease identification using pattern recognition techniques," Computer and Information Technology, 2009.

[20] Gohokar ,V. V., Mundada, R., "Detection and Classification of Pests in Greenhouse Using Image Processing," Journal of Electronics and Communication Engineering , 5(6)(2013), 57-63.

[21] Singh , V. and Misrab, A.K. 2016. "Detection of plant leaf diseases using image segmentation and soft computing techniques", Information Processing in Agriculture, 4(2016), 41-49.

[22] Cheng, X., Youhua, Z., Yiqiong, C., Yunzhi, C. and YiYue, W. 2017. "Pest identification via deep residual learning in complex background," Computers and Electronics in Agriculture, 141(2017), 351-356.

[23] Huddar, S. R., Gowri, S., Keerthana, K., Vasanthi, S. and Rupanagudi, S. R. 2012. "Novel algorithm for segmentation and automatic identification of pests on plants using image processing," Computing Communication & Networking Technologies , (2012).

[24] Kawasaki, Y., Uga, H., Kagiwada, S. and Iyatom, H. 2015. "Basic study of automated diagnosis of viral plant diseases using convolutional neural networks," Advances in Visual Computing, (2015),638-645.

[25] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D. and Stefanovic, D.2016. "Deep neural networks based recognition of plant diseases by leaf image classification," Computational Intelligence and Neuroscience, (2016), 11.

[26] Yao, Q., Chen, G., Wang, Z., Zhang, C., Yang, B. and Tang, J. 2017. "Automated detection and identification of white-backed planthoppers in paddy fields using image processing," Journal of Integrative Agriculture, 16(7)(2017), 1547-1557

[27] Torrey, L. and Shavlik, J. 2010. "Transfer Learning," in Handbook of Research on Machine Learning Applications and Trends: Algorithms, Methods, and Techniques, Madison, Wisconsin, USA, Information Science Reference, (2010), 242.

[28] Cruz, A. C., Luvis, A., Bellis, L. D. and Ampatzidis, Y. 2017. Vision-based plant disease detection system using transfer and deep learning, St. Joseph, Michigan: American Society of Agricultural and Biological Engineers, (2017).

[29] Ambler ,S. W. 2012. "Agile Modeling and Extreme Programming," Retrieved September 2017, from Ambysoft Inc.: http://agilemodeling.com/essays/agileModelingXP.htm.

[30] Wells, D. 2013. "Extreme Programmng: A Gentle Introduction," Retrieved September 2017, from : http://www.extremeprogramming.org/.

[31] Szegedy, C., Vanhoucke ,V., Ioffe, S., Shlens, J. and Wojna, Z. 2016. "Rethinking the inception architecture for computer vision," The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), (2016), 2818-2826.

[32] Ng, A., Ngiam, J., Foo, C. Y., Mai ,Y., Suen, C., Coates, A., Maas A., Hannun, A., Huval, B., Wang, T. and Tandon, S., "Convolutional neural network," Retrieved October 2017, from Standford: http://ufldl.stanford.edu/tutorial/supervised/ConvolutionalNeuralNetwork.

[33] "Convolutional neural networks for visual recognition," Retrieved October 2017, from Standford University: http://cs231n.github.io/convolutional-networks/.

[34] "Rice case worm," Retrieved October 2017 from Agropedia: http://agropedia.iitk.ac.in/content/rice-case-worm [Accessed 14 October 2017].