Deep Learning Based Classification for Paddy Pests & Diseases Recognition

Ahmad Arib Alfarisy
Shanghai Jiao Tong University
Dongchuan Road, Minhang, Shanghai. China
(+86) 13262547101
ahmadarib@sjtu.edu.cn

Quan Chen
Shanghai Jiao Tong University
Dongchuan Road, Minhang, Shanghai. China
(+86) 2134207239
chen-quan@cs.sjtu.edu.cn

Minyi Guo
Shanghai Jiao Tong University
Dongchuan Road, Minhang, Shanghai. China
(+86) 2134204438
guo-my@cs.sjtu.edu.cn

ABSTRACT
Pests and diseases are a threat to paddy production, especially in Indonesia, but identification remains to be a challenge in massive scale and automatically. Increasing smartphone usage and deep learning advance create an opportunity to answer this problem. Collecting 4,511 images from four language using search engines, and augment it to develop diverse data set. This dataset fed into CaffeNet model and processed with Caffe framework. Experiment result in the model achieved accuracy 87%, which is higher than random selection 7.6%.

CCS Concepts
• **Applied Computing → Agriculture**

Keywords
Paddy pests; Paddy diseases; Deep Convolutional Neural Networks.

1. INTRODUCTION
Indonesia is the 3rd biggest rice producer in the world, just behind China and India, also 3rd biggest rice consumer. Indonesia so depending on rice that the calorie intake of rice is 48%, this is high compared to China 27% and India 29% [1]. Around 37.7 million of Indonesian are paddy farmer and most of them living under poverty line [2].

Every action that could increase paddy productivity will directly affect millions of paddy farmer in Indonesia. One primary factor of paddy productivity is pests and diseases attack in the paddy field. Estimated paddy farmer loss 37% paddy production annually because of paddy pests and diseases [3]. Most of the paddy farmer in Indonesia only know the attack after it is too late and the pests or diseases already do damage to paddy production. This phenomenon perhaps because of lowly educated paddy farmer and a low number of agriculture-extension from the government.

ICMAI '18, April 20–22, 2018, Chengdu, China

ACM ISBN 978-1-4503-6420-1/18/04…$15.00
https://doi.org/10.1145/3208788.3208795

Early and accurate diagnosis is one pillar of precision agriculture [4]. It is essential to make an informed decision about what kind of paddy pests or diseases that attacking a specific paddy field in near real-time to make appropriate decision.

Naïve approaches doing precise agriculture is educating all 37.7 million farmers or distribute enough extension worker to cover this job. Both methods perhaps will not work in Indonesia since the government budget cannot afford this, educating farmer and recruit extension worker will cost much and population density of paddy farmer are sparse and divided into so many islands making approaching them one by one time consuming and bear a high cost.

Recently government and universities in Indonesia try to address this problem with building web katam.litbang.pertanian.go.id to assist farmer decision making. The web providing map with general pests and diseases that historically attack that specific area. One university develop web www.opete.info to inform the farmer about the characteristic of some pests and diseases, complete with physical description but lack of image. While both solution help brings the general idea to the farmer, they lack the level of precision that could tell when the farmer sees the pests or diseases. If they could know what pests or diseases that attack their paddy field in real-time, they could make a decision how to address this problem at the same time.

A smartphone is a novel approach for this need because it equipped with computing power, display, and camera. Smartphone adoption rate in Indonesia is 20.7%, and keep increasing year by year. It is common to find a smartphone with a price under RMB 500 in Indonesia, and typical practice for village citizen to buy a smartphone with a system called credit-system in Indonesia, so they take the goods first and able to using it, while they pay monthly the original goods price plus interest fee.

At the same time, advance in computer vision and object recognition, show promising opportunity to address the problem in precision agriculture. In ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [5] that based on the ImageNet dataset have been used as a benchmark in computer vision. The training process of deep learning model is computationally expensive, and it requires high computation power. But the inference process itself cheap in computation, so it could be applied to a smartphone.

To train deep learning model, it requires image dataset to train the model, like ImageNet that contain 14 million images. Or like PlantVillage dataset [6] that have 54,306 images of 14 crop species and 26 diseases (or healthy). But as far as we know, after an extensive literature review, such dataset that freely available that have large paddy pests and diseases image are did not exist.

To address this problem, we create paddy image dataset that has 4,511 images for 13 class paddy pests and diseases.

The method in this paper is a new approach to detect both paddy pests and diseases using deep learning trained and fine-tuned to fit accurately on the dataset. Our contribution is the model that address precision detection for both paddy pests and diseases. Section 2 presents related work; Section 3 presents methodology; Section 4 presents result and discussion; and section 5 conclusions.

2. RELATED WORK

2.1 Agriculture Pests Classification

Pests classification was already done to classify pests in tea [7] utilizing 609 images for 11 classes tea pests that fed into ANN classifier. Author claim achieves 100% correct classification rate.

Then also another work [8] that using Support Vector Machine (SVM) to classify three pests that infected agriculture product leaf from 500 images processed in MATLAB.

There is another work utilizing SVM with MATLAB to detect pests on leaves [9]. SVM method seems reliable to classify 200 images from Google and private repository for 20 class paddy pests [10].

Recent work on paddy pests [11] already utilizing Deep Learning to classify 12 paddy pests that trained from 5,000 image dataset collected from various search engines with multiple languages able to achieve 95% accuracy.

2.2 Agriculture Disease Classification

Plant diseases classification is usually looking at leaf section that infected by diseases, some early work on this topic are using SVM on hyperspectral reflectance [12] to classify disease on sugar beet with three classes of diseases.

Another work [13] classify five classes of diseases from a general plant, using K-Means and Neural Network in MATLAB.

Tea leaf diseases recognition is developed by the author [14] with Neural Network Ensemble. This method able to recognize a pattern in tea leaf that infected by diseases, the author claim to achieve 91% accuracy with 50 image sample.

A team of authors [15] presented deep learning method to classify 13 diseases from 5 plant species, pear, peach, apple, pair, and grapevine. They collect 4,483 images to feed into deep learning model that has final overall accuracy 96.3%.

Meanwhile another method [16] utilizing deep learning model trained by openly available dataset PlantVillage with 54,306 images and 38 classes for 14 crop species. The final accuracy varied from 85.53% to 99.34% for a PlantVillage dataset. When the model evaluated with 121 wild images from search engine and agriculture extension service they could obtain 31.40% overall accuracy.

2.3 Technology for Image Classification

Object recognition using visual features idea already explored by academician as early as 1966. This project called The Summer Vision Project by Massachusetts Institute of Technology. This project divided sub-problem of computer vision into a group of students, with final goal object identification that could categorizing object into their matching class. [17]

In the next decade, 1970, work on computer vision lay a foundation on many algorithms that exist today, including extraction of edges from images, labeling of lines, representation of objects as interconnections of smaller structures, optical flow, and motion estimation. [18]

While studies in 1980 more into mathematics, like the concept of scale-space, the inference of shape from various cues such as shading, texture, and focus, and contour models known as snakes. [19]

Move to 1990, one famous work [20] of an author proposed Neural Network with backpropagation technique. This technique was able to recognize handwritten zip code number accurately. This work brings success and shaping image recognition years after this published.

After that, ImageNet image database [21] developed by a team of authors as the benchmark for image recognition and create Large Scale Visual Recognition Challenge (ILSVRC) from 2010 until recently 2017. The 2012 ILSVRC winner, the author [22] propose Convolutional Neural Network for the first time in image recognition that has significantly lower error compared to the previous winner. Since then Convolutional Neural Network (ConvNet) become standard practice for image recognition.

In the same competition, ILSVRC, another team of authors [23] successfully implemented Deep Learning method that involves deep layers of Convolutional Neural Network in it. This technique made them winning ILSVRC 2015, and the model called ResNet.

2.4 Implementation

A team of authors [24] successfully make Leafsnap mobile application, that can recognize what species of plant is it based on a picture taken on a smartphone that installed this app.

Another implementation in agriculture is presented by SoilCares [25] to recognize and tell soil nutrient condition. Based on a hyperspectral image that analyzed by machine learning to generalize input data and make the prediction model.

The problem showed by previous work only tackle one side of the issue, like they only address pests classification or diseases classification only. No action is solving both in the same model until just recently by a team of an author [26] that implement state-of-the-art Deep Learning technique on 5,000 image datasets that they collect by themselves in Korea, for nine class tomato pests and diseases. And the final result of average precision is 83.06%.

In this work, we implement deep learning model for paddy pests & diseases recognition, driven by needs in Indonesia and deep learning advance recently, especially work done by authors above that show possibility deep learning method applied into our problem. An extensive search of literature review shows no evidence that any researcher already explored paddy pests & diseases recognition with deep learning technique.

3. MATERIALS AND METHOD

The whole process to develop our deep learning model in this study described below, starting with image dataset acquisition required to train deep learning model.

3.1 Dataset

Our dataset has 4,511 images for 13 classes, 9 class paddy pests, and 4 class paddy diseases. 13 categories suggested by agriculture expert from Indonesia based on their experience that this 13 group is the typical problem for paddy harvest loss in Indonesia. All the images collected from the internet, using a query of pests and diseases name in a different language that represents the majority of paddy producers in the world, such as Chinese, English, Japanese, and Bahasa Indonesian. This query of varying word used to search image in various search engine most used in the respective country. Such as for English query we use google.com, for simplified Chinese we use baidu.com while for traditional Chinese we use google.com.tw. For Japanese we use google.co.jp and fresheye.com meanwhile for Bahasa Indonesia we use google.co.id. After downloading and collecting all images, all the images separated into 2 part, train set and test set, train set annotated by agriculture expert from Indonesia, and classify them into 13 classes available based on visual features on the picture. Representation of all class shown in Figure 1. For paddy pests, the features are the size, color, and shape of the pests. For paddy diseases, we could recognize it from the leaf color, shape or other characteristic available as suggested by agriculture expert.

We also add an extra one class for the background image to get more accurate classification because deep learning model should understand to classify pests and diseases from the surrounding. Background image we take from Stanford background dataset [27]. Total images with class background are 5,226 data.

Figure 1. Representation of all class paddy pests & diseases, from left to right as represented in Table 1 from 1 to 13

3.2 Data Augmentation

Data augmentation is needed to prevent overfit problem that caused by small dataset to train deep learning model. We need to augment the dataset collected from the first step to increase dataset size and introduce some variation of distortion in the image. Total size dataset after augmentation shown in Table 1.

Table 1: Dataset for paddy pests & diseases classification

Class	Original	Total after Augmented
(1) Pest, Leptocorisa acuta	708	6,308
(2) Pest, Locusta migratoria	616	5,416
(3) Pest, Nephotettix virescens	110	1,310
(4) Pest, Nilaparvata lugens	374	3,574
(5) Pest, Pomacea canaliculata egg	469	4,068
(6) Pest, Pomacea canaliculata adult	176	1,576
(7) Disease, Pycularia oryzae leaf	529	4,529
(8) Disease, Pycularia oryzae neck panicle	245	2,645
(9) Pest, Sogatella furcifera	226	2,426
(10) Pest, Stemborer adult	388	3,588
(11) Pest, Stemborer larva	228	2,528
(12) Disease, Tungro leaf	117	1,317
(13) Disease, Xanthomonas oryzae	325	2,725
(14) Background images	715	715
	5,226	42,726

We augment the image with these properties:

Rotate 90 degree.

Rotate 270 degree.

Flip horizontally.

Flip vertically.

Random crop 50% area of original image.

The process to do data augmentation is using Augmentor, an image augmentation library in Python for machine learning [28].

3.3 Deep Learning Model

Among several state-of-the-art deep learning frameworks available now, we choose to use Caffe, open source deep learning framework developed by BVLC [29]. We also use pre-trained CaffeNet model bundled with Caffe in this experiment. CaffeNet is variation from AlexNet trained on ImageNet ILVRC2012. For our research, we fine-tune CaffeNet with small train and test image batch size because of limitation in our GPU memory.

CaffeNet architecture has eight learning layers, five convolutional layers and three fully connected layers. Last fully connected layer adjusted to producing our 14 classes instead of original 1,000 classes for ImageNet as described in Figure 2.

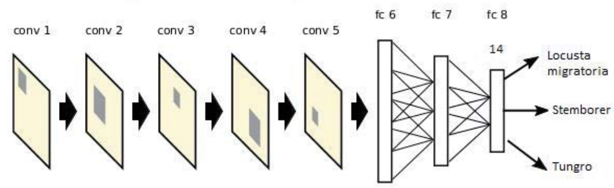

Figure 2. CaffeNet model we use in experiment

We split image dataset 70:30 with 70% for training and 30% for test. For accuracy test, we only consider top 1 result. Because in this experiment, it is essential that we just give one suggestion to paddy farmer about what class of pests or diseases that are attacking their paddy field. Label for classes presented in Table 1.

3.4 Equipment

A single PC used for this experiment, and the deep learning training using Graphics Processing Unit (GPU) mode for pre-trained CaffeNet model takes approximately 3 hours for 30,000 iterations on the machine specified in Table 2.

Table 2: Machine specification

Hardware and software	Specification
(1) Memory	8 Gb
(2) Processor	AMD A10-7850K CPU @ 3.7 GHz x 4
(3) Graphics	GeForce GTX 750 Ti 2 Gb
(4) Operating System	Linux Ubuntu 16.04 64 bits

4. RESULT AND DISCUSSION

The result of experiment presented in this paper related to training entire dataset, both original and augmented image, since deep learning is known to make a better generalization with a bigger dataset.

After fine-tuning hyperparameter of CaffeNet model, 80% accuracy achieved in 5,000 iterations. While training loss keeps decrease and accuracy increase, accuracy starts to saturate until it meets 87% accuracy in 30,000 iterations as suggested in Figure 3.

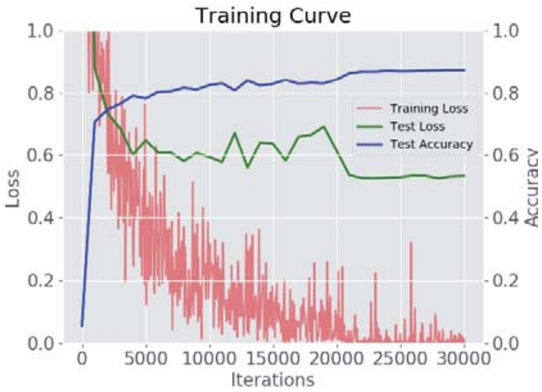

Figure 3. Accuracy of fine-tuned model

Suggested by good practice principle, we should compare our result with some other outcome. During research, we use our dataset image that no one used it until now. And also after an extensive literature review, we found no evidence that anyone has used deep learning to classify both paddy pests and diseases in Indonesia.

But we could compare our result with other methods that using deep learning to identify pests only, disease only or both in different plant variant besides paddy. We see that our result still lack behind. Accuracy improvement could achieve with more iteration, better machine specification and also more fine-tuning experiment.

5. CONCLUSIONS

In this work, we explore a new method using deep learning for paddy pests & diseases classification. To check the feasibility of using automatic tools for helping paddy farmer in Indonesia identify pests & diseases that are attacking their paddy field. The developed model in this paper able to classify 13 classes of paddy pests and diseases with accuracy 87%. We see this accuracy as a proof that automatic classification system for paddy pests & diseases is feasible.

Extension of this study will be on gathering more image with more language query that not explored yet, like the Hindi language, Vietnamese and Tagalog that also represent big paddy producer in Asia. And improving machine specification to handle more image batch to make training faster, even trying more model and fine-tuning parameter to compare which model works best on paddy pests and diseases classification problem. Another extension that we could do is inserting one more category beside pests and diseases, which is a weed. Because weed also make paddy production decrease, while not all plant seeing in the paddy field is a weed, some of the plants are beneficial for the paddy.

This study is the next step after our idea validation in Telkom Indonesia Socio Digi Leaders idea competition. With the end goal to make a mobile app that helps paddy farmer in Indonesia easily detect pests & diseases in their paddy field. And give appropriate solution for their problem, to increase paddy productivity in Indonesia.

6. ACKNOWLEDGMENTS

This work is partially sponsored by the National Basic Research 973 Program of China (No. 2015CB352403), the National Natural Science Foundation of China (NSFC) (61602301, 61632017). Research in this paper also supported by Indonesia Education Endowment Fund (LPDP, Lembaga Pengelola Dana Pendidikan).

7. REFERENCES

[1] J. Maclean, B. Hardy, and G. Hetel, Rice Almanac, 4th edition, International Rice Research Institute, 2013.

[2] “Poverty Report 2017”, 2017, http://www.bps.go.id (in Bahasa Indonesia).

[3] Dobermann A, Witt C, Dawe D, editors. Increasing productivity of intensive rice system through site-specific nutrient management. Enfield, N.H. (USA) and Los Banos (Philippines): Science Publisher, Inc. and International Rice Research Institute, 2004.

[4] S. A. Miller, F. D. Beed, and C. L. Harmon, Plant disease diagnostic capabilities and networks, Annual Review of Phytopathology, vol. 47, pp. 15-38, 2009.

[5] Russakovsky O et al, ImageNet Large Scale Visual Recognition Challenge, International Journal of Computer Vision (IJCV), 115(3):211-252.

[6] Hughes DP, Salathe M, An open access repository of images on plant health to enable the development of mobile disease diagnostic. CoRR abs/1511.08060, 2015.

[7] R. K. Samantha, I. Ghosh, Tea insect pest classification based on artificial neural networks, International Journal of Computer Engineering Science (IJCES), vol. 2 no. 6, 2012.

[8] Journal of Machine Learning and Computing (IJMLC), vol. 4 no. 1, 2014.

[9] R.U. Rani, P. Amsini, Pest Identification in Leaf Images using SVM Classifier, International Journal of Computational Intelligence and Informatics (IJCII), vol. 6 no. 1, 30-41, 2016

[10] M. Manoja, J. Rajalakshmi, Early detection of pest on leaves using support vector machine, International Journal of Electrical and Electronics Research (IJEER), vol. 2 no. 4, pp. 187-194, 2014.

[11] K. Venugoban, A. Ramanan, Image classification of paddy field insect pest using gradient-based features, International

[12] Liu, Z. et al. Localization and classification of paddy field pest using a saliency map and deep convolutional neural network. Sci. Rep. 6, 20410; doi: 10.1038/srep20410, 2016.

[13] T. Rumpf et al. Early detection and classification of plant diseases with support vector machine based on hyperspectral reflectance. Computers and Electronics in Agriculture, vol. 74, 91-99, 2010.

[14] H. Al-Hiary et al. Fast and accurate detection and classification of plant diseases. International Journal of Computer Application (IJCA), vol. 17 no. 1, 31-38, 2011.

[15] B. C. Karmokar. Tea leaf diseases recognition using neural network ensemble. International Journal of Computer Application (IJCA), vol. 114 no. 17, 27-30, 2015.

[16] S. Sladojevic et al. Deep neural networks based recognition of plant diseases by leaf image classification. Computational Intelligence and Neuroscience, vol. 2016.

[17] Papert, Seymour. "The Summer Vision Project." MIT AI Memos (1959 - 2004), 1966.

[18] Richard Szeliski. Computer Vision: Algorithms and Applications. Springer Science & Business Media. pp. 10–16. ISBN 978-1-84882-935-0, 2010.

[19] Takeo Kanade. Three-Dimensional Machine Vision. Springer Science & Business Media. ISBN 978-1-4613-1981-8, 2012.

[20] LeCun, Y., et al. Backpropagation applied to handwritten zip code recognition. Neural Computation 1:541–51, 1989.

[21] O. Russakovsky et al. ImageNet large scale visual recognition challenge. International Journal of Computer Vision (IJCV), vol. 115 no. 3, 211-252, 2015.

[22] Alex K., Ilya S., G. E. Hinton. ImageNet classification with deep convolutional neural networks. Advances in neural information processing systems. 2012.

[23] Kaiming He et al. Deep Residual Learning for image recognition. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770-778, 2016.

[24] Kumar N, Belhumeur P, Biswas A, Jacobs D, Kress W, Lopez I, Soares J. Leafsnap: a computer vision system for automatic plant species identification. In: Fitzgibbon A..Lazebnik S, Perona P, Sato Y, Schmid C, editors. Computer vision–ECCV. Lecture notes in computer science, vol 7573. Berlin: Springer; p. 502–16, 2008.

[25] "SoilCares: Putting the knowledge in the hands of the farmers", 2017, http://www.soilcares.com.

[26] A. Fuantes et al. A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors, 17, 2022; doi:10.3390/s17092022. 2017.

[27] S. Gould, R. Fulton, and D. Koller, Decomposing a scene into geometric and semantically consistent regions, in Proceedings of the 12th International Conference on Computer Vision (ICCV '09), pp. 1-8, kyoto, Japan, October 2009.

[28] Marcus D. Bloice, Christof Stocker, and Andreas Holzinger, Augmentor: An Image Augmentation Library for Machine Learning, arXiv preprint arXiv:1708.04680, https://arxiv.org/abs/1708.04680, 2017.

[29] Y. Jia, E. Shelhamer, J. Donahue et al. Caffe: convolutional architecture for fast feature embedding, in Proceedings of the ACM Conference on Multimedia (MM'14), pp.675-678, ACM, Orlando, Fla, USA, 2014.