Application of Artificial Intelligence in the Identification of Banana Bunch Top Virus (BBTV) in Mozambique

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ABSTRACT

Agricultural production faces many challenges, such as disease and pest infestation, which can lead to severe crop loss and environmental impacts due to the excessive use of chemicals. Artificial intelligence has become a key technique to solve different agricultural-related challenges. The main objective of this study was to train and validate artificial intelligence algorithms for the detection of Banana Bunchy Top Virus (BBTV) in banana crops. Approximately 2,500 images of healthy and BBTV-infected leaves were collected, stratified according to the stage of plant development, and used to calibrate and validate an artificial intelligence algorithm for the detection of BBTV. Pre-trained models such as VGG 16, ResNet50, and InceptionV3 were tested. The ResNet50 model achieved a training accuracy of 99.56% and validation precision, recall, and F1 score of 96.53%, 94.94%, and 95.73%, respectively, outperforming the other models in detecting BBTV-infected plants.

Keywords-artificial intelligence; banana; BBTV; deep learning; disease detection; convolutional neural networks

I. INTRODUCTION

Artificial Intelligence (AI) is an area of computer science that focuses on developing systems that can be taught to make decisions and predictions within specific contexts [1]. The application of AI for agricultural system monitoring and classification has great potential to replace traditional technologies aimed at meeting the demand for food, which is associated with the current high growth in the world population [2]. By analyzing large datasets and optimizing farming practices, AI enables more sustainable and productive agricultural operations and is pivotal in precision agriculture due to its adaptability, high performance, accuracy, and cost-efficiency [3-6].

Agricultural production faces several challenges, of which insect pests and disease infestations are regarded as the most alarming problems that lead to large economic losses [7]. In Mozambique's large urban centers, fruit consumption increasingly constitutes the basis of food and nutritional security and a source of income for communities, with bananas being one of the most abundant and consumed [8]. As such, banana production has become an important part of the food and nutrition security strategies of most rural families. Bananas are produced mainly by small farmers and are planted in low-lying areas and/or along rivers. Commercial banana farms can also be found in the vicinity of the Maputo and Chimoio cities [9]. Banana cultivation in Mozambique, specifically in the southern zone, faces serious challenges, including the low level of technology and input use and the infestation by the Banana Bunchy Top Virus (BBTV). BBTV is one of the most economically important viral diseases that affect banana cultivation [10]. This virus is responsible for a dramatic reduction in leaf area and causes up to 100% loss of production [11]. The conventional method for identifying BBTV involves in situ interpretation of visual symptoms [12]. This method is time-consuming, and its accuracy and reliability are highly dependent on technical experience and scientific knowledge [13].

To address these challenges, several initiatives have been conducted, including the development of AI algorithms. The study in [14] provided an overview of this topic, focusing on enhancing communication and compatibility between diverse agent systems through advanced deep-learning techniques. In particular, three widely recognized architectures, ResNet50, VGG16, and InceptionV3, have been employed to enhance the accuracy and efficiency of banana disease identification, such as Sigatoka (Sugathoka) and Panama disease [15]. The ResNet50 architecture, which is prominent for its deep structure and skip connections, has been instrumental in capturing intricate patterns related to banana diseases. This algorithm successfully distinguished healthy and Sugathoka-infected banana plants and the symptoms associated with black Sigatoka in banana leaves [16, 17]. In [18], ResNet-50 was used to develop a model for common bean bacterial blight disease detection using a deep learning approach. Similarly, InceptionV3, known for its inception modules and global average pooling, was successfully applied to classify Panama disease symptoms [19, 20]. In [21], this issue was investigated using deep learning models for crop quality and disease detection on a PlantVillage dataset, including 510 images of banana leaves with Banana Black Sigatoka (BBS) and Banana Bacterial Wilt (BBW), to train and test the networks.

Further advances in banana disease diagnosis have been achieved by combining multiple architectures into ensemble models. In [22], an ensemble model was developed, incorporating ResNet50, VGG16, and InceptionV3 to diagnose Fusarium wilt (TR4) in bananas. This ensemble demonstrated improved accuracy, highlighting the potential of ensemble models for comprehensive disease diagnosis. In [23], deep feature extraction and deep learning techniques were used on the PlantVillage dataset to detect diseased plants. Features were extracted using SVM and KNN, followed by transfer learning and fine-tuning, and three deep learning models, namely VGG16, Google Net, and ResNet50, were tested. In [24], a transfer learning-based deep Convolutional Neural Network (CNN) was proposed for the detection of Fusarium wilt in banana crops [24]. In [25], an AI-powered banana disease and pest detection was proposed, collecting images from various hotspots of banana disease and pest symptoms/damage in Africa and southern India. The dataset consisted of various types of data, and light conditions depended on the time of image acquisition, season, and different environmental locations. The images were collected in different growing phases of the crop (vegetative and reproductive). The dataset covered Healthy Plants (HP), Dry/Old-aged Leaves (DOL), and a balanced number of images (700 images) of five major diseases, namely, Xanthomonas Wilt of Banana (BXW), Fusarium Wilt of Banana (FWB), Black Sigatoka (BS), Yellow Sigatoka (YS), and BBTV, along with the Banana Corm Weevil (BCW) pest class. This study used three different architectures: ResNet50, InceptionV2, and MobileNetV1.

These studies collectively contribute to a more comprehensive approach to banana disease diagnosis, offering farmers and researchers powerful tools for timely and accurate identification and ultimately aiding in effective disease management strategies. Nevertheless, to the best of our knowledge, no data on BBTV or other banana diseases have been collected in Mozambique for AI-based disease identification. Therefore, since BBTV does not present a specific lesion on the leaf surface, it poses an additional challenge for CNN models to learn. In this context, the main objective of this study was to develop an innovative tool conducive to more efficient and accurate identification of BBTV at different infestation stages in Mozambique.

II. METHODOLOGY

The data were collected from Banana cultivation fields on Josina Machel island. Josina Machel island is 188 km^2 wide and located at the confluence of the Incomati River, approximately 50 km northeast of the village in the district of Manhiça, in the province of Maputo, southern Mozambique. Subsistence agriculture is the main activity on the island, and bananas are one of the most important crops [26]. Figure 1 presents the location of the study area.

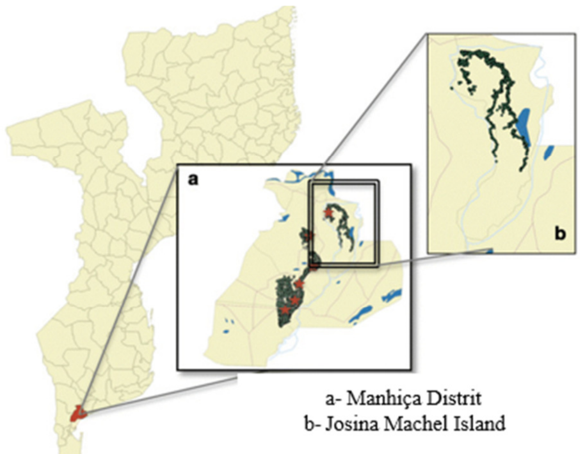

Fig. 1. Location of the study area.

A. *Sampling Procedures*

The sampling units consisted of healthy and BBTV-infected leaves of banana plants. An intentional sampling procedure was implemented, deliberately selecting leaves from healthy and infected plants throughout the cultivation fields in the study area. The selection was carried out to include different stages of plant growth and disease development. Three growth stages of the banana crop (soca, adult, and fruiting stages) were considered for the sample, as presented in Figure 2, and five levels of disease development were identified, as illustrated in Figure 3.

Fig. 2. Stratification of diseased plants according to different growth phases: A: Soca plant, B: Adult plant, C: Fruiting stage.

B. Data Collection

The data consisted of images of healthy and BBTV-infected leaves of banana plants. The images were taken with a professional digital camera (Nikon D7500 DSLR, 4k 20.9 MP). The images were taken between 11:00 and 14:00 hours local time to minimize the effect of the sun's zenith angle. All the pictures were taken at a size of 5568×3712 pixels. 2,500 images were taken, including 2,146 images of soca plants, 234 images of adult plants, and 120 images of fruiting plants. The image distribution reflects the relative level of infestation between plant stages.

Fig. 3. Levels of BBTV infection: 1: Dark green and streaked on leaf veins, 2: Marginal leaf chlorosis, 3: Leaf dwarfism mixed with necrosis, 4: Spots on center veins, necrosis, and loss of leaf shape, 5: Leaf death.

C. Data Analysis

1) Image Preprocessing

Image preprocessing consisted of cleaning the dataset by eliminating poorly captured and blurred images and images with a potentially confounding background. The images were resized to a uniform format. The dataset was then randomly divided into three subsets:

- The training subset, with a share of 80%, was used to train the model to detect healthy and infected leaves. It was used to identify the best function to represent the classes in the dataset.
- The validation subset, in a proportion of 10%, was used to conduct an unbiased evaluation of each model while adjusting the hyperparameters. This subset was used to check the efficiency of the model and identify possible overfitting problems.
- The test subset comprised 10% of the total sample size. This set was used for the final evaluation of the models after training and validation, which helped to measure the performance with real data for future predictions.

2) Image Processing

The basic architecture used to train the system to detect BBTV in banana plants was CNN (convolution neural networks), according to the method in [26]. The model was trained using TensorFlow because it allows users to train models in Graphic Processing Units (GPUs) and Central Processing Units (CPUs). Experiments were carried out for the ResNet50, InceptionV3, and VGG16 models using a computer with the specifications described in Table I. ResNet-50 is a deep neural network with 50 layers. Its depth allows it to capture complex hierarchical features from input images. ResNet-50 is often used as a pre-trained model on large image datasets, such as ImageNet. Pretraining on such datasets allows the model to learn general features before being fine-tuned for specific tasks with smaller datasets. Its architecture with skip connections has been influential in addressing challenges related to training very deep neural networks [27].

InceptionV3 is a deep CNN architecture designed for image classification and object detection. It is part of the Inception family of models developed by Google researchers. The "V3" indicates that it is the third version of the Inception architecture. Similar to other deep learning architectures, InceptionV3 is often used as a pre-trained model on large datasets such as ImageNet. This pretraining allows the model to learn generic features [28]. VGG16 is a deep CNN architecture that consists of 16 weight layers, including 13 convolutional layers and 3 fully connected layers. In summary, a pre-trained VGG16 model is a versatile tool in computer vision, offering the benefits of transfer learning by leveraging the knowledge gained from a large and diverse dataset to improve performance on specific tasks with smaller datasets [29].

The models were developed using Python 3.8, as it is a basic and universally accepted programming language with a robust image processing library, OpenCV. The implementation was carried out using the Keras library because of its high performance in numerical computing with TensorFlow in the backend. The models were trained in Google Colab with the following specifications: runtime type: Python 3, hardware accelerator: GPU, and Notebook size: 20 MB.

TABLE I. SUMMARY OF HARDWARE AND SOFTWARE USED IN THIS STUDY

	Specifcations
Memory	16 GB DDR4 RAM/2 TB Ultra-Fast
Processor	Intel 12th Gen Core i5-12400F 4 GHz
GPU	NVIDIA Tesla 4 GPU
Operating system	Windows 11 Home (64bit)
Deep learning library	TensorFlow
Programming language	Python 3.8

D. Accuracy Assessment

Model accuracy was evaluated using the test dataset and some statistical metrics, including accuracy, precision, recall, and F1 score. Performance evaluation was carried out by averaging the metrics over six runs for each division of the dataset. Figure 4 shows the general scheme representing the main steps followed during the development of the algorithms. The metrics were determined according to the equations below:

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

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

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

$$\text{F1} - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \quad (4)$$

where TP denotes True Positives (the number of images with BBTV classified as having BBTV), TN denotes True Negatives (the number of images without BBTV classified as not having BBTV), FP denotes False Positives (the number of images without BBTV classified as having BBTV), and FN denotes False Negatives (the number of images with BBTV classified as not having BBTV). Figure 4 shows an overview of the steps taken to develop the models.

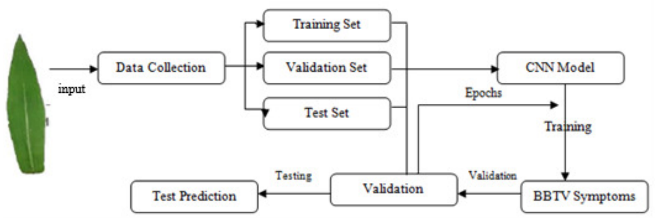

Fig. 4. Overview of the proposed method.

III. RESULTS AND DISCUSSION

Figure 5 shows the accuracy and loss diagrams of the IncerptionV3 model during the training and validation process. The losses of the two processes were estimated after each training epoch. The training and validation accuracy curves start at 86% and 88%, respectively, reaching a sharp loss at Epoch 28. According to the loss diagram, the training loss decreases rapidly as the training process progresses. The loss function decreases monotonically during the training phase. At the end of the training, the curves were adjusted well to each other, and the losses stabilized, indicating that the model learned and segmented the characteristics of BBTV-infested leaves well without overfitting.

For the VGG16 model, the accuracy graphs in Figure 6 show that the model did not learn satisfactorily from the data entered for both training and validation, starting with 84% and 0% accuracy, respectively. Both curves showed sharp increases in accuracy before Epoch 3, when they stabilized, although the validation curve oscillated in some epochs, representing an abnormality in the data trend. It was necessary to stop training at epoch 30 because there was a continuing trend in the asymmetry of the training and validation curves, which created a slight overfitting effect (the accuracy of the training being greater than the accuracy of the validation), so the model would start to memorize what it had learned.

(a)

(b)

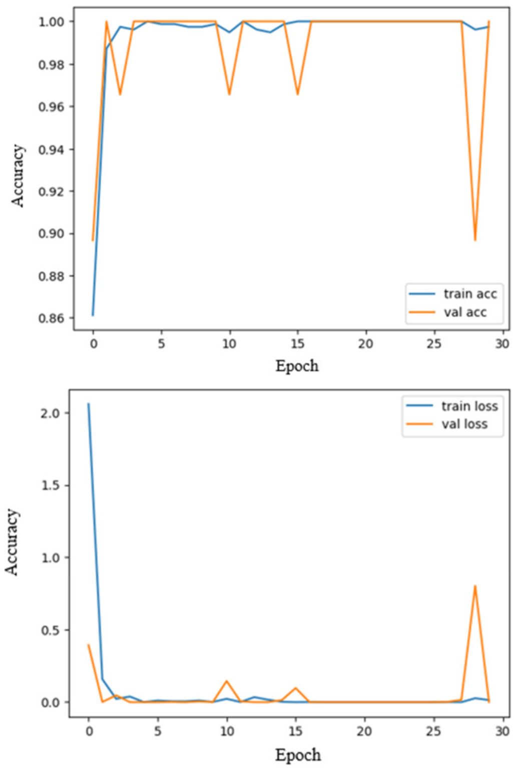

Fig. 5. Accuracy (a) and loss (b) graphs for the InterceptionV3 model.

(a)

(b)

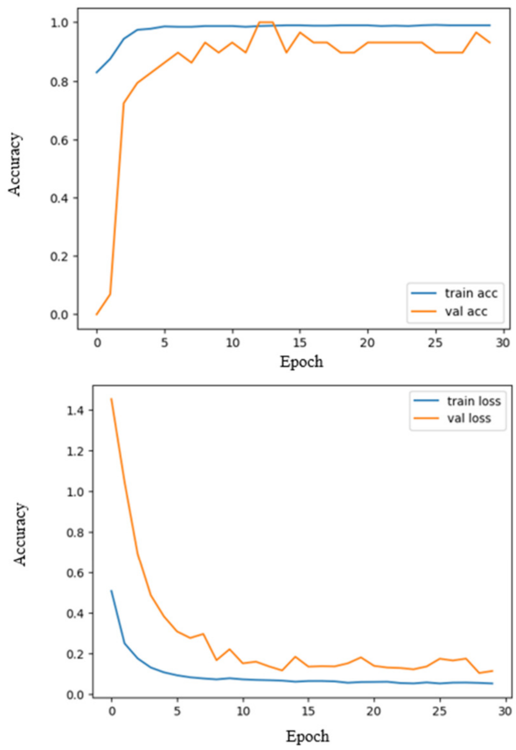

Fig. 6. Accuracy (a) and loss (b) graphs for the VGG16 model.

As shown in Figure 7, for the ResNet50 model, both training and validation start with accuracy rates above 90%, with a tendency for training to stabilize between 87.5% and 100%. The accuracy proved to be fairly stable but reached an extreme at its lowest value of approximately 87.5% in Epoch 11, which stabilized slightly from Epoch 12 to Epoch 30 when training was stopped due to the change in the graph's trend.

(a)

(b)

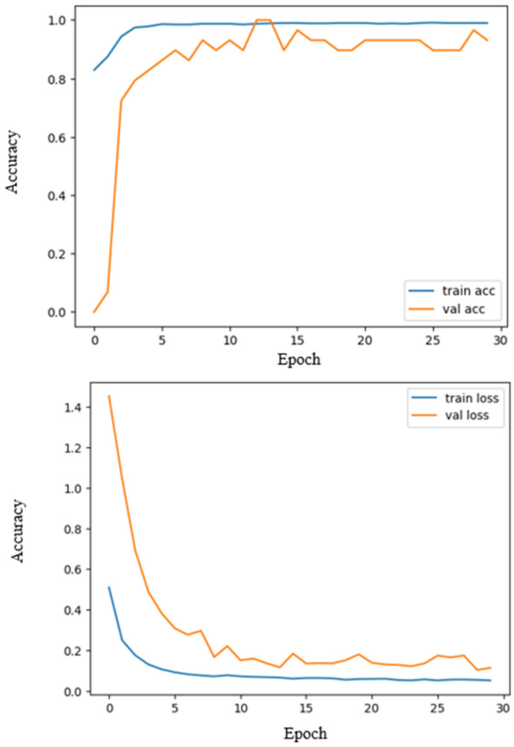

Fig. 7. Accuracy (a) and loss (b) graphs for the ResNet50 model.

Apart from detection rates, the efficiency of the model is another important issue in the performance criteria. Table II shows the accuracy, loss, and training time in seconds for all the banana leaf images for each method used. The average training time for ResNet50 is 159.2 s/epoch, which is 47.6 and 3.5 s less than that of InceptionV3 and VGG16, respectively. This could be because ResNet50 is moderately sized compared to VGG16 and InceptionV3. Although VGG16 is a large model due to its extensive use of parameters, it is less efficient than InceptionV3.

TABLE II. ACCURACY, LOSS, AND TRAINING TIME FOR EACH METHOD USED IN THIS STUDY.

Models	Time (s/epoch)	Training accuracy %	Validation accuracy %	Training loss %	Validation loss %
Resnet50	159.2	99.6	99.3	5.2	3.5
InceptionV3	206.8	99.2	99.3	8.4	5.5
VGG16	162.7	97.7	87.2	9.1	28.9

ResNet 50 showed excellent performance with high training and validation accuracy. The model achieved low training and validation losses, indicating robust learning. Inception V3 performed well with high accuracy, although it took longer per epoch than ResNet50. The model showed slightly higher losses than ResNet 50 but remained effective. VGG16 exhibited good training accuracy but a significant decrease in validation accuracy, suggesting possible overfitting. A high validation loss indicates that the model may not cope well with new datasets. The high accuracy rates achieved by the CNN models suggest their potential for practical deployment in the field. The ResNet50 model, in particular, exhibited robust performance in both the training and validation phases.

TABLE III. MODEL PERFORMANCE: PRECISION, MEAN RECALL, F1–SCORE, AND OVERALL ACCURACY.

Metrics	Models (%)		
	ResNet50	InceptionV3	VGG16
Precision	96.53	94.66	75.05
Recall	94.94	92.16	90.52
F1-score	95.73	93.89	81.43
Accuracy	99.42	99.22	90.99

ResNet-50 achieved high precision, recall, F1 score, and accuracy, making it a robust model for BBTV diagnosis. InceptionV3 demonstrated excellent performance across all metrics, with a balance between precision and recall. The VGG16 model exhibited slightly lower precision than the other models but achieved high recall. Its F1 score and accuracy were also competitive. In [30], using BananaSqueezeNet, ResNet50 achieved 86.25% accuracy, 89.26% precision, 86.25% recall, and 96.17% F1 score. The Inception-V3 model achieved an accuracy of 90.00%, a precision of 91.96%, a recall of 90%, and an F1 score of 89.30%. For VGG16, precision was 95%, accuracy was 95.45%, recall was 95%, and F1 score was 94.84%. These results are less than those obtained in this study, except for the VGG16 model.

The results suggest that the ResNet 50 model has better consistency for both training and validation and has the shortest training time. Although the InceptionV3 model had the longest training time, it also had good consistency. In Tanzania, a mobile app was developed using deep learning to detect Fusarium wilt race 1 and black Sigatoka diseases in bananas using two CNN architectures, namely Resnet152 and InceptionV3 [31]. The former achieved an accuracy of 99.2% and the latter an accuracy of 95.41% [31]. Similarly, ResNet 50 performed the best of the five models compared in [32] for the early detection of rice disease. Similarly, ResNet 50 outperformed other models in the identification of Fusarium wilt infections in banana leaves [24], for the early detection of banana leaves in general [33], and for disease detection in several plant species [23]. The same conclusion was reached in [21] for deep learning models for crop quality and disease detection, as ResNet50 outperformed the other models with 88.54% validation accuracy. These results indicate the potential to improve banana yield for small farmers using a tool for early detection of diseases.

IV. CONCLUSION

This study presented a comprehensive investigation into the application of AI for the identification of BBTV in banana crops in Mozambique. Despite the increasing importance of AI in agriculture, particularly in disease detection, there has been a notable knowledge gap regarding the specific application of AI for BBTV detection in Mozambique. This study aimed to address this gap by developing and validating ML algorithms capable of accurately detecting BBTV-infected plants. The novelty of this work lies in its focus on a specific banana disease that has a significant economic impact in Mozambique. Through the analysis of approximately 2,500 images of healthy and BBTV-infected banana leaves, collected from fields on the Josina Machel island, these models were trained and evaluated for their performance in BBTV detection. The results demonstrated the efficacy of the ResNet50 model, which achieved a mean accuracy of 99.56% in the training phase, while precision, recall, and F1-score were 96.53%, 94.94%, and 95.73%, respectively, in the validation subsets, outperforming the other models tested. The ResNet50 model showed robust performance with high accuracy, low loss rates, and efficient training times, making it a promising tool for BBTV diagnosis in Mozambique. These findings are consistent with existing literature, especially on the best-performing model for disease detection, suggesting the versatility and effectiveness of the ResNet-50 model in identifying diseases across different agricultural settings and crops. In general, this study contributes to ongoing efforts to increase the application of AI in agriculture, providing a tailored solution for BBTV detection in Mozambican banana crops. The proposed AI model offers farmers and researchers powerful tools for timely and accurate disease detection, enabling effective disease management strategies and, ultimately, enhancing the productivity and sustainability of banana crops in Mozambique.

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REFERENCES

[1] A. Gwagwa *et al.*, "Road map for research on responsible artificial intelligence for development (AI4D) in African countries: The case study of agriculture," *Patterns*, vol. 2, no. 12, Dec. 2021, https://doi.org/10.1016/j.patter.2021.100381.

[2] Y. Ai, S. Lee, and J. Lee, "Drinking water treatment residuals from cyanobacteria bloom-affected areas: Investigation of potential impact on agricultural land application," *Science of The Total Environment*, vol. 706, Mar. 2020, Art. no. 135756, https://doi.org/10.1016/j.scitotenv.2019.135756.

[3] D. I. Patrício and R. Rieder, "Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review," *Computers and Electronics in Agriculture*, vol. 153, pp. 69–81, Oct. 2018, https://doi.org/10.1016/j.compag.2018.08.001.

[4] N. C. Eli-Chukwu, "Applications of Artificial Intelligence in Agriculture: A Review," *Engineering, Technology & Applied Science Research*, vol. 9, no. 4, pp. 4377–4383, Aug. 2019, https://doi.org/10.48084/etasr.2756.

[5] M. T. Linaza *et al.*, "Data-Driven Artificial Intelligence Applications for Sustainable Precision Agriculture," *Agronomy*, vol. 11, no. 6, Jun. 2021, Art. no. 1227, https://doi.org/10.3390/agronomy11061227.

[6] L. Loyani and D. Machuve, "A Deep Learning-based Mobile Application for Segmenting Tuta Absoluta's Damage on Tomato Plants," *Engineering, Technology & Applied Science Research*, vol. 11, no. 5, pp. 7730–7737, Oct. 2021, https://doi.org/10.48084/etasr.4355.

[7] G. Bannerjee, U. Sarkar, S. Das, and I. Ghosh, "Artificial Intelligence in Agriculture: A Literature Survey," *International Journal of Scientific Research in Computer Science Applications and Management Studies*, vol. 7, no. 3, May 2018.

[8] J. C. Smart, D. Tschirley, and F. Smart, "Diet Quality and Urbanization in Mozambique," *Food and Nutrition Bulletin*, vol. 41, no. 3, pp. 298–317, Sep. 2020, https://doi.org/10.1177/0379572120930123.

[9] A. C. van Westerhoven *et al.*, "Dissemination of Fusarium Wilt of Banana in Mozambique Caused by Fusarium odoratissimum Tropical Race 4," *Plant Disease*, vol. 107, no. 3, pp. 628–632, Mar. 2023, https://doi.org/10.1094/PDIS-07-22-1576-SC.

[10] A. T. Uazire *et al.*, "Preliminary evaluation of improved banana varieties in Mozambique," *African Crop Science Journal*, vol. 16, no. 1, 2008, https://doi.org/10.4314/acsj.v16i1.54325.

[11] L. Tripathi, V. O. Ntui, J. N. Tripathi, and P. L. Kumar, "Application of CRISPR/Cas for Diagnosis and Management of Viral Diseases of Banana," *Frontiers in Microbiology*, vol. 11, Jan. 2021, https://doi.org/10.3389/fmicb.2020.609784.

[12] G. P. Henz, F. A. de Alcantara, and F. V. Resende, "Produção orgânica de hortaliças: o produtor pergunta, a Embrapa responde.," Sidalc, 2013.

[13] F. K. Dal Soglio, "A fitopatologia numa perspectiva agroecológica," presented at the XXXIX Congresso Brasileiro de Fitopatologia, Aug. 2006.

[14] N. E. A. Amrani, O. E. K. Abra, M. Youssfi, and O. Bouattane, "A Novel Deep Learning Approach for Semantic Interoperability Between Heteregeneous Multi-Agent Systems," *Engineering, Technology & Applied Science Research*, vol. 9, no. 4, pp. 4566–4573, Aug. 2019, https://doi.org/10.48084/etasr.2841.

[15] K. L. Narayanan *et al.*, "Banana Plant Disease Classification Using Hybrid Convolutional Neural Network," *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, 2022, Art. no. 9153699, https://doi.org/10.1155/2022/9153699.

[16] S. K. Chakraborty, N. S. Chandel, D. Jat, M. K. Tiwari, Y. A. Rajwade, and A. Subeesh, "Deep learning approaches and interventions for futuristic engineering in agriculture," *Neural Computing and Applications*, vol. 34, no. 23, pp. 20539–20573, Dec. 2022, https://doi.org/10.1007/s00521-022-07744-x.

[17] V. S. Dhaka *et al.*, "A Survey of Deep Convolutional Neural Networks Applied for Prediction of Plant Leaf Diseases," *Sensors*, vol. 21, no. 14, Jan. 2021, Art. no. 4749, https://doi.org/10.3390/s21144749.

[18] A. Senbato and T. Ayalew, "Developing Common Bacteria Blight Disease Detection Model for Common Bean Using Deep Learning Approach." Research Square, Oct. 31, 2023, https://doi.org/10.21203/rs.3.rs-3512095/v1.

[19] A. Mittal and H. Gupta, "An Experimental Evaluation in Plant Disease Identification Based on Activation-Reconstruction Generative Adversarial Network," in *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, Greater Noida, India, Apr. 2022, pp. 361–366, https://doi.org/10.1109/ICACITE53722.2022.9823924.

[20] A. Abade, P. A. Ferreira, and F. de Barros Vidal, "Plant diseases recognition on images using convolutional neural networks: A systematic review," *Computers and Electronics in Agriculture*, vol. 185, Jun. 2021, Art. no. 106125, https://doi.org/10.1016/j.compag.2021.106125.

[21] P. Sahu, A. Chug, A. P. Singh, D. Singh, and R. P. Singh, "Deep Learning Models for Crop Quality and Diseases Detection," in *Proceedings of the International Conference on Paradigms of Computing, Communication and Data Sciences*, Kurukshetra, India, 2021, pp. 843–851, https://doi.org/10.1007/978-981-15-7533-4_67.

[22] Y. Chen *et al.*, "Discovery of Niphimycin C from Streptomyces yongxingensis sp. nov. as a Promising Agrochemical Fungicide for Controlling Banana Fusarium Wilt by Destroying the Mitochondrial Structure and Function," *Journal of Agricultural and Food Chemistry*, vol. 70, no. 40, pp. 12784–12795, Oct. 2022, https://doi.org/10.1021/acs.jafc.2c02810.

[23] F. Mohameth, C. Bingcai, and K. A. Sada, "Plant Disease Detection with Deep Learning and Feature Extraction Using Plant Village," *Journal of*

Computer and Communications, vol. 08, no. 06, pp. 10–22, 2020, https://doi.org/10.4236/jcc.2020.86002.

[24] K. Yan, M. K. C. Shisher, and Y. Sun, "A Transfer Learning-Based Deep Convolutional Neural Network for Detection of Fusarium Wilt in Banana Crops," *AgriEngineering*, vol. 5, no. 4, pp. 2381–2394, Dec. 2023, https://doi.org/10.3390/agriengineering5040146.

[25] M. G. Selvaraj *et al.*, "AI-powered banana diseases and pest detection," *Plant Methods*, vol. 15, no. 1, Aug. 2019, Art. no. 92, https://doi.org/10.1186/s13007-019-0475-z.

[26] B. Galatas *et al.*, "A prospective cohort study to assess the micro-epidemiology of Plasmodium falciparum clinical malaria in Ilha Josina Machel (Manhiça, Mozambique)," *Malaria Journal*, vol. 15, no. 1, Aug. 2016, Art. no. 444, https://doi.org/10.1186/s12936-016-1496-y.

[27] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, Jun. 2016, pp. 770–778, https://doi.org/10.1109/CVPR.2016.90.

[28] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, Jun. 2016, pp. 2818–2826, https://doi.org/10.1109/CVPR.2016.308.

[29] S. Tammina, "Transfer learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images," *International Journal of Scientific and Research Publications (IJSRP)*, vol. 9, no. 10, Oct. 2019, Art. no. p9420, https://doi.org/10.29322/IJSRP.9.10.2019.p9420.

[30] Md. A. B. Bhuiyan, H. M. Abdullah, S. E. Arman, S. Saminur Rahman, and K. Al Mahmud, "BananaSqueezeNet: A very fast, lightweight convolutional neural network for the diagnosis of three prominent banana leaf diseases," *Smart Agricultural Technology*, vol. 4, Aug. 2023, Art. no. 100214, https://doi.org/10.1016/j.atech.2023.100214.

[31] S. L. Sanga, D. Machuve, and K. Jomanga, "Mobile-based Deep Learning Models for Banana Disease Detection," *Engineering, Technology & Applied Science Research*, vol. 10, no. 3, pp. 5674–5677, Jun. 2020, https://doi.org/10.48084/etasr.3452.

[32] S. R. Shah, S. Qadri, H. Bibi, S. M. W. Shah, M. I. Sharif, and F. Marinello, "Comparing Inception V3, VGG 16, VGG 19, CNN, and ResNet 50: A Case Study on Early Detection of a Rice Disease," *Agronomy*, vol. 13, no. 6, Jun. 2023, Art. no. 1633, https://doi.org/10.3390/agronomy13061633.

[33] S. Sanga, "Development of an early detection tool for banana diseases: A case of Mbeya and Arusha region," M.S. Thesis, Nelson Mandela African Institution of Science and Technology, Arusha, 2020.