Application of Real-Time Deep Learning in integrated Surveillance of Maize and Tomato Pests and Bacterial Diseases

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Abstract

Limited access to agricultural expertise and reliable crop disease diagnostic technologies by small-scale farmers in Kenya greatly hinders food production and security in the country. This study was aimed at investigating the potential of the use of machine learning (ML) for real-time diagnosis of common tomato and maize diseases and pests using crop images captured by mobile phone cameras. Images were acquired from farmers' fields in two counties in Kenya and used for training and testing two Convolution Neural network (CNN) models for the classification of six classes of tomato crop disease and pest infections and a binary classifier for the identification of fall armyworms in maize fields. Classification accuracies of 97.08% for the tomato model and 100% for the maize Fall Army Worm models were recorded. The image dataset and code used for training and evaluating the models have been published in publicly accessible repositories. The recorded results strongly suggest the high potential of using ML tools to complement or supplement human extension services to small-scale farmers.

Keywords: ML, CNN, Tomato Disease, Maize Pest, Smartphone App, Kenya, Farmer Extension, Precision Agriculture, Resource-Constrained Regions.

Introduction

Kenya's agricultural sector occupies a pivotal position in the nation's socio-economic landscape. It serves as a significant pillar of the Kenyan economy, contributing 21.17% to the national GDP(Statista, 2022). Beyond its economic influence, agriculture underpins food security and provides livelihoods for over 80% of the rural population and 40% of the total workforce(UNDP, 2023). This makes it the lifeblood of millions of Kenyans, shaping their economic well-being and access to vital sustenance. Within this crucial sector, two crops reign supreme: maize and horticultural produce. Maize, the dominant staple food consumed by over 80% of the population(National Geographic, 2022), forms the bedrock of national food security. Kenya stands as the leading maize producer in East and Central Africa, boasting an annual output exceeding 4 million metric tons(World Bank, 2023). This production prowess ensures national food availability and underpins the nutritional status of millions. Besides maize production, Kenya is emerging as a leader in the production of horticultural crops. In addition to contributing to food and nutritional needs for the country, horticultural farming empowers over 8 million Kenyans with income opportunities, particularly in rural communities, serving as a vital tool for poverty reduction and rural development (National Geographic, 2022).

Crop pests and diseases remain major causes of crop production losses in the country jeopardizing food security, livelihoods, and economic growth. Maize, the cornerstone of food security, is particularly vulnerable. Fall armyworm infestations can result in yield losses of up to 80%(Nyarko et al., 2019), while maize streak virus can cause losses of 40-70%(Sichangi et al., 2016). Similarly, tomatoes, a crucial source of income for small-scale farmers, are highly vulnerable to pests and diseases. Bacterial wilt can lead to complete crop failure (Anand et al., 2016) and Tuta absoluta, a destructive moth, can cause losses of up to 80% (Guimapi et al., 2016). These are just a few examples of the numerous pathogens and pests that plague Kenyan agriculture, inflicting annual losses reaching billions of dollars. The economic impact extends far beyond financial figures; these losses translate to food insecurity and hunger, particularly for vulnerable populations who rely on subsistence farming. While the challenges posed by crop diseases and pests in Kenya are daunting, a ray of hope shines from the horizon in the form of emerging technologies like computer vision (CV) and machine learning (ML). These revolutionary tools possess the potential to transform the diagnosis and management of crop threats, empower farmers, and safeguard food security.

Literature Review

This section highlights a brief review of the literature reporting the implementation of CV and ML for crop pest and disease diagnosis.

Accuracy and Speed: Studies like Chen et al. (2016) showcase promising results, achieving 95.7% accuracy in diagnosing fall armyworm and bacterial wilt in maize and tomato using deep learning algorithms. Similarly, Adhikari et al. (2015) report 92.7% accuracy in classifying coffee leaf diseases with SVM classifiers. Such impressive accuracy facilitates timely intervention and minimizes yield losses.

Early Detection: ML algorithms excel at analyzing vast datasets of agricultural data, including weather patterns, soil conditions, and historical outbreaks, to predict potential infestations before symptoms even appear. This proactive approach enables preventive measures and optimizes resource allocation (Zarca et al., 2020).

Accessibility and Empowerment: Smartphone-based applications leveraging CV and ML algorithms hold immense potential for resource-constrained settings. Apps like PlantVillage and Plantix empower farmers with real-time diagnosis tools and pest management recommendations, boosting their autonomy and decision-making capabilities (Luvisi et al., 2019).

Challenges and Considerations

Data Limitations: Reliable algorithms require substantial, high-quality datasets, which can be difficult and expensive to acquire, especially in diverse environmental conditions. Additionally, limited access to internet connectivity in rural areas poses a challenge for data upload and sharing (Ghosal et al., 2018).

Algorithmic Bias: ML models can perpetuate existing biases present in training data, leading to unequal access or inaccurate diagnoses for certain crops or regions. Careful data curation and testing procedures are crucial to mitigating such biases (Naik et al., 2017).

Technology Access and Training: Implementing complex CV and ML models requires affordable technology and proper training for farmers. Bridging the digital divide and developing user-friendly interfaces are essential for successful adoption (Lwoga & Komba, 2015).

Despite the challenges, the future of CV and ML in crop disease and pest diagnosis is promising. Collaborative efforts should focus on:

- Developing low-cost, user-friendly smartphone applications tailored to local languages and farming practices.
- Investing in data collection and infrastructure to build robust, regionally relevant datasets.
- Implementing capacity-building programs to equip farmers with the skills and knowledge to utilize these technologies effectively.
- Addressing algorithmic bias by incorporating diverse data and rigorous testing procedures.
- Exploring alternative approaches like transfer learning and domain adaptation to leverage existing data resources more efficiently.

This study was geared toward the acquisition of an image dataset of common maize and tomato diseases in Kenya and using this dataset to train an ML model for the diagnosis of diseases and pests in the aforementioned crops. The model was deployed in a smartphone, and validation tests were conducted to assess the model's accuracy.

Materials and Methods

Acquisition of Image Dataset

Images of maize and tomato leaves, fruits (in the case of tomato crops) and whole plants were acquired from two sources. One was images captured using mobile phones from farmers' fields where the crops were grown. Images of maize and tomato leaves, stalks, flows and fruits were acquired from farmer's fields. A total of 1,330 fall armyworm images, 1,200 TutaAbsoluta images, 1,250 leaf spot images and 1,145 images of maize streak images were captured by use of digital cameras at different angles and lighting conditions in the normal farm environment. The image data were acquired from Meru and Murang'a Counties of

Kenya. The second source of images was sourced online from publically accessible datasets that were labelled according to crop disease or pest infestation status.

Image Processing

This step comprised image cropping, resizing, intensity value rescaling, augmentation and labelling. The images were resized to 150 by 50 pixels and labelled according to the condition detected. Some images are shown in Figure 1. Maize crop images were categorized into two classes namely Fall armyworm class and other infestations class. The first class was made of images that had been certified by an expert agronomist as having been acquired for the Fall army warm-infested maize crop. The second category was made of images having different disease infections and pest infestation statuses other than the Fall armyworm. The study decided to generalize the second class of maize infestation owing to the limited number of images per disease/pest infestation in the database. The images were therefore consolidated into a single class to train an ML classifier. Tomato images were classed into six classes based on their pest/disease infection status. The classes comprised of the following diseases, Early bright, Leaf mould, Leaf lot, Bacteria spot, Tuta absoluta leaf images, Tuta absoluta fruit images, and others. The other class comprised of other tomato diseases and pests different from the above-mentioned ones.

Image augmentation entailed the application of the following transformations to the input images.

Rotation (between 0 and 45 degrees), image width shifting, height shifting and shearing (by 20%), image sharing, image zooming (by a range of 20%, horizontal flipping and image reflection to fill spatial regions left void after image translation and rotation.

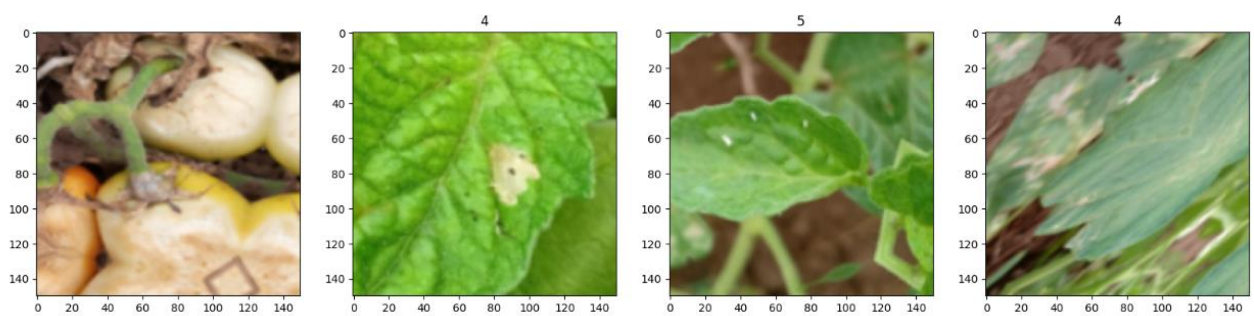

Figure 1: Some preprocessed images showing different classes of both maize and tomato disease infection/pest infestation status.

Building and training of the ML models

Two Convolution Neural Network (CNN) models were assembled and trained to classify maize and tomato diseases and pest infestations. Details of the architectures of the two models are given in Table 1 and Table 2.

Table 1: Architecture of the CNN tomato disease classifier

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 16)	448
max_pooling2d (MaxPooling2D)	(None, 74, 74, 16)	0
conv2d_1 (Conv2D)	(None, 72, 72, 32)	4640
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 32)	0
conv2d_2 (Conv2D)	(None, 34, 34, 16)	4624
max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 16)	0
flatten (Flatten)	(None, 4624)	0
dense (Dense)	(None, 256)	1184000
dense_1 (Dense)	(None, 6)	1542

SoftMax Activation function was used in the final output layer of the CNN, and Adam Optimizer was used as the algorithm for updating the model weights. The maize classifier trained in 20 epochs while the tomato classifier trained with 30 epochs.

Table 2: Architecture of the maize CNN classifier

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 254, 254, 16)	448
max_pooling2d (MaxPooling2D)	(None, 127, 127, 16)	0
conv2d_1 (Conv2D)	(None, 125, 125, 32)	4640
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 32)	0
conv2d_2 (Conv2D)	(None, 60, 60, 16)	4624
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 16)	0
flatten (Flatten)	(None, 14400)	0
dense (Dense)	(None, 256)	3686656
dense_1 (Dense)	(None, 1)	257

Evaluation Indicators

To significantly evaluate the model, accuracy, precision and recall are used. The recall relates to the correct detection of items that should have been detected, while precision relates to the detection of correct items.

This study employed epochs for the extraction of all images that could not fit into the model at once. Epoch represents the number of times the dataset is passed forward and backward by the neural network. The study used five epochs with thirty-six steps per run. The study further used the accuracy metric to test how good the model is for classification tasks (Equation 3).

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \ldots\ldots\ldots\ldots\ldots \quad (1)$$

In True Positives (TP); the value of the actual class is a yes and that of the predicted class is also a yes. For True Negative (TN) the value of the actual class is a no and also that of the predicted class. In False Positive (FP) the value of the actual class is a no whereas the predicted class is a yes. In False Negative (FN) the value of the actual class is a yes whereas the predicted class is a no. The precision score is a fraction of relevant instances among the retrieved instances (Equation 4).

$$Precision = \frac{TP}{TP+FP} \ldots\ldots\ldots\ldots\ldots \quad (2)$$

Recall is the percentage of the total relevant results classified by the algorithm (Equation 5).

$$Recall = \frac{TP}{TP+FN} \ldots\ldots\ldots\ldots\ldots \quad (3)$$

F1 score is a measure of test accuracy that considers both precision and recall to compute the score (Equation 6).

$$F1 = 2 \cdot \frac{precision \cdot recall}{precision+recall} \ldots\ldots\ldots\ldots\ldots \quad (4)$$

The graphical representation of the confusion matrix Figure 5 shows the accuracy levels of the model.

Experiment

The training and test were done using a 2018 Alienware Area 51 R2 Gaming Desktop, Intel Core i7-6800K 6-Core up to 3.6GHz, 32GB DDR4, 2TB 7200RPM + 512GB SSD, Nvidia GeForce GTX 1080 8GB GDDR5X, Bluetooth 4.0, WIFI 802.11ac, Windows 10. The details are illustrated in Table 3.

Table 3: Experimental Equipment

2018 Alienware Area 51 R2 Gaming Desktop	Specification
Memory	32 GB DDR4
Hard Drive	2TB 7200RPM – 512 GB SSD
Graphics	Nvidia GeForce GTX 1080 8GB GDDR5X
Network and Connectivity	Bluetooth 4.0, WIFI 802.1ac
Operating system	Windows 10

In the experiments to attain accuracy, images were trained based on acquired datasets. A faster R-CNN model was trained using the MobileNetV2 to initialise weights of the learning rate to 0.0001 and a batch size of 1. The weight initialization affects the rate of convergence of the network.

Image and Code Repositories

The image dataset used for training the models can be accessed via.
https://www.kaggle.com/amochege/datasets.

The Python code used to build the models can be accessed through the following GitHub links.
https://github.com/dmaitethia/Python-Basics/blob/main/tomato_b.ipynband
https://github.com/dmaitethia/Python-Basics/blob/main/MaizeDiseaseClassifier.ipynb

Results and Discussion

Maize Fall Army Worm CNN Classifier

This was a binary classifier trained with images comprising two classes. Figure 2 gives graphs of training and validation losses and accuracies per epoch. Table 3 gives the model performance evaluation score as evaluated using a test set different from the training set

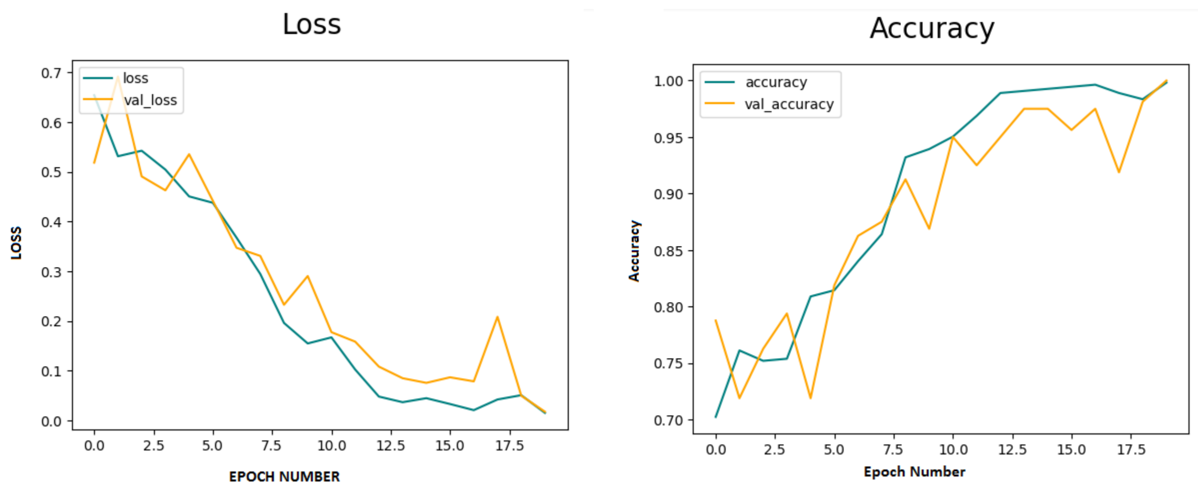

Figure 2: Training losses and Accuracy of the maize Fall Army Worm Classifier

Table 4: Tomato Diseases/Pest CNN Model Evaluation Scores

Metric type	Value
Precision	1.0
Recall	1.0
Accuracy	1.0

The maize fall armyworm CNN model achieved perfect accuracy, precision, and recall on the test set. While this is an impressive result, it should be interpreted with caution due to the limited number of classes (only two) and the possibility of overfitting the training data. Fewer studies have specifically focused on fall armyworm detection using CNNs. However, some studies have used CNNs for maize disease and pest detection, including fall armyworm:

Mbuthia et al. (2021) achieved an accuracy of 92.3% using a CNN for classifying three maize diseases and pests, including fall armyworm. Adeoye et al. (2022) achieved an accuracy of 94.1% using a CNN for classifying four maize diseases and pests, including fall armyworm. Given the limited number of classes in the model, directly comparing its performance with these studies is not straightforward. However, the perfect score on the test set indicates the CNN's potential as an effective classifier for fall armyworm detection but further testing with a larger and more diverse dataset is necessary.

Tomato Disease/Pest CNN Classifier

This was a multiclassifier classifier trained to classify images from six different classes i.e. Early bright, Leaf mould, Leaf lot, Bacteria spot, Tuta absoluta leaf images, Tuta absoluta fruit images, and others. Figure 3 gives graphs of training and validation losses and accuracies per epoch. Table 4 gives the model performance evaluation score as evaluated using a test set different from the training set.

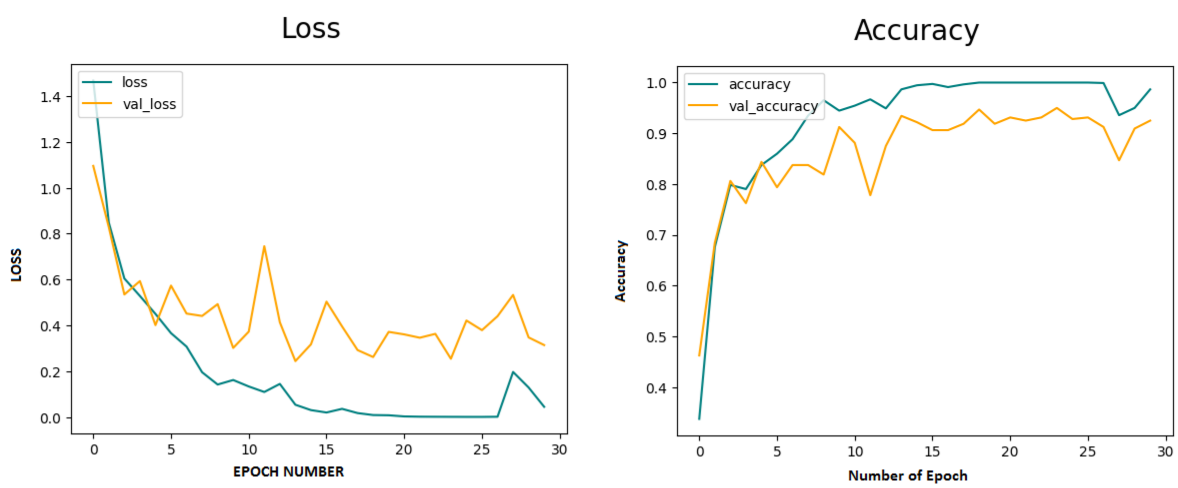

Figure 2: Training losses and Accuracy of the Tomato Disease/Pest Classifier

Table 5: Tomato Diseases/Pest CNN Model Evaluation Scores

Metric type	**Value**
Precision	0.9125
Recall	0.9708
Accuracy	0.9708

The tomato disease/pest CNN model achieved an accuracy of 97.08%, a precision of 91.25%, and a recall of 97.08%. These are excellent results, indicating that the model can effectively distinguish between six different classes of tomato diseases and pests.

Several studies have used CNNs for tomato disease classification, with accuracies ranging from 87% to 95%. Some notable examples include Zhang et al. (2020) achieved an accuracy of 93.7% using a ResNet-50-based CNN for classifying five tomato diseases. Jiang et al. (2021) achieved an accuracy of 95.2% using a MobileNetV2-based CNN for classifying seven tomato diseases. He et al. (2022) achieved an accuracy of 87.2% using a VGG16-based CNN for classifying four tomato diseases.

The performance of the model in the present study falls within the range of these previous studies, demonstrating its effectiveness for tomato disease classification. However, it's important to note that comparing results directly can be challenging due to differences in datasets, evaluation metrics, and model architectures.

Deployment of the Digital Imaging Mobile Application (Tunza Leaf)

Figure 4 (a) shows the homepage where scans can be done; the percentages shown at the bottom of the interface in Figure 4 (b) show the level at which the application can detect stress by showing the accuracy level at which the phone can detect the stress. The higher the percentage the higher the chances of accurately detecting the stress.

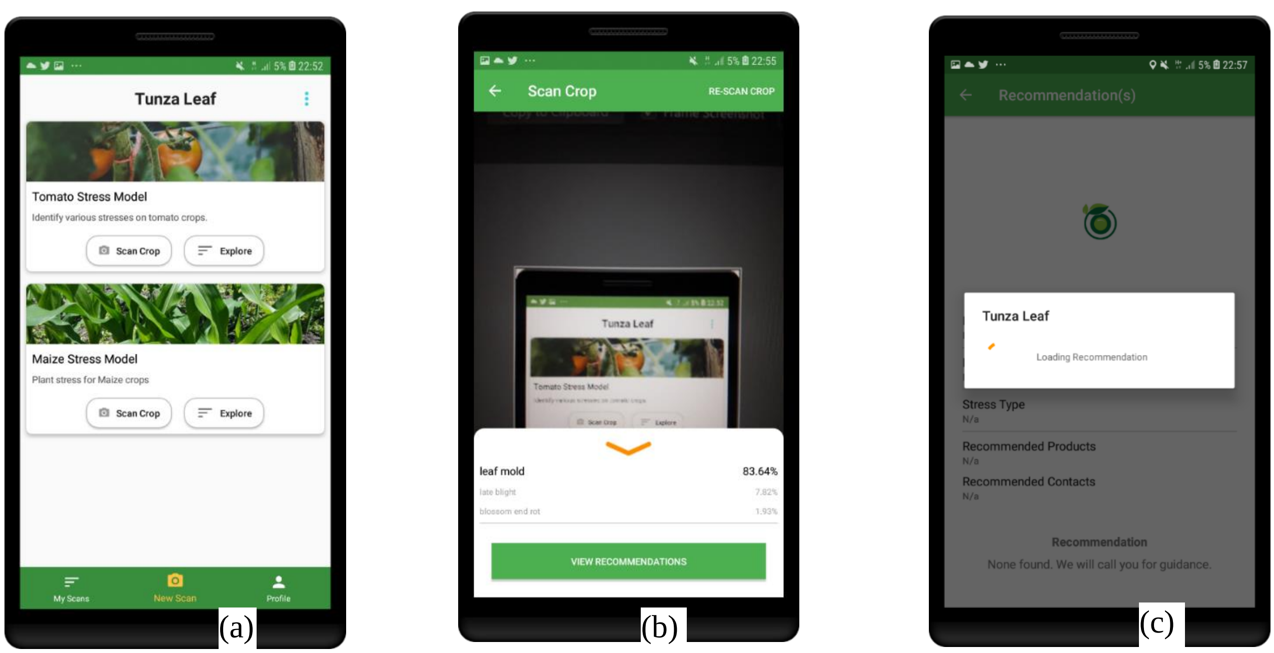

Figure 4: Tunza Leaf Tomato Stress Model Mobile App Interface; (b) Scanning Views for plant Stresses; (c) Recommendation Engine showing the recommended product and contact person for the detected stress.

The recommendation engine in Figure 4 (c), is a structure that recommends the best agricultural products in the market the user can buy to be able to treat the various plant stresses. The recommendation goes further to connect the user to shops (agrovets around them) as well as provide details of agronomist experts within their geolocation. The recommendation engine contains information related to the type of stress detected, the recommended chemical product to remedy the stress detected, and the recommended contact of the agrovet or the agronomist in the region where the stress has been detected.

The web interface in Figure 5, provides a recommender system for products to be used in the farm by the farmers. This feature provides access to registered products from manufacturers. It has an easier-to-use recording plugin that allows the admin to add a product. Any new products that are certified by the Pest Control Product Board (PCPB) (Board, 2019). The certified products provide the farmer with information about the chemical products to be used on the plants as per the accredited institutions that are allowed to supply the chemical products and the post-harvest index (PHI) of each chemical product. The list of accredited products is updated for the framers by the administrator and a list of added products as necessary is shown.

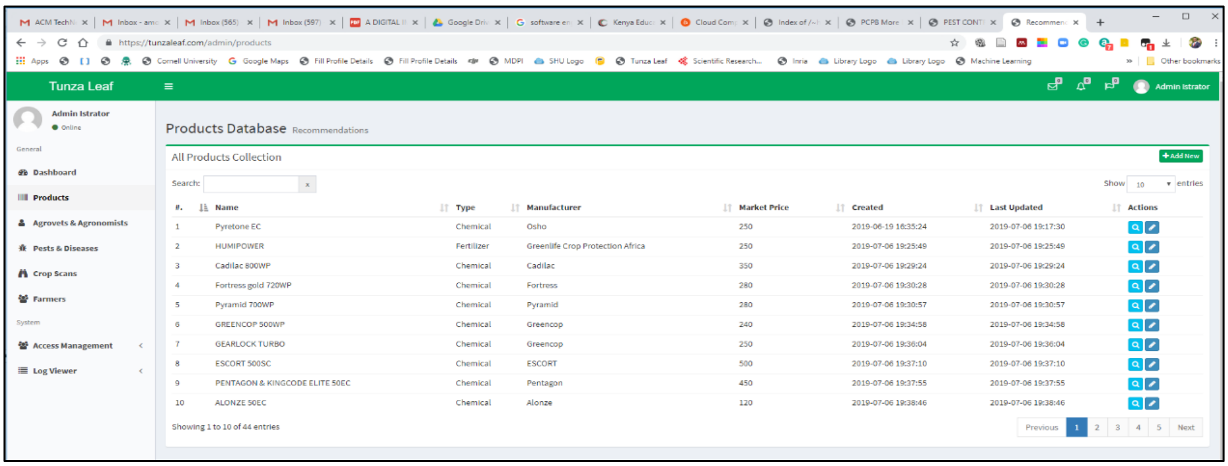

Figure 5: List of Accredited Products for Use by Farmers

The agro vets and agronomist module is for managing collaborators who provide help to farmers on selected issues. The agronomists and agro-vet stores in Figure 6 are referred to as collaborators for this study. They are the stores that stock products for the farmers in the identified regions of study. They include stores in Maili Saba, Tutua, Rwarera, Nchiru and Meru Town. These stores stock products that apply to the tomato plant in this study among other products.

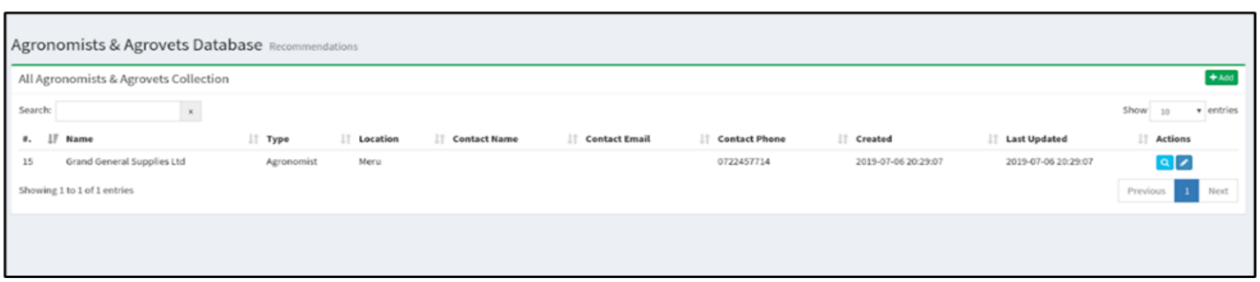

Figure 6: List of Agrovet stores and Agrovets involved in sales

Impact and Application

This technology has the potential to provide several benefits to Kenyan farmers, including (i) Farmer empowerment: The app can empower farmers by providing real-time diagnosis and information about tomato diseases and pests. This can help them make informed decisions about disease management and potentially increase yields and income. (ii) Improved extension services: The app can bridge the gap in farm extension services, offering low-cost, readily available support to even the most remote farmers. This can significantly improve access to essential agricultural knowledge and expertise. (iii) Precision agriculture and input suppliers: The model can be used for targeted recommendations by input suppliers. By analyzing images of crops, the app can identify specific disease risks and recommend appropriate pesticides, fertilizers, or other products. This can improve the efficiency and effectiveness of input use and potentially reduce environmental impact.

Challenges and Future Directions

Several challenges need to be addressed for this technology to reach its full potential in Kenya:

- Data collection and labelling: Collecting and labelling large, diverse datasets in resource-limited settings can be challenging. Potential solutions include crowdsourcing or transfer learning from existing datasets.
- Offline functionality and language barriers: The app needs to function offline and support multiple languages spoken by Kenyan farmers to ensure accessibility in areas with limited internet access and diverse linguistic communities.
- Sustainability and economic models: Sustainable economic models are needed to ensure the app is affordable and accessible for Kenyan farmers. Partnerships with NGOs or agricultural cooperatives could be one potential solution.
- Overall, this study presents a promising approach for using CNNs in smartphone apps for disease and pest diagnosis in maize and tomatoes. Further research and development are needed to address the limitations and explore the full potential of this technology for improving agricultural practices.

Conclusion

This study aimed to investigate the potential of the application of ML in assisting farmers in Kenya with real-time diagnosis of tomato and maize diseases and pests. The objectives of the study were to develop CNN models for classifying six tomato disease/pest classes and another for identifying Fall Army Worm in maize. Image datasets were acquired from farmer fields in Kenya and publicly available sources, totalling 4,469 tomato and 4,955 maize images. The tomato disease/pest CNN model achieved an impressive accuracy of 97.08%, demonstrating its ability to effectively distinguish between multiple classes. The maize Fall Army Worm CNN model obtained perfect accuracy (100%), suggesting its potential for accurate detection of this specific pest. A mobile App was developed to demonstrate how the trained models could be deployed to farmers to assist them in quickly and cheaply diagnosis different pests and diseases affecting their crops. The study has demonstrated potential. Through the provision of instant diagnoses, farmers can make informed decisions about disease management and potentially increase yields and income. The app can also bridge the gap in access to expert advice, particularly in remote areas, empowering farmers and improving agricultural practices. Sport precision agriculture: Targeted recommendations for pest and disease control can be delivered to farmers based on specific diagnoses, promoting efficient use of resources and potentially reducing environmental impact.

Suggestions for future work

- Expand the scope: Include additional crop diseases and pests relevant to Kenyan farmers.
- Address limitations: Enhance offline functionality, support multiple languages, and develop sustainable economic models for app access.
- Further testing and refinement: Conduct larger-scale field trials to evaluate the app's real-world effectiveness and refine the models for improved generalizability.
- Explore integration with other technologies: Combine the app with weather data and sensors to provide farmers with even more comprehensive and context-specific information.

This study demonstrates the immense potential of CNN-based smartphone apps for revolutionizing agricultural practices in resource-constrained regions. By addressing the identified challenges and continuing research efforts, this technology can be a powerful tool for empowering farmers, improving food security, and promoting sustainable agriculture in Kenya and beyond.

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