A Deep Learning Approach for Determining Effects of Tuta Absoluta in Tomato Plants

Denis P. Rubanga *1, Loyani K. Loyani 2, Mgaya Richard 3 & Sawahiko Shimada 1
1 Department of Agricultural Engineering
Tokyo University of Agriculture, Tokyo, Japan
2 School of Computational & Communication Science & Technology & Engineering,
The Nelson Mandela African Institution of Science & Technology, Arusha, Tanzania.
3Department of Engineering Sciences & Technology,
Sokoine University Agriculture, Morogoro, Tanzania.
*denispastoty@gmail.com

Abstract

Early quantification of Tuta absoluta pest’s effects in tomato plants is a very important factor in controlling and preventing serious damages of the pest. The invasion of Tuta absoluta is considered a major threat to tomato production causing heavy loss ranging from 80 to 100 percent when not properly managed. Therefore, real-time and early quantification of tomato leaf miner Tuta absoluta, can play an important role in addressing the issue of pest management and enhance farmers’ decisions. In this study, we propose a Convolutional Neural Network (CNN) approach in determining the effects of Tuta absoluta in tomato plants. Four CNN pretrained architectures (VGG16, VGG19, ResNet and Inception-V3) were used in training classifiers on a dataset containing health and infested tomato leaves collected from real field experiments. Among the pretrained architectures, experimental results showed that Inception-V3 yielded the best results with an average accuracy of 87.2 percent in estimating the severity status of Tuta absoluta in tomato plants. The pretrained models could also easily identify High Tuta severity status compared to other severity status (Low tuta and No tuta).

1 Introduction

The current world population is expected to reach 9.8 billion in 2050 (United Nations, 2017). To ensure global food security and meet the future demand for high quantity and quality food, the agricultural industry must be much efficient and robust. Sub-saharan small scale farmers rely on tomatoes to earn income. However, tomato productivity is threatened by the invasion of an exotic pest known as tomato leaf miner Tuta absoluta (Zekeya et al., 2017). The pest has become a major drawback to tomato production causing heavy losses in tomato produce ranging from 80% to 100% (Desneux et al., 2011; Chidege et al., 2016) (See Figure.1). Since 2008, the pest has invaded and spread to 75% of African countries causing huge economic losses (Guimapi et al., 2016). Nevertheless, the extension service to provide farmers with appropriate knowledge about plant disease and pest managements are limited (Maginga et al., 2018).

Despite existence of various ways of controlling tomato pests, there has not been an efficient mechanism to determine the severity of T.absoluta’s effects at early stages before causing great yield loss to the farmers. Inspired by the advancement and promising results of deep learning techniques in image-based plant pest and disease recognition, this research proposes the use of Convolutional Neural Network (CNN) model to determine the severity status of T.absoluta’s damage on tomato plants at early stage of tomato growth. This will enhance farmers’ intelligently informed decisions in controlling the pest and improve tomato productivity in order to rescue farmers from losses they incur every year.
Figure 1: Larvae, the most dangerous stage of *Tuta absoluta*’s life cycle. (a) Tomato leaf with *T. absoluta* mine (b) *T. absoluta* severe damage on our in-house tomato field (c) Affected tomato fruits (d) Damaged tomato fruit on market.

2 RELATED WORKS

The advances in computer vision and machine learning techniques such as deep learning and specifically Convolutional Neural Networks (CNN) have presented promising and impressive results in tasks such as identification and classification of a diverse range of plant diseases and pests (Singh et al., 2016). For instance, Brahimi et al. (2017) presented deep models (AlexNet and GoogLeNet), trained using a large dataset of 14,828 images to identify 9 tomato diseases. Also, Ferentinos (2018) used several deep models (AlexNet, GoogLeNet and VGG) in recognizing 58 diseases from a dataset of 87,848 leaf images of different plants from PlantVillage repository (Hughes et al., 2015). Zhang et al. (2018) proposed pretrained CNN models to identify 8 tomato diseases from an open access repository of 5550 images. Liang et al. (2019) proposed a multitasking system consisting of ResNet50 architecture capable to diagnose diseases, recognizing the plant species and estimating the severity of diseases using PlantVillage dataset (Hughes et al., 2015). Other works include automatic and multi-task systems based on CNN for classification task (Esgario et al., 2020; Wang et al., 2017).

The aforementioned works address plant disease problems. However, few works have focused on estimating plant pest stress severity challenges. Plant stress severity have been limited to plant diseases. Some of these works such as Wang et al. (2017), Brahimi et al. (2017) and Ferentinos (2018) used images from online repositories, that do not reflect the real-life situation and put these model’s performance into questions that could limit their applicability in real field situations.

Our research, contributes to the very few works on estimating tomato plant pest severity. To the best of our knowledge, this first novel work proposes approaches in determining severity status of *T. absoluta*’s effects on tomato plants. With the lack of image data, we established a data collection strategy and collected our own dataset from the real field. We propose a deep learning-based approach for determining the effects of *T. absoluta* at early stages of tomato plant’s growth. The study will help farmers and extension officers to make intelligently informed decisions that could improve tomato productivity and rescue farmers from the losses they incur every year.

3 MATERIAL AND METHODS

3.1 DATASETS

Four (4) In-house data collection works were conducted in two of the major areas prone to *T. absoluta* infestation (Arusha and Morogoro - Tanzania) as summarized in Table. 1. The table shows factors that were put into consideration to have a vast diverse dataset of the real field situations i.e regions of the country that are highly infested with *T. absoluta*, crop cycle season, mainly grown tomato varieties and mainly practiced farming systems. We planted healthy tomato seedlings (free from other diseases and pests), inoculated some plants on a range of 2 to 8 *T. absoluta* larvae per plant on the second day after transplanting and on a daily basis took pictures of every plant between 08:00 and 10:00 A.M consecutively for two weeks. For this work, we only picked 1384 *T. absoluta* infested plant images, separated them into two categories of *T. absoluta* damage severity status examined by agricultural expert as Low Tuta (plants with less than 3 *T. absoluta*) and High Tuta (more than 3 *T. absoluta*). A total of 692 images of Low Tuta, 692 of High Tuta images and 2768 images of No Tuta
from the whole dataset was used, finally making three classes i.e No Tuta, low Tuta and high Tuta as shown in Figure 2.

| Table 1: Data collection set-up and factors considered for each experiment |
|---------------------------------|---------|--------|-------|-----------------|---------|
| **duration** | **season** | **region** | **variety** | **farming system** | **images** |
| Aug - Nov 2018 | dry | north | 1 | drip, furrow, bund | 2248 |
| Jan - May 2018 | dry | north | 3 | drip | 2012 |
| Oct - Dec 2019 | dry/wet | north | 3 | drip | 4060 |
| Jan - Apr 2020 | wet | east | 2 | drip, furrow, bund | 2916 |

To reduce the bias due to imbalance data (our dataset has more No Tuta images), 10% of the images were held as test set, and the remaining 90% were sub-divided into training and validation sets in the ratio of 85:15. Also, No Tuta images were divided into 4 clusters of images while retaining 10% for testing. Therefore making four datasets each with a total of 1623 for training, 230 images for validation and 218 for testing.

![Figure 2: Some images collected from field showing damage status of T. absoluta.](image)

**METHODS**

The main target of this work was to be able to identify *T. absoluta* damaged tomato plant severity status that could help to make clear distinction between the three classes. We therefore, choose four CNN architectures; VGG16, VGG19 (Simonyan & Zisserman 2014), ResNet50 and Inception-V3 (Szegedy et al. 2016) to train classifiers on our dataset containing the three tomato severity status.

**IMAGE PREPROCESSING.**

To increase image number and reduce the variation within each image for *T. absoluta* severity status classification, augmentations were performed on both the training and validation. All images were first resized to 256 x 256 pixels for VGG16, VGG19 and ResNet50 and 384 x 384 pixel for Inception-V3 and randomly augmented for each epoch of training. Each image was also randomly rotated in the range of (-360, +360), degrees also randomly sheared in the range of 0.3 To account for illumination variance, pixel intensity was randomly shifted within the range (-25, +25), shifting all colour channels uniformly. In addition, pixel intensity was randomly scaled within the range of (0.75, 1.25). The images were also zoomed within (0.5,1) range. Finally, the images were flipped horizontally, cropped back to 224 x 224 pixels for VGG16, VGG19 and ResNet50 for 299 x 299 pixels required for architecture’s input layer (Perez & Wang 2017).
TRAINING OUR CLASSIFIER

We used four ImageNet [Deng et al., 2009] pretrained architectures VGG16, VGG19, ResNet50 and InceptionV3 as classifiers. The fully connected layer for each pretrained architecture was replaced by the new layer (3-class classifier for our dataset). We trained our classifiers using 50 epochs with a batch size of 16 and using Keras [Chollet, 2015] implementation of Adam [Kingma & Ba, 2014], a first-order gradient-based method for stochastic optimization. The initial learning-rate (lr) was set to lr=10e4, and was halved every time the validation loss did not decrease after 32 epochs in batches of 16 images, and aborted if the validation loss did not decrease after 32 epochs. The model with the smallest running validation loss was continuously saved, in order to re-start the training after an abortion. In such cases, training was repeated with the initial learning rate lr=0.5x10e4. With the four subset dataset, we run all the four models on each of the subsets.

IMPLEMENTATION

The experiments were performed on Ubuntu workstation, pre-installed with Ubuntu 18.04 equipped with one Intel Core i9-9900K 3.6 GHz CPU (64 Gb RAM) accelerated by one GeForce RTX 2080Ti Graphical Processing Unit (GPU) (12 GB memory). We trained 50 epoch for each model and it took an average of 41 minute on a complete model training powered by Keras deep learning library using Tensorflow [Abadi et al., 2016] as backend. In total, about 13 hours were required to run training on the 16 runs of the models i.e 4 runs for each of the 4 CNN architecture.

RESULTS AND DISCUSSION

We used evaluation metrics F1–score, precision and recall accuracy and the overall evaluation metrics was a result of averaging over the 4 runs on each dataset of each CNN architecture as summarized in table. 2.

The main goal was severity status of T.absoluta determination. In term determining the severity status images, all models precision accuracy was highest in identifying High Tuta images i.e 90.5%, 90.3% and 91.5%. VGG16 and Inception-V3 had the highest recall accuracy i.e 96.5% on No Tuta images. Also all models had F1-score highest for High Tuta images. All the four models had the lowest evaluation metrics accuracy in determining Low Tuta images. Among the trained models, Inception-V3 model had the highest accuracy of 87.2% on the test set.

Table 2: Four pretrained model evaluation metrics accuracy precision (PRC), recall (RCL), F1–score (F1-S) accuracy and Overall average accuracy and loss on testing dataset.

| Severity   | VGG16   | VGG19   | ResNet50 | Inception-V3 |
|------------|---------|---------|----------|--------------|
|            | PRC     | RCL     | F1-S     | PRC          | RCL     | F1-S     | PRC     | RCL     | F1-S     | PRC     | RCL     | F1-S     |
| No Tuta    | 0.887   | 0.965   | 0.918    | 0.885       | 0.918       | 0.918    | 0.878   | 0.900   | 0.890    | 0.895   | 0.935   | 0.915    |
| Low Tuta   | 0.760   | 0.355   | 0.448    | 0.708       | 0.538       | 0.595    | 0.500   | 0.445   | 0.470    | 0.660   | 0.518   | 0.575    |
| High Tuta  | 0.905   | 0.940   | 0.920    | 0.905       | 0.948       | 0.920    | 0.903   | 0.910   | 0.905    | 0.915   | 0.930   | 0.923    |
| Average Accuracy | 0.871 | 0.783 | 0.839 | 0.871 | 0.783 | 0.839 | 0.871 | 0.783 | 0.839 |
| Loss       | 0.152   | 0.258   | 0.334    | 0.205       |             |          |         |         |          |         |         |

4 CONCLUSION AND FUTURE WORK

This paper proposes pretrained deep learning models for determining severity status of T.Absoluta tomato damages plants. For the accomplishment of this work, we used images containing health and T.Absoluta infested tomato plant images collected from in-house experiments. Among the pretrained models, we showed that Inception-V3 model performed best, achieving an averaged accuracy of 87.2% on the test set compared to other models.

Among, the three severity status, all models could more easily identify High tuta images than other severity status based on the evaluation metrics. The comparison of the evaluation metrics on each of the severity status reveals that it is a bit harder to detect Low Tuta than High Tuta and No Tuta images. With the goal of early identification of T.Absoluta severity status in tomato plants, we clearly show the success of using deploying CNN models in such tasks. High Tuta severity status
being determined as early as the first two weeks of plant growth cycle is important to reduce severe
loss that are accounted when no preventive and management practices are not done.

In future work, we intend to experiment on other CNN based models for task such as instance
segmentation for localization of T.Absoluta images. In fact, ongoing work includes, annotation of
images at infested plant based and localised T.Absoluta patches on the plant leaves for instance
segmentation tasks.

REFERENCES

Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S
Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, et al. Tensorflow: Large-scale machine
learning on heterogeneous distributed systems. arXiv preprint arXiv:1603.04467, 2016.

Mohammed Brahini, Kamel Boukhalfa, and Abdelouahab Moussaoui. Deep learning for tomato
diseases: classification and symptoms visualization. Applied Artificial Intelligence, 31(4):299–
315, 2017.

Maneno Chidege, Shakil Al-zaidi, Nayem Hassan, Abisgold Julie, Eliaililia Kaaya, and Sheila Mro-
goro. First record of tomato leaf miner tuta absoluta (meyrick)(lepidoptera: Gelechiidae) in tan-
zania. Agriculture & Food Security, 5(1):17, 2016.

Francois Chollet. Keras: Deep learning for humans, 2015. URL https://github.com/
keras-team/keras. Last accessed 16 February 2020.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hi-
erarchical image database. In 2009 IEEE conference on computer vision and pattern recognition,
pp. 248–255. Ieee, 2009.

Nicolas Desneux, María G Luna, Thomas Guillemaud, and Alberto Urbaneja. The invasive south
american tomato pinworm, tuta absoluta, continues to spread in afro-eurasia and beyond: the new
threat to tomato world production. Journal of Pest Science, 84(4):403–408, 2011.

José GM Esgario, Renato A Krohling, and José A Ventura. Deep learning for classification and
severity estimation of coffee leaf biotic stress. Computers and Electronics in Agriculture, 169:
105162, 2020.

Konstantinos P Ferentinos. Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145:311–318, 2018.

Ritter YA Guimapi, Samira A Mohamed, George O Okeyo, Frank T Ndjomatchoua, Sunday Ekesi,
and Henri EZ Tonnang. Modeling the risk of invasion and spread of tuta absoluta in africa. Ecological Complexity, 28:77–93, 2016.

David Hughes, Marcel Salathé, et al. An open access repository of images on plant health to enable
the development of mobile disease diagnostics. arXiv preprint arXiv:1511.08060, 2015.

Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint
arXiv:1412.6980, 2014.

Qiaokang Liang, Shao Xiang, Yucheng Hu, Gianmarc Coppola, Dan Zhang, and Wei Sun. Pd2se-
net: Computer-assisted plant disease diagnosis and severity estimation network. Computers and electronics in agriculture, 157:518–529, 2019.

Theofrida J Maginga, Thibault Nordey, and Mussa Ally. Extension system for improving the man-
agement of vegetable cropping systems. 2018.

Luis Perez and Jason Wang. The effectiveness of data augmentation in image classification using
deep learning. arXiv preprint arXiv:1712.04621, 2017.

Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image
recognition. arXiv preprint arXiv:1409.1556, 2014.
Arti Singh, Baskar Ganapathysubramanian, Asheesh Kumar Singh, and Soumik Sarkar. Machine learning for high-throughput stress phenotyping in plants. *Trends in plant science*, 21(2):110–124, 2016.

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2818–2826, 2016.

United Nations. World Population Prospects: The 2017 Revision, Key Findings and Advance Tables. 2017. [https://esa.un.org/unpd/wpp/publications/files/wpp2017_keyfindings.pdf](https://esa.un.org/unpd/wpp/publications/files/wpp2017_keyfindings.pdf).

Guan Wang, Yu Sun, and Jianxin Wang. Automatic image-based plant disease severity estimation using deep learning. *Computational intelligence and neuroscience*, 2017, 2017.

Never Zekeya, Musa Chacha, Patrick A Ndakidemi, Chris Materu, Maneno Chidege, and Ernest R Mbega. Tomato leafminer (tuta absoluta meyrick 1917): A threat to tomato production in africa. *Journal of Agriculture and Ecology Research International*, pp. 1–10, 2017.

Keke Zhang, Qiufeng Wu, Anwang Liu, and Xiangyan Meng. Can deep learning identify tomato leaf disease? *Advances in Multimedia*, 2018, 2018.