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A simple Convolutional Neural Network Architecture for monitoring *Tuta absoluta* (Gelechiidae) infestation in tomato plants.

Sixbert K. Mourice[1]*, Festo Joseph Mlebus[1], Kadeghe G. Fue[2]

[1]Department of Crop Science and Horticulture

P. O. Box 3005, Chuo Kikuu, Morogoro, Tanzania.

[2]Centre for Information and Communication Technology

P.O. Box 3218, Chuo Kikuu, Morogoro Tanzania.

*corresponding author: sixbert.mourice@sua.ac.tz

Abstract

Tomato leaf miner (*Tuta absoluta* (Gelechiidae)) is a serious tomato insect pest in Tanzania, and its management or control still posess significant challenge. If left uncontrolled, the loss inflicted by the miner can be as high as 100%. Successful management of the pest may leverage on an integrated pest management (IPM) approach which, requires high throughput data on damage signs over space and time. This needs, in turn, a robust technique for pest monitoring. This study uses a deep learning technique to detect infestation symptoms of *T. absoluta* on tomato plants. The technique is rapid, automated and doesn't require trained or experienced personnel. An experiment was carried out at Sokoine University of Agriculture (SUA), where two sets of tomato plants (cv. Asila F1) were planted in a screen house and in an open field. High-quality images of the tomato leaves were captured from both sets at seven days intervals for 70 days following transplanting. More images were collected from tomato gardens around Morogoro town. Collected images were labeled as being infested or non-infested. A simple convolution neural network (CNN) architecture with four convolution layers, three pooling layers, one flat layer and one dense layer, powered by Keras library and python's Tensorflow backend, was developed in R-Software. The model accuracy was 90% on training and 82% on test data sets. This study suggests that the model can accurately identify *T. absoluta* infestation in tomato plants to a considerable extent. An in-depth discussion of the technique is provided in the paper.

Keywords: Machine vision, Deep Learning, Neural Networks, Lepidoptera, Artificial Intelligence

Introduction

Tomato is one of the most important vegetable crops in Tanzania, primarily as a source of income and livelihood and as food due to its high content of phenolic compounds, carotenoids, vitamins and glycoalkaloids, essential for prevention of chronic degenerative disorders in humans (Chaudhary *et al*., 2018). The tomato subsector is apparently dominated by small-scale farmers, whose yields range from 2.2 tons/ha to 16 tons/ha, far below the potential of 40 t/ha (Msogoya and Mamiro, 2016). Pests and diseases are among the most significant barriers to achieving high tomato productivity (Aloyce *et al*., 2019; Materu and Losujaki, 2019). Lately, the tomato leaf miner (*Tuta absoluta* (Gelechiidae)) has been acknowledged as a severe tomato insect pest in the Eastern African region, capable of inflicting 100% loss if left uncontrolled (Illakwahhi and Srivastava, 2017; Esther *et al*., 2019). *T. absoluta* was first reported in northern Tanzania in 2014 (Chidege *et al*., 2016) and has, since then spread all over the country. Nevertheless, its management or control still pose considerable challenge mainly because of its prolific reproduction nature and concealment of larvae which feed under the plant tissues. Several studies have reported several approaches to control *T. absoluta,* including the use of insecticides (Rwomushana *et al*., 2019), natural enemies and parasitoids (Soares *et al*., 2019; Zekeya *et al.*, 2019) or integrated pest management (IPM) (Illakwahhi and Srivastava, 2017).

IPM approaches have been reported to be promising in the management of *T. absoluta* scourge. However, IPM entails comprehensive crop pest monitoring to provide growers with a practical decision-making tool (Preti *et al*., 2021). The pest monitoring data can feed into pest prediction models for forecasting the next insect outbreak. A wide range of techniques for insect monitoring exists, including traps and assessing the visual signs of damage (Preti *et al*., 2021). In all cases, trained personnel have to directly visit the observation points, resulting in increased costs, inefficiency, and limited sample size. Besides, the correctness of monitoring depends on the knowledge and experience of the technician and therefore prone to subjectivity.

As a leap step towards monitoring *T. absoluta*, we developed a computer vision tool for detecting visual damage signs of the pest on tomato leaves based on images taken by cameras. While traditional *T. absoluta* monitoring involves sending out technicians to the field to collect data, the current study presents a deep learning approach to detect the presence or absence of pests. If integrated into a smartphone application, farmers and other persons can use the tool to send real-time data regarding infestation status to the organizations responsible for IPM or plant protection services. This is important because there is a considerable potential for cross-analysis and a basis for pest outbreak prediction when coupled to other data types.

Deep learning is a part of machine learning techniques that, when presented with data, learn all the features about it in one pass without the need for feature engineering by a human expert. Unlike in other techniques (shallow learning), which require transformation of input data into one or two representation spaces through simple transformations such as support vector machine or decision trees, feature engineering is automated in deep learning. Concise accounts of the deep learning approach have been given by Deng and Yu (2014), Rusk (2016), and Paszke *et al*. (2019). Convolutional neural network (CNN) is an extension of the deep learning technique, getting this name from mathematical linear operation between matrixes called convolution (Albawi *et al*., 2017). CNN has wide applications, especially in image data classification, computer vision (Khan *et al*., 2018), and in natural language processing (NLP) (Yin *et al*., 2017). A simplified treatment of CNN techniques is provided by O’Shea and Nash (2015).

CNN architectures in plant diagnostics leverage the distinctive appearance of diseased or infested plant organs instead of those free from disease or insects. Considerable successes have been reported over the use of CNN models in plant disease/insect damage diagnostics. Sladojevic *et al*. (2016) applied a pre-trained CaffeNet CNN architecture to detect about 13 types of plant diseases based on leaf image classification with an average accuracy of 96.3%. Zhang *et al*. (2018) implemented such CNN architectures as AlexNet, GoogLeNet and ResNet to identify the tomato leaf diseases, where ResNet was considered the best among all the architectures used. Arsenovic *et al*. (2019) proposed PlantdiseaseNet CNN architecture to detect diseases in real agricultural field, achieving an accuracy level of 93.4%. Remarkably few studies have dealt with *T. absoluta* detection within the context of CNN techniques. Mkonyi *et al*. (2020) compared pre-trained CNN architectures, namely VGG16, VGG19 and ResNet50 in terms of their performance metrics in detecting *T. absoluta* infestation in tomatoes, where VGG16 attained the highest accuracy of 91.9%. Rubanga *et al*. (2020) implemented four pre-trained CNN architectures (VGG16, VGG19, ResNet and Inception-V3), where Inception-V3 achieved the highest accuracy (87.2%) in classifying *T. absoluta* infested from non-infested tomato leaves. Unlike in the reported studies above, our approach is unique since we use a custom-built CNN architecture to detect *T. absoluta* damage signs in tomato plants under both controlled and field conditions. The custom-built CNN model allows flexibility for adapting specific contexts related to *T. absoluta* infestation and can work in a low volume of training data sets.

The objective of this study was to develop a machine vision model for the detection of *T. absoluta* infestation in tomato fields. Specifically, a simple convoluted neural network (CNN) model was developed, trained, validated and tested for its ability to classify the presence or absence of damage signs of *T. absoluta* exhibited by burrows on tomato leaves.

The rest of this paper is organized as follows: the materials and methods section, results discussion and the conclusion section winding the paper.

Materials and Methods

An experiment was carried out at Sokoine University of Agriculture (SUA) within the Horticulture Unit (Morogoro Urban), where two sets of tomato plants (cv. Asila F1) were planted. One set of 10 plants in 4-litre pots was grown in the screen house, and another set of ten plants was grown in the open field. The screen house set was free from *T. absoluta* infestation, unlike the open field set, which was severely infested as evidenced by adult moths obtained from sweep net trappings conducted during the experiment. A digital camera (Nikon COOLPIX AW120) was used to capture high-quality images of the tomato plant leaves at seven days interval for the next 70 days after transplanting. In addition, images of tomato plant leaves were collected from tomato gardens around Morogoro town at Mazimbu (Morogoro Urban), Sangasanga and Mlali villages in Mvomero District (Fig 1). Collected images were labeled as being infested (if there were burrow lines) or non-infested if there were none. Therefore, a total of 2,600 images were collected. In each class, 80% of the images were allocated for training and validation while 20% was used to test a deep learning model.

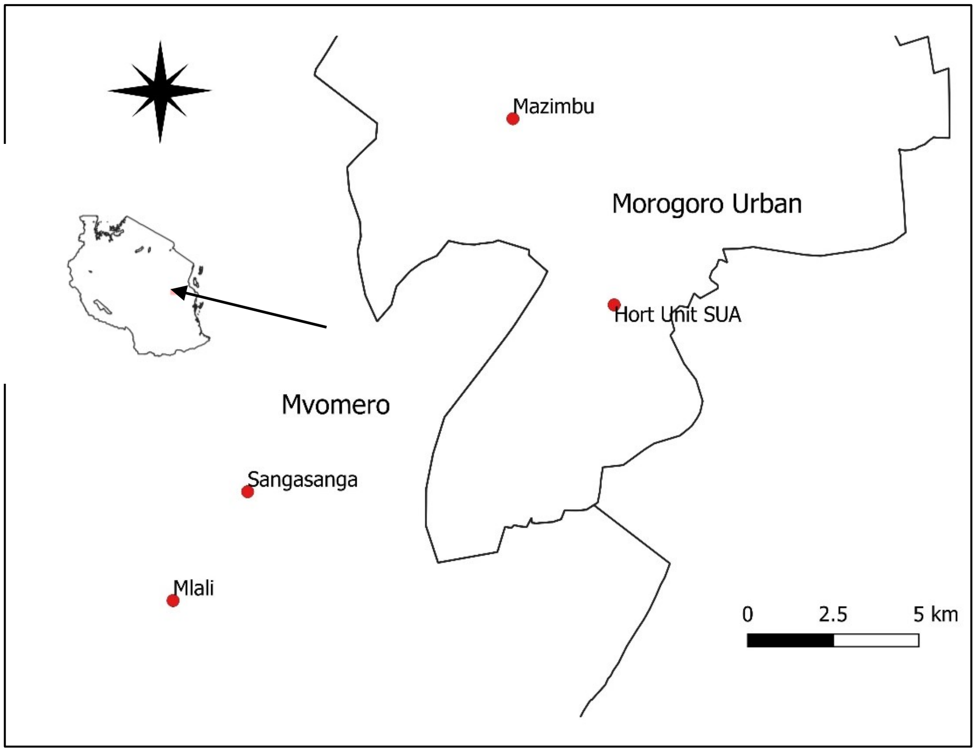

Figure 1 Map of Tanzania (inset), Mvomero District, and Morogoro Urban. Red dots indicate locations where images for training, validation and testing were collected from

CNN architecture

Input images were resized to 400*400 pixels and assigned to categorical labels of 0 and 1 (infested and non-infested, respectively). The CNN model consisted of four convolutional, three pooling, and fully connected layers (Fig 2). A 3x3 convolutional kernel was slid over the width, height, and depth (spectral bands within the image) and then passed to a non-linear activation function, rectified linear unit (ReLU), which returns values for input greater than 0, 0 otherwise (Equation 1) and its' derivative (Equation 2) (Agarap, 2018).

$$gR_{yk\prime} = \max(0, yk') \text{ --1}$$

$$g'R_{yk'} = \begin{cases} 1 \; y_{k\prime} > 0 \\ 0 \; y_{k'} < 0 \end{cases} \text{ ---2}$$

A stride (a space step over which a convolutional kernel slides over an input layer) of 1 was used to ensure more overlaps between the receptive fields. A 2x2 maximum pooling window was employed to downsample (reduce the dimensionality) the feature maps. The filter counts were less in initial layers to avoid model overfitting, increasing in deeper layers as follows: 32x32 for first convolutional layer, 64x64 for the second convolutional layer, 128x128 for third and fourth convolutional layers and 256x256 for the one-dimensional fully connected (FC) layer. A *softmax* activation function (Equation 3) (Wang *et al*., 2018) was used in the FC layer for binary classification of the feature maps. Model overfitting, which would have hindered the CNN model from performing plausibly due to the small size of the training dataset, was dealt with a dropout technique (Srivastava *et al*., 2014).

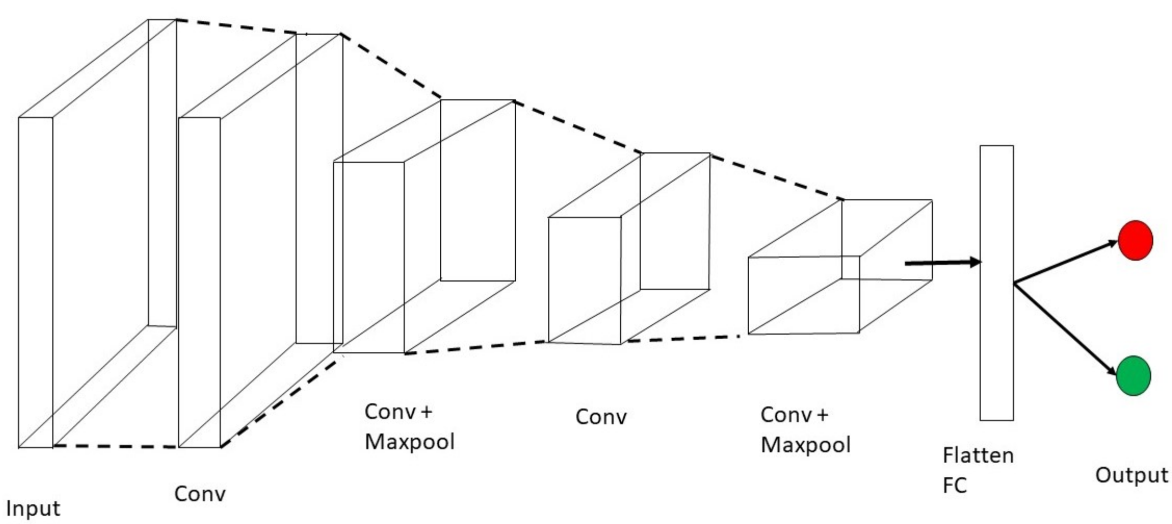

Figure 2. Illustration of a Ssimple CNN architecture ***(Author creation)***

$$f(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}} \; (i = 1,2, \ldots, N) \text{ --3}$$

where $x_1, x_2, ..., x_N$ are the input values of the FC layer, and the output values $f(x_i)$ represents the probability that the sample belongs to the i^{th} category. The CNN architecture was run under the Keras library (Arnold, 2017) and Python's TensorFlow distribution backend (Dillon *et al.*, 2017) in an R-environment (R Core Team, 2020). The CNN model had four convolution layers, three pooling layers (no parameters for this layer), one flat layer and one FC layer with a total of 36,258,851 parameters. A CNN architecture works as an information distillation pipeline where the raw RGB images are continually transformed so that irrelevant information is filtered out. In contrast, useful information is magnified and refined (Figure 3). The model training was run on a Dell Precision Tower 7910 Workstation and took about 26 hours to complete.

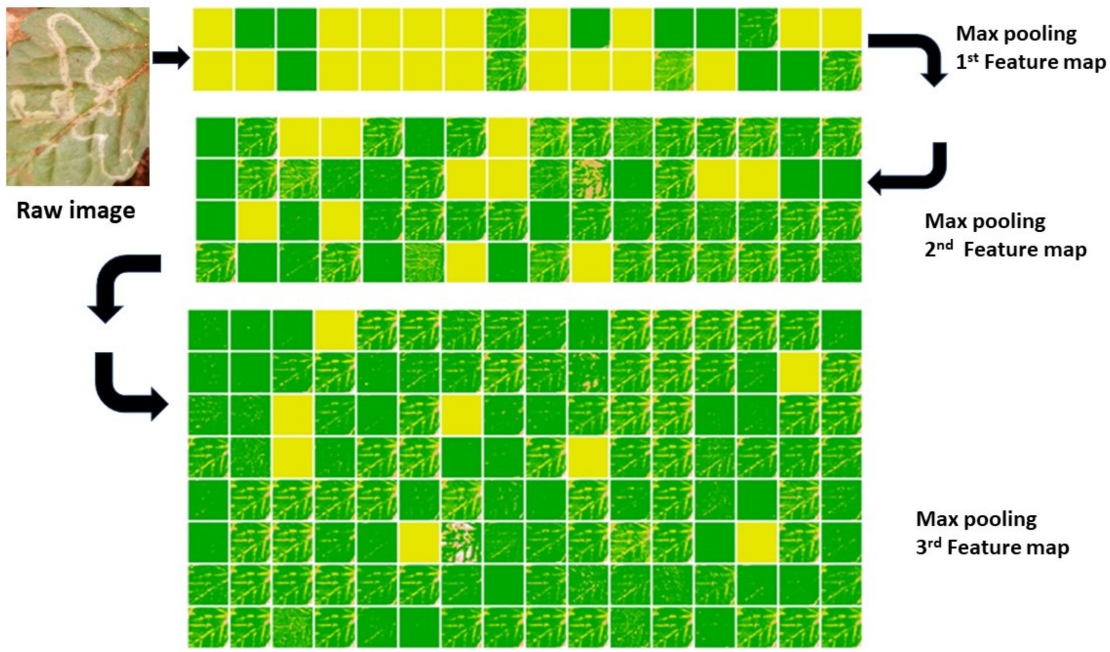

Figure 3 Features map extracted from the raw image by CNN architecture. The first feature map retains most features of the raw image, whereas the 3rd feature map carries less of the visual content of the image but more of the information that is related to the class of the image

CNN architecture performance metrics

The CNN architecture's performance was evaluated based on an overall accuracy obtained over three model runs (Equation 4)

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{-- } 4$$

where TP = "True Positive", number of infested and classified as infested, TN = "True Negative", number of non infested images and classified as non-infested. FP = "False Positive", number of non-infested and classified as infested and FN = "False Negative", number of infested images and cclassified as non-infested.

Results

CNN training and validation

Model training and validation was carried out in 60 epochs (iterations), where the training and validation losses decreased up to the 5th and 20th epochs, respectively (Fig 4). On the other hand, training and validation accuracy attained maximum values at the tenth and 15 epochs, respectively. The model attained a training loss of 0.8288 whereas its training accuracy was 90%, meaning the model placed most (90%) of the images into their appropriate classes.

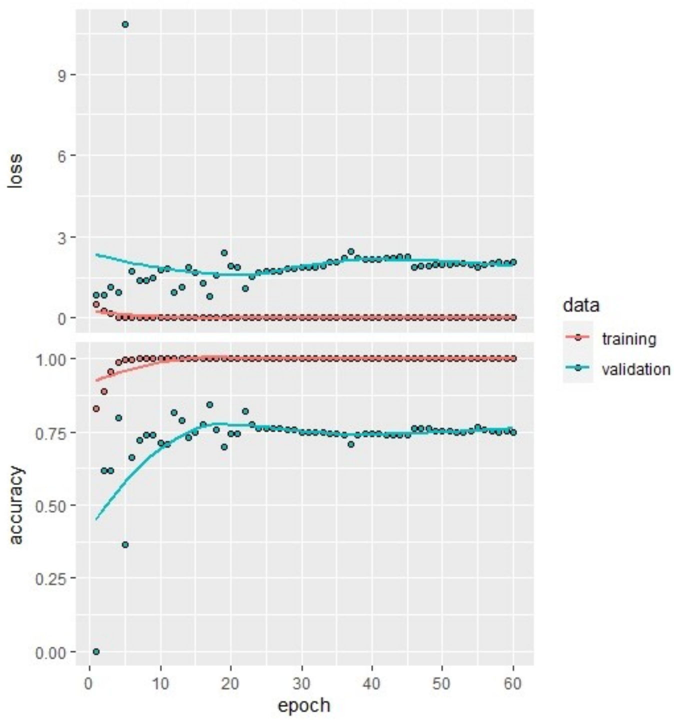

Figure 4 Training and validation metrics of the simple CNN model for detection of Tuta absoluta infestation

CNN testing

During training, 60 epochs were applied in the training of the CNN model. An accuracy of 82% was obtained when the model was presented with the test data set.

CNN predictions

For practical purposes, the trained CNN was used to make predictions over 200 image dataset, which was not among the training, validation or testing sets, as presented in a confusion matrix (Figure 5). The model was confident for 79 images, less confident in 15 images within the non-damaged class sample, and confident with 85 images and less confident with 21 images in the damaged class sample.

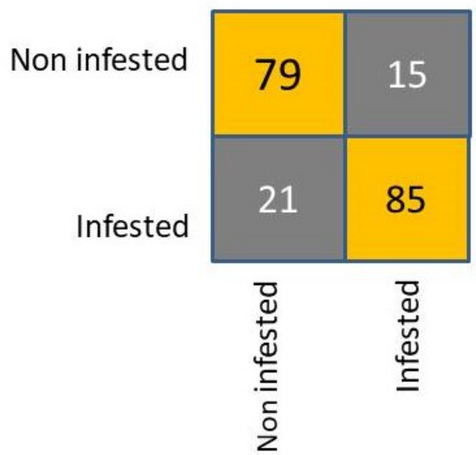

Figure 5. Confusion matrix indicating CNN architecture's prediction confidence for 100 images from infested label and 100 images from non-infested label

Discussion

This is one of few studies related to the use of CNN architecture to monitor *T. absoluta* infestation in tomato gardens in Tanzania. Mkonyi *et al.* (2020) compared three convolutional neural network architectures (VGG16, VGG19 and ResNet50) to classify infested against non-infested tomato leaves, whereas the highest accuracy was obtained from VGG16 architecture at 90.1% on the training dataset. In another study, Rubanga *et al.* (2020) employed four pre-trained CNN architectures to quantify the severity of *T. absoluta* infestation in tomato leaves, where the best performing was Inception-V3, attaining an average accuracy of 87.2%. The CNN model in this study achieved 90% accuracy on the training dataset, which is comparable to that of VGG16 and Inception-V3 architectures. The difference between this and the studies mentioned above. The generic CNN with four convolutional layers was employed by Agarwal *et al.* (2019) to detect potato diseases and eventually attaining 99.5 and 99.8 training and testing accuracy, respectively. A small training dataset may have caused the discrepancy between training and testing accuracy in this study. This may deteriorate further if a completely new test dataset is used and the characteristics depart from those in the training set. This is an essential limitation to the wide use of CNN in constructing disease or pest damage classifiers beyond the controlled experiments (Soekhoe *et al*., 2016).

Conclusion

The convolutional neural network was used to segregate tomato leaves with damage signs by *T.absoluta* from healthy ones. The training and test accuracy from this study compares well with other studies that have dealt with plant leaves in disease or insect damage classification using complex CNN architectures. Given that technical challenges in constructing a suitable image database for training, such as labeling and storage, are overcome, this intelligent monitoring system can feed an IPM strategy for controlling *T.absoluta*.

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