Global Scientific JOURNALS
GSJ: Volume 11, Issue 8, August 2023, Online: ISSN 2320-9186
www.globalscientificjournal.com

Review of Challenges in Image acquisition on plant-based disease detection in Africa

Peter E. Okimba[1], Virginia E. Ejiofor[2]
1, 2 Nnamdi Azikiwe University, Nigeria
rhemapok30@gmail.com

Abstract. Owing to issues of food security and unmitigated shortages in food produce, automated plant detection systems have been proposed as a panacea that allows for early identification and diagnosis. By reviewing the literature on this subject as well as experiences of image acquisition in yam fields in Otuocha, Anambra State, Nigeria, we were able to generate several challenges that plague the computer vision enthusiast, who may wish to alleviate the manual and time consuming process of early disease identification and remediation faced by farmers in Africa. In this paper, a survey of plant disease detection work on the continent was presented. Several challenges identified include skepticism on the part of growers, experts' unwillingness for accurate labeling, the absence of sophisticated capturing devices, the risks associated with encountering the murderous, mirthless Fulani herdsmen, a lack of funds, and the difficulty attendant to capturing images on the vine. We hope the study will help prepare the minds of enthusiasts and potential researchers in this clime.

Keywords: Image acquisition, Plant Disease, Computer Vision, Machine learning, Deep Learning, Transfer Learning

1 Introduction

The examination of diseases in the early stages of plant life has been mostly measured as prevalence (presence or absence) at the farmland, field, village, or landscape level, and the technique is difficult, grueling, and consumes a lot of time on a substantial scale[1]. According to Selvaraj et al. [2], this method of disease detection is called human scouting. Due to the associated constraints, scientists have been exploring sophisticated and unique approaches for obtaining information on plant health in a timely and cost-effective manner. This information is most necessary in Africa, where several diseases have ravaged crops, causing grave losses and hunger for millions of people on the continent. Crop diseases pose a substantial hazard to human survival as they can trigger droughts and famines and can result in significant losses in circumstances when agriculture is undertaken for profit [3]. Specifically, huge losses have been noted in cassava yield due to the mosaic virus epidemic [4]; and for bananas, the bunchy top disease (BBTD) and Xanthomonas wilt of banana (BXW) have caused significant danger to food security in East and Central African regions [2].

The application of computer vision (CV) and machine learning (ML) might enhance illness identification and treatment. These artificial intelligence (AI)-based methods have been used in recent times because "the early and timely identification of plant diseases positively impacts crop yield and quality" [5]. CV is a kind of artificial intelligence (AI) in which computers are used to interpret and recognize things. Addition- ally, it improves the precision of disease prevention in crops, thus enhancing food security [3]. These AI algorithms are seen as machine learning (ML) and deep learning (DL) models applied for research in agriculture [6]. These AI-based studies mostly employ transfer learning, "where a model that has been trained on a large image dataset isretrained for new classes, offering a shortcut to training deep learning models because of lower computational requirements" [7]. In the light of the above, this study is aimedat identifying the African-based plant disease detection studies in order to observe the efforts so far. Additionally, the challenges of image acquisition were identified using acase study of yam fields in Otuocha, Anambra State, Nigeria. The paper is arranged asfollows: Section 2 contains the related literature; Section 3 contains the challenges of image acquisition; and Section 4 contains the conclusion and future directions.

2 Review of African-based Plant Diseases' Detection Studies

At this point, we reviewed the few plant disease detection studies performed in Africa to understand the amount of effort that has been directed in this area. Several popular databases were searched using the following terms: Africa; plants; crops; machine learning; deep learning; detection; disease; and classification, etc. Note that by examining the methodology section of each reviewed paper, the African study area was identified. The inclusion criteria are as follows: studies must have been published in English between 2010 till date; the research papers should be peer-reviewed; image data must have been captured in an African nation; and the AI-based method applied must be used for plant disease detection. Papers that did not meet these criteria were excluded from the table analysis. For instance, this study excluded the optimal estimation of maize maturity [8], which employed an artificial neural network (ANN) and a convolutional neural network (CNN) possessing the ResNet 50 architecture with accuracies of 64.5% and 68%, respectively. Other studies excluded from this review because they were not done in Africa are as follows: (Hassan et al., [5]; Ayu et al., [9]; Mohanty et al. [10]). Table 1 contains the results of the review with the following columns: authors; crop(s) & diseases; location (Africa); Al algorithm; accuracy and equipment of data collection.

African countries identified include Uganda [11-15]; South Africa [16-18], Tanzania [7, 19], Nigeria [20] and Egypt [20]. From the tabular analysis, it is evident that CV research has involved the following ML algorithms: Naive Bayes (NB), two-layer MLPnetworks (MLPN) [11], support vector machines (SVM), k-nearest neighbor (KNN), divergence-based learning vector quantization (DBLVQ), decision trees (DT), and random forest (RF). CNNs were used in the following papers: Refs [2, 14-16, 18, 19, 21]. Additionally, the identified CNN architectures include InceptionResnetv2, Inceptionv3, Resnet50, VGG16, Resnet18, Resnet152 and NASNet. The major plants and diseases identified from the above review include cassava: (cassava brown streak disease (CBSD), cassava mosaic virus disease (CMD), brown leaf spot (BLS), red mite damage (RMD), green mite damage (GMD), cassava bacterial blight (CBB), cassava green mottle (CGM)) and cowpea (Cercospora leaf spot). Other plant/diseases include; banana (BBTD, BXW, Fusarium wilt of banana (FWB), black sigatoka (BS), yellow sigatoka (YS), and banana corm weevil (BCW)); maize (northern corn leaf blight (NLB), gray leaf spot (GLS), common rust (CR)); corn (leaf rust disease (LRD), leaf spot disease (LSD), and leaf blight disease (LBD)) and potato (late blight (LB), early blight (EB)). Besides noting that accuracy is the most popular metric used in these papers, other metrics used include the loss function, mAP score, and confusion matrix [2].

Table 1: Studies of Plant Disease Detection and Diagnosis

Authors	**Crop(s) & Diseases**	**Location in Africa**	**Al Algorithm and Architecture**	**Accuracy**
Aduwo et. al. [11]	Cassava (CMD)	Uganda	ML (NB, MLPN, SVM, KNN, DBLVQ)	Classifier accuracies (HSV (74% - 87%), SURF (91% to 98%), SIFT (94% - 98%))
Ramcharan et. al. [7]	Cassava (BLS, RMD, GMD, CBSD, CMD)	Tanzania	DL (CNN)	96% (RMD), 95% (GMD), 98% (CBSD), and 96%
Owomugisha et. al. [13]	Cassava (CBSD CMD)	Uganda	ML (KNN, SVM, DT)	70% - 100%
Selvaraj et al. [23]	Banana diseases (8) and pest	Congo, Central Uganda, Burundi and Benin Republic	DL (CNN) – ResNet50, InceptionV2 and obileNetV1	Between 70 and 99%
Sweetwilliams et al [22]	Banana (BS)	South Africa	ML (Multilayer Perceptron ANN)	98%
Selvaraj et al. [2]	Banana (BBTD; BXW; HBC and IBP)	DR Congo, Benin	ML (RF and SVM)	99.4% (BBTD); 92.8% (BXW); 93.3% (HBC) and 90.8% (IBP) and overall accuracy of 97%
Sanga et al. [19]	Banana (FWB, BS)	Tanzania	CNN (VGG16, Resnet18, Resnet50, Resnet152 and InceptionV3)	99%

Sambasivam & Opiyo [14]	Cassava (CGM, CBB, CMD, CBB)	Uganda	CNN	93% (CMD, CBSD, CBB, CGM (cassava green mite)
Mankal et al. [15]	Cassava (CMD, CGM, CBSD), and CBB)	Uganda	CNN (Inception-resnetv2, Inceptionv3, and Resnet50), Open CV	83.01% (InceptionV3), 84.77% (Inception ResnetV2) and 78.29% (ResNet50)
Sibiya & Sumbwanyambe [16]	Maize (NCLB, CR, GLS)	South Africa	K Means Clustering, Fuzzy logic	45.21% (Healthy); 54.79% (Diseased)
Sibiya & Sumbwanyambe [17]	Maize (NCLB, CR, GLS)	South Africa	CNN	99.9% for Northern Corn Leaf Blight, 91% for Gray Leaf Spot, 87% for Common Rust and 93.5% of healthy maizeleaves.
Adedoja et al. [18]	Apple (Apple scab), Grape (black rot)	South Africa	CNN and the NASNet architecture	93.82%
Adekunle [20]	Corn (LRD, LSD and Healthy leaf)	Nigeria	SVM, RF, Neural Networks	93.6% (SVM); 96.7% (RF); 95.3% (Neural Networks)
Mohamed [21]	Potato (LB, EB and Healthy potato leaf)	Egypt	CNN	98%

Recall that we reviewed machine learning (ML) and deep learning (DL) for the following crops such as yam, cassava, banana, apple, maize, and potato. Though, the review has presented several approaches, techniques and methodologies that would aid the fulfilment of earlier stated objectives. From the review; several knowledge gaps came to the fore and they include;

1. No ML or DL (using CNN) consideration for yam diseases detection even though these ailments have threatened overall production in West Africa.
2. From the reviewed studies with CNN architectures, none involved yam diseases on the leaves or the tubers.

3. Considering the reviewed studies with multiple visualization techniques, none involved yam diseases on the leaves and the tuber.
4. Most of the studies reviewed above, used only one plant database for transfer learning. This study applies two; namely ImageNet and PlantVillage.

The aforementioned gaps as well as the humongous gains to be accrued motivated this study.

Summary of Literature Review

Here, the synopsis of pertinent review alongside areas were DL/ML enthusiasts can invest research efforts were presented. et al., [13] employ data augmentation and our work would apply it as mentioned therein. It is noteworthy to mention that most of the studies reviewed above involved collection of leaf images, and this is because, as it can be said, the majority of plant diseases can be identified by their leaf symptoms. et al., [11].

Actually, from the surveyed works, it was discovered that data collection was mostly done by a digital camera while some researchers used other methods such as UAV on potato [2] and banana diseases image collection et al., [7]. Note that UAV was chosen because of some advantages which include; "robustness in collection of aerial images from multiple altitudes and provision of a higher temporal and spatial resolution compared to the satellite images, and also increases cost-effectiveness depending upon the study area". Data acquisition also involved small unmanned aircraft system (UAS, commonly known as a drone) in the study by et al., [27]. Most of the classifications involved both healthy and diseased leaves, this is to enable the CNN learn to differentiate between the two and to aid the farmers ultimately, who may not be able to identify and accurately treat these infections. Using the UAV, et al., [7] took a different direction from the disease detection standpoint but still maintained the application of deep learning, CNN and transfer learning but towards counting of plants and increasing overall yield.

On the banana plant, we reviewed DL/ML application for several diseases such as banana bunchy top virus, black sigatoka, xanthomonas wilt, banana corm weevil, and banana speckle. On the other hand, studies for pests were not seen such as; burrowing nematode and fusarium wilt. From the review, et al., [22] was implemented on the web alongside the CNN, and can allow the farmers to upload images for detection using their smart devices. For studies that employed segmentation, the Fuzzy C and K-Means clustering enjoyed the most usage. A segmentation method was described; it is conducted using the active contour model based on global gradient and local information (Figure 1.).

GSJ: Volume 11, Issue 8, August 2023
ISSN 2320-9186

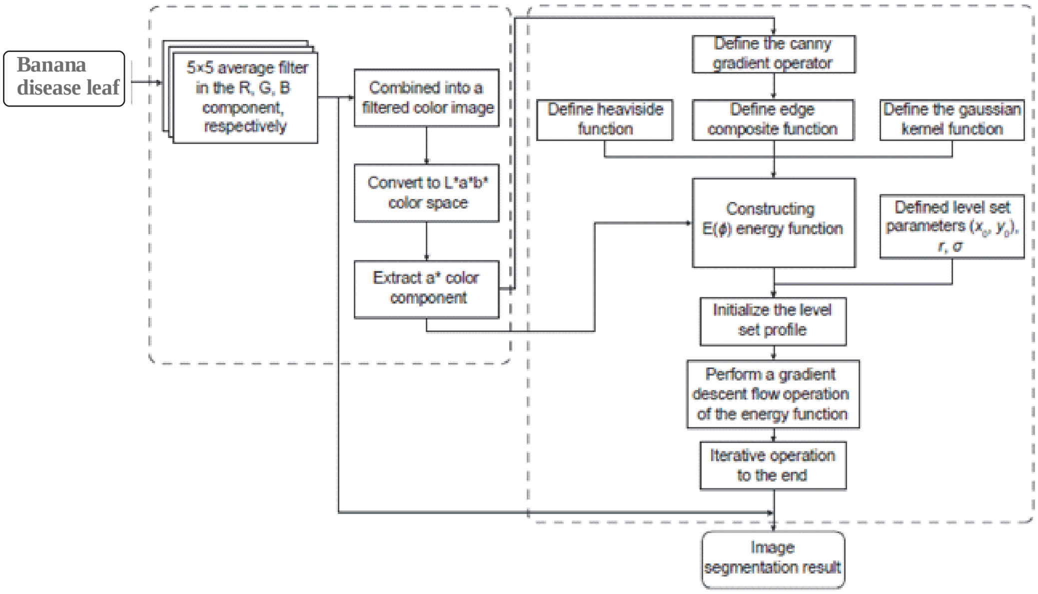

Figure 1.: Flowchart of cotton diseased leaves image segmentation **[22]**.

However, most of the reviewed works retrained their newly collected images with an already existing CNN, the reason for this is explained with the following statements, transfer learning can enhance the performance of big CNNs in situations with limited training data and computational resources because training a network from scratch is a computationally demanding process that needs a large set of labeled inputs. This is one advantage of starting with GoogLeNet, a CNN trained on over a million images. The weights and offsets describing the filters and neural interconnects of the network start at values that extract features that are effective for classifying a wide range of different shapes, textures, colors, and patterns. In comparison to training from scratch, retraining Google Net can be relatively quick (hours as opposed to days or weeks), utilizing a relatively small training set (thousands as opposed to millions of photos) suited to the task at hand [21].

3 Challenges of Image Acquisition

Perez-Sanz et al. [24] define image acquisition as "the process by which we obtain a digital representation of a scene." This representation is known as an image, and its parts are simply known as "pixels" or picture elements. Image collection is a critical component of computer vision studies [7, 13, 16, 17], hence we examine the difficulties encountered by researchers. The traditional method of obtaining picture data for neural network training, testing, and validation has been to collect image data from the actual environment, followed by manual annotation and labeling of the generated image data [25]. Image acquisition in Otuocha yam fields in Anambra State, Nigeria with difficult terrains were done using Smartphone cameras. The challenges encountered in the field are listed and explained below:

A. Lack of sophisticated capturing equipment

It has been established that image-capturing devices or equipment are needed to collect the required dataset, and examples include remote sensing, Unmanned Aerial Vehicles (UAVs) or drones, high-definition cameras, etc. However, Ramcharan et al. [7] confirmed that conventional disease identification methods depend on agricultural support agencies for assistance, but they are constrained in (African) countries with inadequate logistical and human infrastructural capabilities, and they are costly to scale up. From table 1, it is clear that some studies used a digital camera [11, 12, 7, 23, 19, 23], while others used smart phone cameras [13, 23, 16, 17]. The unmanned aerial vehicle (UAV)-MS with a

MicaSense RedEdge multispectral camera was used by Selvaraj et al. (2020), whereas crowdsourcing was used by Sambasivam & Opiyo [14]. Considering that the collection of our yam leaf images was captured using a smartphone camera and the review herein, one can conclude that African researchers are yet to fully involve remote sensing for computer vision research. Additionally, this is in line with opinions [2] that internet connectivity, smartphones, and UAV technology now provide novel instruments for in-farm crop disease diagnosis depending on automatic image identification, which may help vastly in earlier detection. This study therefore proposes that remote sensing technology should be encouraged image acquisition in farm lands in Africa.

B. Lack of Resources

The underdeveloped world has been under-resourced in terms of image-based identification of plant diseases. While some attribute it to a scarcity of professionals [12], others attribute it to a lack of cash and financing organizations [26]. According to the review above, the National Crops Resources Research Institute [11, 13], as well as the AI lab at Makerere University in Kampala, have been instrumental in agriculture-based CV research. Because our yam disease detection is not organizational research, attracting financing and assistance from Nigerian agricultural organizations proved challenging. The implication is that we contributed to and funded our visits to Otuocha farmlands in Anambra state. Sometimes, monetary incentives were given to farm extension workers from the Anambra state ministry of agriculture. This, to some extent, reduced the unwillingness on the part of the extension workers as it may be considered that the fund is not enough for them to embark on such assignment. Government intervention will be required to help remedy these situations.

C. Manual Disease Identification, Labelling and Annotation Issues

A qualified plant pathologist can typically detect diseases with a high degree of certainty by viewing an image of affected tissue or leaves [27]. Unfortunately, this visual diagnosis is not scalable; even though each crop or leaf could be properly documented, one individual cannot quickly analyze every plant in a vast region. While capturing the yam images, we also noticed that the locals have their local names, which can hardly be related to the English names of these diseases. At times, when we could not get the full cooperation of the extension workers due to a lack of monetary incentives, this constituted a lot of difficulties. Due to the problems in gathering image data, there has been a surge in demand for synthetic datasets as a possibly less expensive and more available substitute to collecting actual data for training, while numerous data types are employed in the area of computer vision [25].

D. Complex Image backgrounds and Capture Conditions

Selvaraj et al. [23] identified challenges in the form of "background variations caused by the surroundings of the field, dried leaves on the floor, and overlapping leaves from neighboring plants". This complicated background can be filled with "shadows and unstable luminosity" [28]. In addition to the above, we faced similar challenges of variations and overlap while capturing diseased leaves on the stem or vine. To address these issues, we proposed the cutting of diseased leaves and capturing the leaf images while placed on a white background. However, this method can only be effective if there are enough manpower and the images are captured on the first day. This is because by the next day, the collected diseased images could shrink.

E. Risks/Fears Associated with Encountering Fulani herdsmen in Farms

In recent times, farmlands in Nigeria have been ravaged by terrorists such as Fulani herdsmen [29]. Besides crop destruction [30], these herdsmen sometimes masquerade as nomadic cattle herders armed to the teeth with weapons, and they kidnap, dish out terror and mayhem to farmers in the region. The growers go to their farms without adequate protection, and due to fear, they only cultivate very little. Consequently, this may also lead to insufficient supplies of agricultural products [29]. Low cultivation mayequal low data points, which inadvertently leads to the inability to spot a particular disease in a particular yam field. While capturing images for yam diseases, the people involved (researchers, farm growers, and extension workers) entertained fears of possible attacks from herdsmen, and this caused rescheduling of visits to the farmlands, thus elongating the time allocated for image acquisition.

F. Mixed complex agriculture systems

Agricultural systems that favour predominantly mixed cropping [31] in African farm-lands may pose challenges for researchers who may want to capture images for computer vision in agriculture. Indeed, to a large extent, the mixed cropping system can strengthen the challenge of non-uniform backgrounds [32]. This is true even with the use of UAVs for banana farms, which are "often mixed with other classes (e.g., buildings, pastures, trees)" [2]. Selvaraj et al. [2] also confirmed that the Sentinel-2 mapping [33] of banana failed to achieve great overall accuracy (76%), owing to the low quantityof the data points and the "mixed-complex setting" of African environments. Yams have been included in mixed cropping systems in Nigeria [34, 35]. However, while capturing yam leaves, the mixed-cropping systems complicated disease identification, especially when the yam farmlands were visited without the locals and extension workers. In this situation, the researchers, filled with confusion, may tend to capture the wrong images or collect images that have already been collected. There is therefore need for separate cropping.

G. Symptom Variation and Co-infection

Symptom variations were counted among phytosanitary challenges in a study by Boulant et al. [32]. This variation may be over a period of time and among varieties, or it may reflect the potential for numerous abnormalities/diseases manifesting concurrently. Various pathogens (viruses, bacteria) can prompt plant co-infection, making dis- ease detection more complicated [36]. Co-infection is a commonly occurring challenge[37], and it was very evident in the yam farms. For yam varieties, the symptoms seem to vary over time, at least for the researchers, but with the clarifications provided by thegrowers or the extension workers, progress was made. Symptom variations may also be further complicated with a mixed cropping system. These issues depict the need forexpertise in assessing the phytosanitary conditions of farms [32].

H. Skepticisms and unwillingness of the growers

The growers in certain areas refused entry into their yam farms for fears of crop destruction and damage. Most of them are still mourning and grieving the destructions perpetuated by cattle herders. In some places, the farmers are disappointed when they discover we are researchers and not from the government. This is because they are expecting government funding to increase their cultivation or to obtain free fertilizers. This issue elongated the image acquisition phase as we had to visit more farms to be able to collect useful images.

4 Conclusion

Early diagnosis and identification are a critical initial step in managing and controllingthe detection and progression of plant diseases. This has necessitated the use of CV, ML, and DL, which mostly involve transfer learning. Some of the challenges identified are as follows; lack of sophisticated capturing equipment, lack of resources, manual disease identification, labeling, and annotation issues. Other include; complex image backgrounds and capture conditions, risks/fears associated with encountering Fulani herdsmen in farms, mixed complex agriculture systems, skepticism or unwillingness on the part of the growers, symptom variation, and co-infection. Literature on the use of CV in agriculture also identified climatic conditions, but this was not highlighted asa serious issue for both the reviewed studies herein and the yam disease image collection. Detecting diseases with the human eye is a difficult challenge for growers and professionals, and finding crop abnormalities with identical characteristics in various illnesses is quite difficult. However, current advances in computer vision and deep learning have enabled the identification of deep characteristics of several illnesses regardless of picture background or image capture settings.

References

[1] Heim, R. H. J., Wright, I. J., Allen, A. P., Geedicke, I., & Oldeland, J. (2019). Developing a spectral disease index for myrtle rust (Austropuccinia psidii). *Plant Pathology*, 68(4), 738–745. https://doi.org/10.1111/ppa.12996

[2] Selvaraj, G. M., Vergara, A., Montenegro, F., Alonso Ruiz, H., Safari, N., Raymaekers, D.,Ocimati, W., Ntamwira, J., Tits, L., Omondi, A. B., & Blomme, G. (2020). Detection of banana plants and their major diseases through aerial images and machine learning methods: A case study in DR Congo and Republic of Benin. *ISPRS Journal of Photogrammetry and Remote Sensing*, 169(September), 110–124. https://doi.org/10.1016/j.isprsjprs.2020.08.025

[3] Khan, R. U., Khan, K., Albattah, W., & Qamar, A. M. (2021). Image-Based Detection of Plant Diseases: From Classical Machine Learning to Deep Learning Journey. *Wireless Com- munications and Mobile Computing*, 2021. https://doi.org/10.1155/2021/5541859

[4] Legg, J. P., Jeremiah, S. C., Obiero, H. M., Maruthi, M. N., Ndyetabula, I., Okao-Okuja, G.,Bouwmeester, H., Bigirimana, S., Tata-Hangy, W., Gashaka, G., Mkamilo, G., Alicai, T., &Lava Kumar, P. (2011). Comparing the regional epidemiology of the cassava mosaic and cassava brown streak virus pandemics in Africa. *Virus Research*, 159(2), 161–170. https://doi.org/10.1016/j.virusres.2011.04.018

[5] Hassan, S. M., Maji, A. K., Jasiński, M., Leonowicz, Z., & Jasińska, E. (2021). Identification of Plant-Leaf Diseases Using CNN and Transfer-Learning Approach. Electronics, 10(12).

[6] Yang, B., & Xu, Y. (2021). Applications of deep-learning approaches in horticultural re- search: a review. Horticulture Research, 8(1). https://doi.org/10.1038/s41438-021-00560-9

[7] Ramcharan, A., Baranowski, K., McCloskey, P., Ahmed, B., Legg, J., & Hughes, D. P. (2017). Deep learning for image-based cassava disease detection. Frontiers in Plant Science, 8(October), 1–7. https://doi.org/10.3389/fpls.2017.01852

[8] Ayuba, P., Luhutyit, P. D., & Sa'adatu, A. (2020). Determining the Optimum Maturity of Maize Using Computational Intelligence Techniques. American Journal of Neural Networks and Applications, 6(1), 1. https://doi.org/10.11648/j.ajnna.20200601.11

[9] Ayu, H. R., Surtono, A., & Apriyanto, D. K. (2021). Deep learning for detection cassava leaf disease. Journal of Physics: Conference Series, 1751(1). https://doi.org/10.1088/1742- 6596/1751/1/012072

[10] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7(September), 1–10. https://doi.org/10.3389/fpls.2016.01419

[11] Aduwo, J. R., Mwebaze, E., & Quinn, J. A. (2010). Automated Vision-Based Diagnosis of Cassava Mosaic Disease. Proceedings of ICDM Workshop on Data Mining in Agriculture, 114–122.

[12] Quinn, J. A., Leyton-Brown, K., & Mwebaze, E. (2011). Modeling and monitoring crop disease in developing countries. Proceedings of the National Conference on Artificial Intel-ligence, 2, 1390–1395. https://doi.org/10.1609/aaai.v25i1.7811

[13] Owomugisha, G., Melchert, F., Mwebaze, E., Quinn, J. A., & Biehl, M. (2018). Machine learning for diagnosis of disease in plants using spectral data. 2018 World Congress in Com- puter Science, Computer Engineering and Applied Computing, CSCE 2018 - Proceedings of the 2018 International Conference on Artificial Intelligence, ICAI 2018, 9–15.

[14] Sambasivam, G., & Opiyo, G. D. (2021). A predictive machine learning application in agri- culture: Cassava disease detection and classification with imbalanced dataset using convo- lutional neural networks. Egyptian Informatics Journal, 22(1), 27–34. https://doi.org/10.1016/j.eij.2020.02.007

[15] Mankal, M., Kiran Kumar, C., & Nagaraj, S. (2021). Detection of Casava Plant related Dis- eases using Deep Learning. International Research Journal of Plant Science, 12(3), 1–6.

[16] Sibiya, M., & Sumbwanyambe, M. (2019a). A Computational Procedure for the Recognition and Classification of Maize Leaf Diseases Out of Healthy Leaves Using Convolutional Neu- ral Networks. AgriEngineering, 1(1), 119–131. https://doi.org/10.3390/agriengineer- ing1010009

[17] Sibiya, M., & Sumbwanyambe, M. (2019b). An Algorithm for Severity Estimation of Plant Leaf Diseases by the Use of Colour Threshold Image Segmentation and Fuzzy Logic Infer- ence: A Proposed Algorithm to Update a “Leaf Doctor” Application. AgriEngineering, 1(2), 205–219. https://doi.org/10.3390/agriengineering1020015

[18] Adedoja, A., Owolawi, P. A., & Mapayi, T. (2019). Deep learning based on NASNet for plant disease recognition using leave images. IcABCD 2019 - 2nd International Conference on Advances in Big Data, Computing and Data Communication Systems, 1–5. https://doi.org/10.1109/ICABCD.2019.8851029

[19] Sanga, S. L., Machuve, D., & Jomanga, K. (2020). Mobile-based Deep Learning Models for Banana Disease Detection. Engineering, Technology & Applied Science Research, 10(3), 5674–5677. https://doi.org/10.48084/etasr.3452

[20] Adekunle, I. M. (2020). Implementation of Improved Machine Learning Techniques for Plant Disease Detection and Classification. International Journal of Research and Innovation in Applied Science, 5(6), 1–4.

[21] Mohamed, A. P. S. I. (2020). Potato Leaf Disease Diagnosis and Detection System Based on Convolution Neural Network. International Journal of Recent Technology and Engineer- ing (IJRTE), 9(4), 254–259. https://doi.org/10.35940/ijrte.d4954.119420

[22] Sweetwilliams, F. O., Matthews, V. O., Adetiba, E., Babalola, D. T., & Akande, V. (2019). Detection of Sigatoka Disease in Plantain Using IoT and Machine Learning Techniques. Journal of Physics: Conference Series, 1378(2). https://doi.org/10.1088/1742- 6596/1378/2/0220

[23] Selvaraj, M. G., Vergara, A., Ruiz, H., Safari, N., Elayabalan, S., Ocimati, W., & Blomme, G. (2019). AI-powered banana diseases and pest detection. Plant Methods, 15(1), 1–11. https://doi.org/10.1186/s13007-019-0475-z

[24] Perez-Sanz, F., Navarro, P. J., & Egea-Cortines, M. (2017). Plant phenomics: An overview of image acquisition technologies and image data analysis algorithms. GigaScience, 6(11). https://doi.org/10.1093/gigascience/gix092

[25] Man, K., & Chahl, J. (2022). A Review of Synthetic Image Data and Its Use in Computer Vision. Journal of Imaging, 8(310), 1–33.

[26] Bjornlund, V., Bjornlund, H., & Van Rooyen, A. F. (2020). Why agricultural production in sub-Saharan Africa remains low compared to the rest of the world–a historical perspective. International Journal of Water Resources Development, 00(sup1), 1–34. https://doi.org/10.1080/07900627.2020.1739512

[27] Wu, H., Wiesner-Hanks, T., Stewart, E. L., DeChant, C., Kaczmar, N., Gore, M. A., Nelson, R. J., & Lipson, H. (2019). Autonomous Detection of Plant Disease Symptoms Directly from Aerial Imagery. Plant Phenome Journal, 2(1), 1–9. https://doi.org/10.2135/tppj2019.03.0006

[28] Ouhami, M., Hafiane, A., Es-Saady, Y., El Hajji, M., & Canals, R. (2021). Computer vision, IoT and data fusion for crop disease detection using machine learning: A survey and ongoing research. Remote Sensing, 13(13). https://doi.org/10.3390/rs13132486

[29] Bello, B., & Abdullahi, M. M. (2021). Farmers–Herdsmen Conflict, Cattle Rustling, and Banditry: The Dialectics of Insecurity in Anka and Maradun Local Government Area of Zamfara State, Nigeria. SAGE Open, 11(4), 1–11. https://doi.org/10.1177/21582440211040117

[30] Adelakun, O., Adurogbanga, B., & Akinbile, L. (2015). Socioeconomic Effects of Farmer- Pastoralist Conflict on Agricultural Extension Service Delivery in Oyo State, Nigeria. Jour- nal of Agricultural Extension, 19(2), 59. https://doi.org/10.4314/jae.v19i2.5

[31] Maiangwa, M. G. (2008). Adoption of mixed cropping by farmers in the north-west zone of Nigeria.pdf. Global Journal of Agricultural Sciences, 7(2), 167–175.

[32] Boulent, J., Foucher, S., Théau, J., & St-Charles, P. L. (2019). Convolutional Neural Net- works for the Automatic Identification of Plant Diseases. Frontiers in Plant Science, 10(July). https://doi.org/10.3389/fpls.2019.00941

[33] Sonobe, R., Yamaya, Y., Tani, H., Wang, X., Kobayashi, N., & Mochizuki, K. (2018). Crop classification from Sentinel-2-derived vegetation indices using ensemble learning. Journal of Applied Remote Sensing, 12(02), 1. https://doi.org/10.1117/1.jrs.12.026019

[34] Kuye, O. O., & Ettah, O. I. (2016). Contributions of Urban Mixed-Cropping to Household Food Security in Nigeria and Around the Globe. International Journal of Environment, Ag- riculture and Biotechnology, 1(2), 284–301. https://doi.org/10.22161/ijeab/1.2.24

[35] Uzo, J. O. (1983). Mixed cropping of yam, telfairia, maize and okra in a compound farming system of south eastern Nigeria. Acta Horticulturae, 123, 305–316. https://doi.org/10.17660/ActaHortic.1983.123.28

[36] Wang, Y. M., Ostendorf, B., Gautam, D., Habili, N., & Pagay, V. (2022). Plant Viral Disease Detection: From Molecular Diagnosis to Optical Sensing Technology—A Multidisciplinary Review. Remote Sensing, 14(7). https://doi.org/10.3390/rs14071542

[37] Tamborindeguy, C., Hata, F. T., Molina, R. de O., & Nunes, W. M. de C. (2023). A New Perspective on the Co-Transmission of Plant Pathogens by Hemipterans. Microorganisms, 11(1), 156. https://doi.org/10.3390/microorganisms11010156