7. The Dataset

- **Dataset** - 5335 tomato images.
- **Material** - Canon EOS Canon EOS Kiss X7 - High resolution (5184 x 3456) and Samsung SM-G570F - Low resolution (320 x 240).

Table 1: Data collection setup and factors considered for each experiment

Duration	Season	Region	Variety	Farming System	Number of Images
Oct - Dec 2019	dry/wet	north	3	drip	2319
Jan – Apr 2020	wet	east	2	Drip, furrow, bund	2916

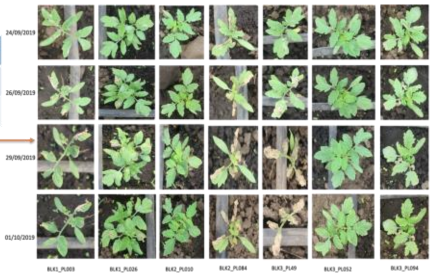

Fig. Different tomato plant images at different dates

8. Research methodology

Image Pre processing

- Labelling & Cropping (Arusha – **1107 H** & **1212 NH**, Morogoro - **1870 H** & **1046 NH**).
- Image Annotation
  - ✓ Tools – **Labelme** & **VIA** tool
  - ✓ Formats – **VOC** (1212 Images) & **COCO** (1240 Images)
- Resizing the Images – **512x512**
- Augmentation (rotation, shifts, shear, zooming, flips)

Model Development

- U-Net for Semantic Segmentation
- Mask RCNN for Instance Segmentation
- Quantification - OpenCV library

Model Evaluation

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

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

- Mask RCNN Loss Function

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

Experimental Setup

- Computer – Windows 10, Intel® Core™ i7-8550U 3.6 GHz CPU, Intel® Iris® Plus Graphics, 512 GB SSD storage, and 16 GB RAM.
- Google Collaboratory with Tesla P100-PCIE GPU and 27GB High-RAM.
- Python 3, TensorFlow, Keras library

9. Results

The Dataset

Table 2: Train/test set splits

Model	Data Ratio	Training set	Test set	Total
U-Net (VOC format)	80:20	969	243	1212
Mask RCNN(COCO format)	80:20	992	248	1240

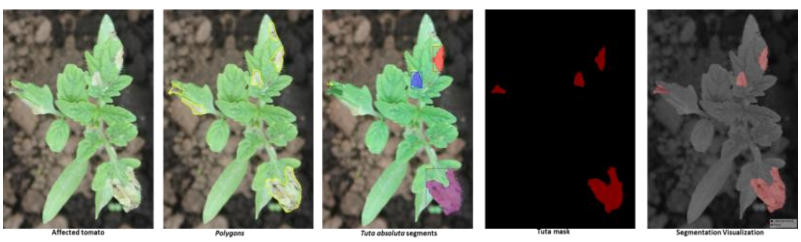

Fig. Image annotations

U-Net Loss Results

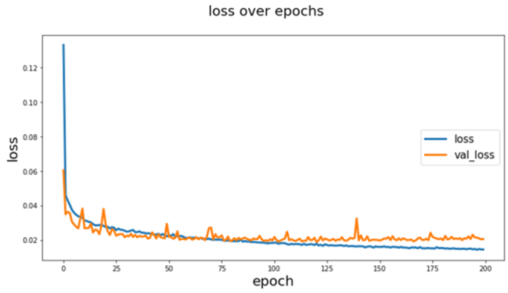

Fig . Training and validation loss for U-Net.

Mask RCNN Loss Results

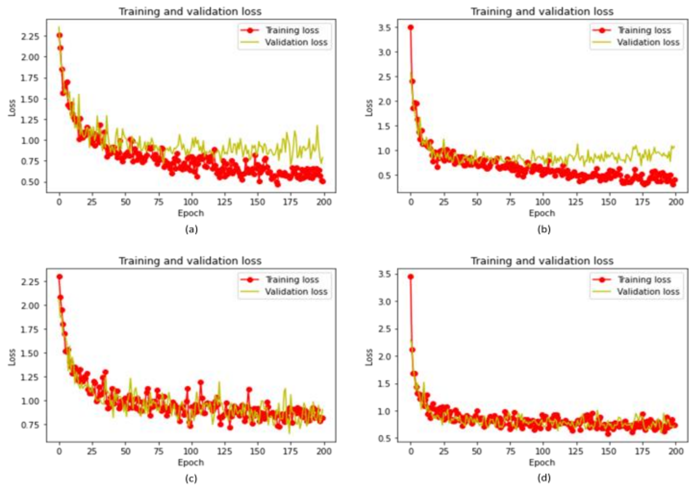

Fig. Training and validation loss curve for Mask RCNN. Loss graph for (a) Mask RCNN-ResNet50, (b) Mask RCNN-ResNet101, (c) Mask RCNN-Resnet50 with augmentations, and (d) Mask RCNN-Resnet101 with augmentations.

Evaluation and Sample Detections

Table 3: Evaluation Metrics Results

	Evaluation Metric (s)		
Method (s)	**mAP (%)**	**Jaccard Index/IoU (%)**	**Dice Coefficient (%)**
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**

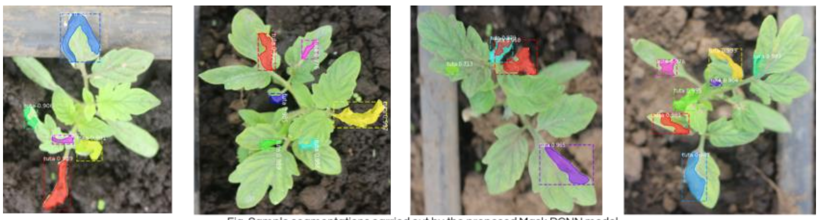
Fig. Sample segmentations carried out by the proposed Mask RCNN model

Quantification Results

- A custom model function built on top of the Mask RCNN model for counting detected *tuta* mines.


Fig. Sample quantification results.

10. Conclusion and Recommendations

- Deep learning is the new promising technology for fully automatic plant disease diagnosis.
- Automated solution reduces the workload of the limited extension officers in the country.
- 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, we intend to develop a CNN decision support system and link farmers with nearby agrovet shops.