Segmentation of *Tuta Absoluta*'s Damage on Tomato Plants: A Computer Vision Approach

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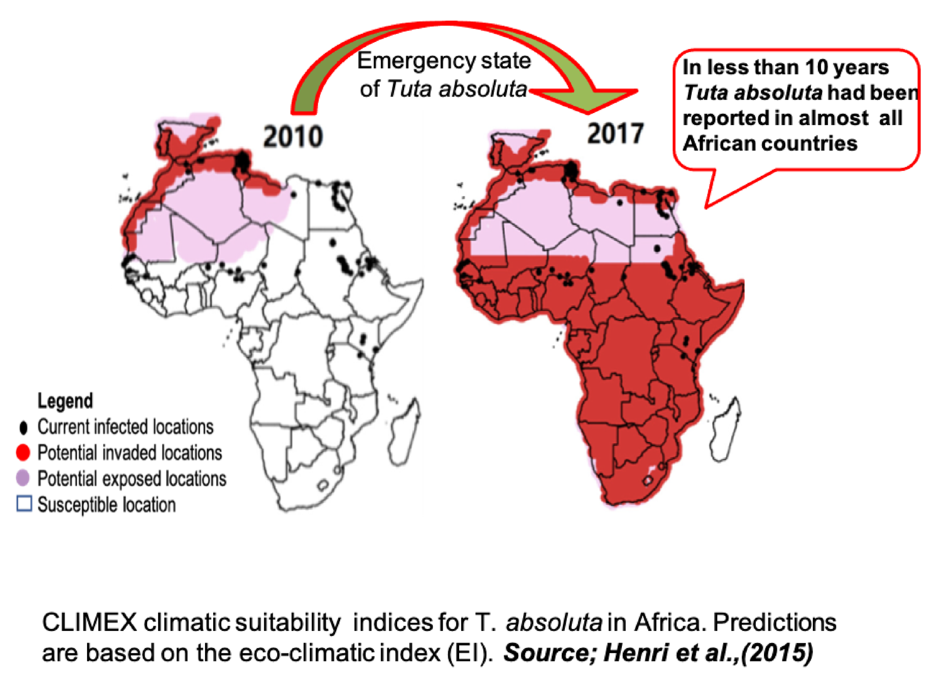
Background of the Problem

- *Tuta Absoluta* **threatens** tomato productivity globally.
- Originated from South America then **spread swiftly** to the rest of the world (Desneux, 2011).
- It causes a **heavy loss** in tomato produce ranging from **80% to 100%**.
- Farmers are giving up production due to costs and losses it causes in tomato production.
- Excessive use of chemicals develops **pests' resistant**.
- Limited agriculture extension services.
- **No effective way for early detection** and quantification of *Tuta Absoluta*'s damage.



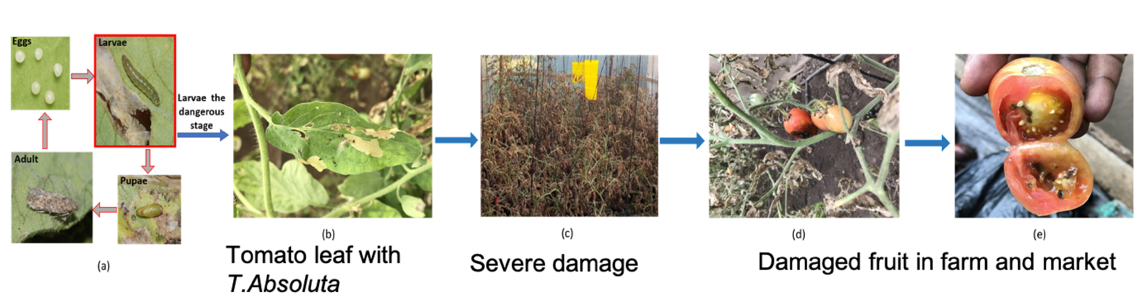


Figure 1. Lava the most dangerous stage of *Tuta Absoluta*'s life cycle.

Therefore, an **early detection** and **quantification** solution using Computer vision.

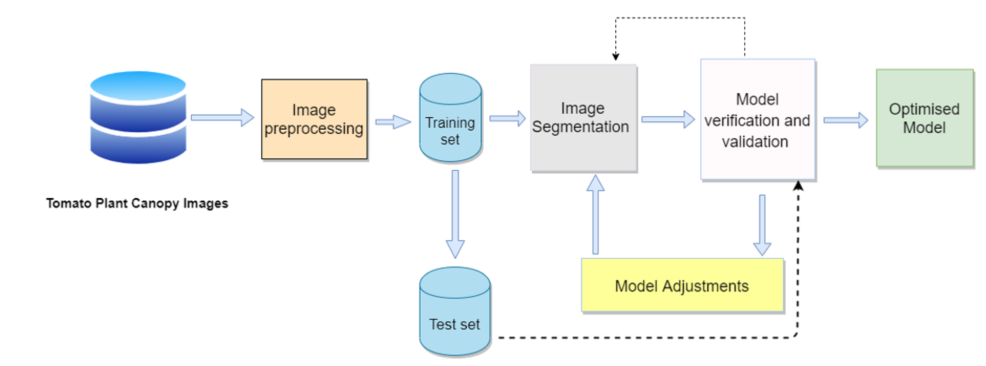
Targeted SDGs

Related Works

Role of Deep Learning on plant diseases diagnostics

- Deep learning methods (**AlexNet, GoogleNet, CaffeNet**) for early **identification** and **classification** of plant diseases (Brahimi, 2017; Sladojevic et al., 2016).
- Mkonyi et al. (2019) developed a **VGGNet** model for early **identification** of *Tuta absoluta* on tomato plants. 91.9% accuracy.
- A **ResNet50** multi tasking system for identifying and **estimating plant disease severity** (Liang et al., 2019).
- A CNN multitask system for classification and **severity estimation** (Esgario et al., 2020).

Conceptual Framework



The Dataset

- **Study area** – Arusha and Morogoro, Tanzania.
- Two (2) inhouse experiments were set up in Arusha and Morogoro regions.
- **Dataset** - 5335 tomato images.
- **Material** - Canon EOS Canon EOS Kiss X7 - High resolution (5184 x 3456).

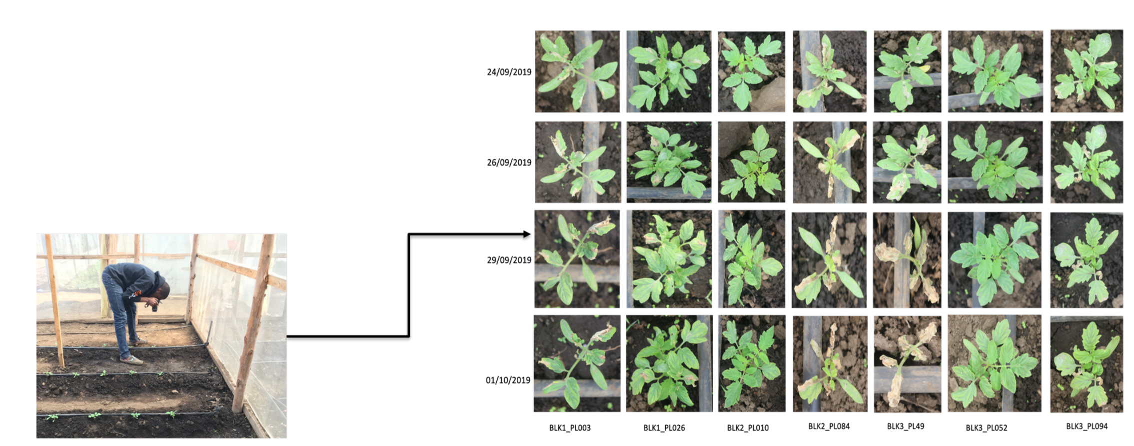


Figure 2. Different tomato leaf images of different dates.

The images were labelled into healthy and infested classes. Then annotated using Labelme VIA tools, resized and augmented.

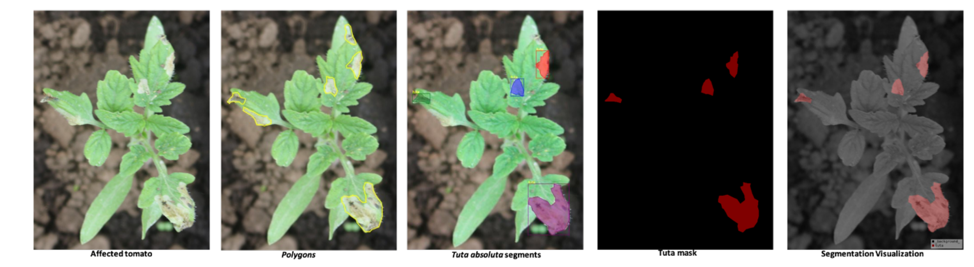


Figure 3. Image Annotations.

Research Methodology

Model Development

- U-Net for Semantic Segmentation.
- Mask RCNN for Instance Segmentation.

Model Evaluation

- **U-Net** - IoU & Dice Coefficient/F1-Score.
- **Mask RCNN** - mean Average Precision (mAP).
- U-Net Loss Function:

$$L = \sum_{i=1}^{m} -(y_i log(p_i) + (1 - y_i) log(1 - p_i)) \quad (1)$$

- Mask RCNN Loss Function:

$$L_T = \sum_i L_{cls}(p_i, g_i) + \sum_i g_i L_{reg}(t_i, t_i^*) + \sum_i g_i L_{mask}(m_i, m_i^*) \quad (2)$$

Results

U-Net Loss Results

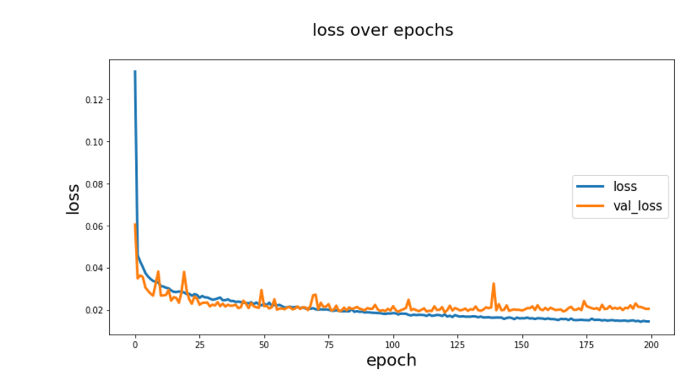


Figure 4. Training and validation loss for U-Net.

Mask RCNN Loss Results

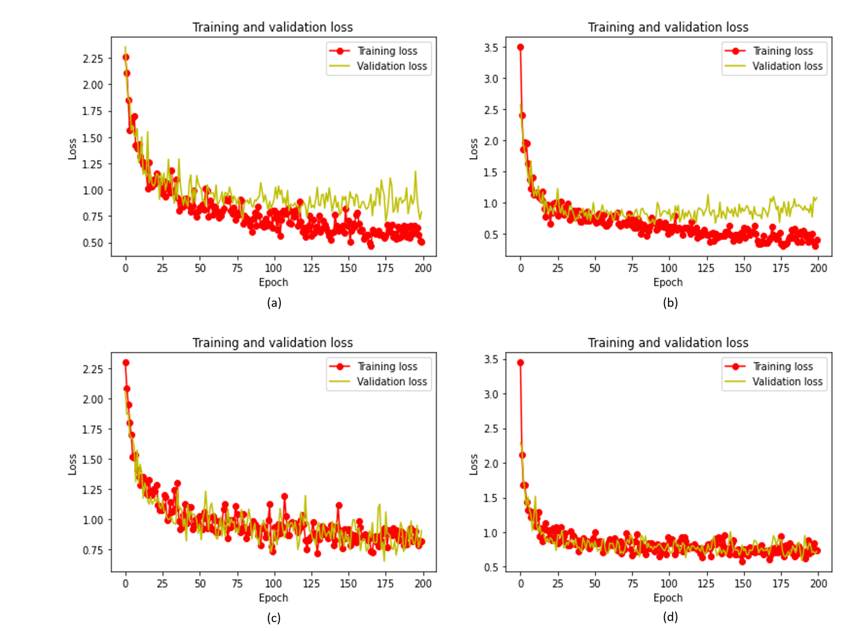


Figure 5. Loss graph for (a) Mask RCNN-ResNet50, (b) Mask RCNN-ResNet101, (c) Mask RCNN-Resnet50 with augmentations, and (d) Mask RCNN-Resnet101 with augmentations.

	Evaluation Metrics		
Method(s)	mAP (%)	IoU (%)	F1-Score(%)
Mask RCNN-ResNet50	81.01		
Mask RCNN-ResNet50 with augmentations	**85.67**		
Mask RCNN-ResNet101	81.09		
Mask RCNN-ResNet101 with augmentations	**83.60**		
U-Net		78.60	**82.86**

Table 1. Evaluation Metrics Results.

Figure 6. Sample segmentations carried out by the proposed Mask RCNN model.

Conclusion and Future Work

- Taking appropriate control measures early could reduce costs, rescue farmers from losses and improve tomato productivity.
- Further improve robustness of the proposed model by expanding the diversity of tomato pests and diseases.
- **In the future** - Develop an expert system that suggests control measures based on estimated severity. Link farmers with nearby agrovet shops.

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