African Journal of Rural Development, Vol. 10 (2): April - June, 2025: pp 157-173 ISSN 2415-2838

A Portable Plant Physiological Feature Image Processing Technique for Groundnuts Rosette Disease Diagnosis

SSENKOOTO, S. ±, MIREMBE, D. P. ±, NAKIBUULE, R.± and OKELLO, D. K. ¥

±College of Computing and Information Sciences, Makerere University, P.O. Box 7062, Kampala, Uganda
¥The National Agricultural Research Organization (NARO), P.O. Box 295, Entebbe, Uganda
Corresponding Author: drake.mirembe@mak.ac.ug

ABSTRACT

Agriculture is the backbone of most economies in Africa, including Uganda, and groundnut is one of the five most important oilseeds produced in the world and in Uganda. The crop plays a critical role in the food and nutrition security of both animals and humans. The optimal production of the crop is challenged by several factors, including limited access to quality seed, limited access to quality extension service, poor management of pests and diseases, and weak farm records management, among others. The crop is susceptible to many diseases, causing a decline in productivity and quality, all of which affect the agricultural economy. Traditional detection methods by farmers and researchers are knowledge-intensive, time-consuming, costly, and less accurate, necessitating the need to develop newer approaches which are more reliable and usable by farmers who have limited expert knowledge. Five major foliar diseases of groundnuts include groundnut rosette, early and late leaf spots, Bacterial wilt, and rust. Therefore, the main purpose of this study was to investigate the effectiveness of Artificial Intelligence to enable mobile models to detect groundnut rosette disease. The model described in this paper was developed with and without stepwise resizing and simultaneously validated using cross-entropy loss. The dataset used for training and validation purposes was manually created. To evaluate the performance of the model, various performance metrics such as accuracy, sensitivity, F1 score, and precision were applied and achieved a perfect precision value of 100% at a high confidence threshold of 0.964 and F1 score of 0.8 at a high confidence threshold of 0.454 demonstrating the model's balanced effectiveness in identifying groundnut rosette disease. The Groundnut Rosette Disease Diagnosis Using Plant Physiological Feature Image Processing Technique model achieved reliable accuracy with a limited dataset of 9 groundnut rosette scale rates.

Keywords: Detection, Deep Learning, groundnut leaf diseases, Neural Networks, Uganda

Cite as: Ssenkooto, S., Mirembe, D. P., Nakibuule, R. and Okello, D. K. 2025. A Portable Plant Physiological Feature Image Processing Technique for Groundnuts Rosette Disease Diagnosis. *African Journal of Rural Development* 10 (2):157 – 173.

RÉSUMÉ

L'agriculture est le pilier de nombreuses économies africaines, dont l'Ouganda, et l'arachide figure parmi les cinq principales oléagineuses au monde et dans le pays. Cette culture joue un rôle clé dans la sécurité alimentaire et nutritionnelle, tant pour l'animal que pour l'humain. Sa production optimale est toutefois entravée par des facteurs tels que l'accès limité à des semences de qualité, des services de vulgarisation insuffisants, une gestion lacunaire des ravageurs et maladies et une tenue défaillante des registres de ferme. L'arachide est sensible à de nombreuses maladies, causant un déclin de la productivité et de la qualité, avec des retombées macroéconomiques négatives. Les méthodes traditionnelles de détection, mobilisées par les agriculteurs et les chercheurs, requierent des connaissances poussées, sont chronophages, coûteuses et imprécises, ce qui justifie le développement d'approches nouvelles, plus fiables et utilisables par des producteurs non spécialistes. Les cinq principales maladies foliaires comprennent la rosette de l'arachide, les taches foliaires précoces et tardives, le flétrissement bactérien et la rouille. L'objectif de cette étude est d'évaluer l'efficacité de l'intelligence artificielle pour permettre à des modèles embarqués sur mobile de détecter la rosette de l'arachide. Le modèle décrit a été développé avec et sans redimensionnement progressif et validé simultanément via la perte d'entropie croisée. Le jeu de données d'entraînement/validation a été constitué manuellement. Pour evaluer la performance du model, plusieurs métriques tels que l'exactitude, sensibilité/rappel, score F1, précision ont été utilisés and ont montré une précision parfaite de 100 % à un seuil de confiance élevé de 0,964 et un score F1 de 0,8 à un seuil de 0,454, démontrant l'efficacité équilibrée du modèle pour identifier la rosette. Le modèle « diagnosis de la rosette de l'arachide utilisant la technique d'exploitation des images des paramètres physiologiques de la plant » atteint une exactitude fiable avec un jeu de données limité à neuf niveaux d'échelle de sévérité de la rosette.

Mots clés: détection, apprentissage profond, maladies foliaires de l'arachide, réseaux de neurones, Ouganda.

INTRODUCTION

Uganda is implementing the Fourth National Development Plan (NDP IV), which seeks to transform the country into a 500-billion-dollar middle-income economy driven by five major sectors: agriculture, services, tourism, construction, and manufacturing. In the agriculture sector, oil crops, including groundnuts, have been earmarked as strategic value chains for sector transformation. Groundnut (*Arachis hypogaea* L.) is a legume crop that is being grown worldwide and plays an important role in the agriculture sector and for food security. The crop is a major source of vegetable oil and protein for human consumption, as well as a cash crop for farmers in many regions (Reddy *et al*., 2003; Okello *et al.* 2015a). In Uganda, groundnuts are a source of income and employment for many value chain stakeholders (Mugisha *et al*., 2014), both Male and Female, with an estimated 557 million dollars per year on the Ugandan economy. Most of the varieties traditionally grown by farmers in Uganda are landraces adapted more for survival than yield (Okello *et al.,* 2010). Key varieties grown in Uganda include Serenut 14R, 8R, 5R, 11T, 9T Redbeauty, and Igola, grown under moderate rainfall that is well distributed and relatively low altitude below 1500mm (Okello *et al.,* 2015b). The crop is primarily grown in Uganda's Northern and Eastern regions by small-scale farmers. However, despite the contribution of the crop to household food security and income, pests and diseases, particularly groundnut Rosette (Okello *et al.*, 2010b), are the most important production constraint. The groundnut Rosette disease has the potential of destroying the crop and resulting in 100% yield loss if not detected and prevented early enough before the crop reaches the flowering stage (Okello *et al.*, 2010; Mugisa *et al.*, 2016). The advent of Information and Communication Technologies (ICTs), especially the Internet and Artificial Intelligence, has revolutionized the way we live and work (Mirembe *et al*, 2019). From enhancing delivery of agriculture extension services (Mirembe *et al*, 2016), delivery of financial services to unserved communities (Mirembe *et al.*, 2008), to delivery of online classes in education (Mpirirwe *et at.*, 2021), these technologies continue to reshape the way humans live and work, more so how farmers manage their enterprises for enhanced farm productivity (Mwesigwa *et at.*, 2016). Thus, advanced image processing techniques coupled with the advancement of smartphone computation capabilities provide an excellent opportunity for real-time detection and mapping of groundnut diseases. It is important to note that early detection of groundnut rosette diseases is the most important step in the management of the disease and mitigating its spread. Traditional or classical crop disease detection and identification approaches heavily rely on tacit knowledge of agricultural experts who are limited in number to provide timely diagnosis to farmers to support effective decision making (Ramcharan *et al*., 2017). It is worth noting that Uganda's agriculture sector still struggles with an insufficient number of extension workers, resulting in farmers having limited access to quality extension services (Mirembe *et al*, 2016). Therefore, the Artificial Intelligence and associated opened up new possibilities for real-time, cost-effective crop disease detection, identification and diagnosis in the field (Ramcharan *et al.*, 2017). Image recognition and deep learning techniques, such as deep convolutional neural networks, have shown promise in accurately identifying and classifying crop diseases based on leaf images (Zhou *et at.*, 2024). These advancements in technology have significantly improved disease management and enhanced the productivity of the groundnut value chain.

Automated image recognition and deep learning for crop disease detection and severity level prediction have been demonstrated for crops such as wheat (Sapre *et al.*, 2021), beans (Abed *et al.*, 2021; Laixiang *et al.*, 2023; Gomez *et al.*, 2024; Noviyanto *et al.*, 2024), and cassava (Anusha *et al.*, n.d.; Gopi *et al.*, 2024). Groundnut disease diagnosis has also been demonstrated, such as binary classification into healthy and unhealthy (Sangeetha *et al.*, 2024), Multi-classification for different disease classes (Tambe *et al.*, 2024) by previous research, but research on disease severity is lacking. Thus, the main purpose of this study was to develop a mobile device-based deep learning model for infield-based diagnosis of groundnut rosette disease severity detection to provide rapid, reliable, and timely results, thereby saving the crop. The study was inspired by the need to provide an easy-to-use, practical solution to farmers with low literacy and minimal expertise. Literature Review Different researchers have used different deep learning models to obtain accurate results for groundnut disease detection and diagnosis using images. Convolution Neural Network (CNNs), separable convolutions, Visual Geometry Group, ResNet, DenseNet, MobileNetV2, and Inception V3 transfer learning and YOLO models are some of the deep learning models that have been used (Jagan Mohan and Mohammed Nazer, 2022). Groundnut Disease Detection using Convolutional Neural Networks (CNN): The CNN family defines a class of deep learning models that perform object detection in two phases (Du *et al.*, 2018). Various researchers have used CNN and their variants to address the problem of automated groundnut disease diagnosis. Kukadiya *et al.* (2024) introduced a Deep Convolution Neural Network model, CNN8GN, with transfer learning to classify groundnut diseases into six classes, namely, Healthy, Alternaria, Early leaf Spot, Late leaf spot, and rust, and achieved an accuracy of

99.11% during training and 91.25%. Independently, Rajmohan *et al.* (2022) using a Convolutional Neural Network (CNN) model in combination with k-means clustering to segment and classify the ground diseases into four classes with an average accuracy of 93 %. Furthermore, studies by Sivasankaran *et al.* (2022) and employed the VGG 16 Model neural network utilizing the Adam optimizer to detect and classify groundnut disease into five classes with an accuracy of 99.82%.

Similarly, Vaishnnave *et al.* (2020) used the deep Convolutional Neural Network (DCNN) to classify 10 groundnut diseases (Alternaria leaf, Pestalotiopsis, Bud necrosis, tikka, Phyllosticta, Rust, Pepper spot, Choanephora, early and late leaf spot). This research achieved 99.88% accuracy. In 2022, Rakholia *et al.* (2022) proposed CNN- based architecture with progressive resizing to classify six major groundnut diseases (leaf spot, armyworms effect, wilts, yellow leaf, and healthy leaf). This study achieved a detection accuracy of 96.12%, again demostrating a high effectiveness of these CNN models. Futhere studeies by Kursun *et al.* (2023) which used the AlexNet in conjunction with Grad-cam for model explainability to classify groundnut diseases into five classes and achieved a 99.02% accuracy, while that of Anbumozhi and Shanthini (2024) which proposed Groundnut Leaf Diseases Identification, Classification with Convolutional Neural Network (GLDICCNN) to classify five classes of groundnut diseases achieved a respectable accuracy of 99.73%. Relatedly, Anbumozhi and Shanthini (2023) proposed the progressive Convolutional Neural Network (PGCNN) to classify groundnut leafy images in healthy and unhealthy; the unhealthy classes comprise the four classes of groundnut diseases that include Early spot, late spot rust, and Rosette. The model produces an accuracy of 97.58%. Patayon and Renato (2022) examined the performance of pre-trained 16, VGG16, VGG19, InceptionV3, MobileNet, DenseNet, Xception, InceptionResNetV2, and ResNet50 architectures and different deep learning optimizers on the classification of groundnut Leaf Spot disease; with e DenseNet-169 producing a high accuracy of 98%. Paramanandham *et al.* (2024) introduced a deep learning model architecture called the leaf net and used it to classify groundnut diseases into six classes using the groundnut leaf dataset. The classes of concentration were early leaf spot, early rust, healthy leaf, nutrient deficiency, rust, and late leaf spot, and achieved an accuracy of 97.225%. Table 1 shows the accuracy of the different algorithms that have been tested.

Table 1. Summary of different algorithms that are used in groundnut disease detection and classification.

Paper	**Algorithm**	**Part of plate image data used**	**Number of images**	**Diseases classified**	**Accuracy**
Kukadiya *et al.*, (2024)	Deep Convolutional Neural Network (GNN8GN) with transfer learning	Leafy	5322	• Early leaf spot • Late leaf spot • Alternaria • EarlyRust • Late Rust • Healthy	99.11% on training 91.25% on testing
Rajmohan *et al.*, (2022)	CNN with K-means clustering	Leafy	Not specified	• Early leaf spot • Late leaf spot • Alternaria leaf • Rust	93%

Sivasankaran *et al.* (2022) Jagan Mohan and Mohammed Nazer (2022)	CNN with K-means clustering	Leafy	54,306	• Early leaf spot • Late leaf spot, • Alternia leaf, • Rust Disease • Bud Necrosis • Health leaf	93%
Vaishnnave *et al.* (2020)	CNN	leafy	6400	• Alternaria leaf, • Pestalotiopsis, • Bud necrosis, • tikka, • Phyllosticta, • Rust, • Pepper spot, • Choanephora, • Early leaf spot • late leaf spot	99.88%
Rakholia *et al.* (2022)	CNN with progressive resize	leafy	1289	• leaf spot, • armyworms effect, • wilts, • yellow leaf, • healthy leaf	96.12%
Kursun *et al.* (2023)	AlexNet with with Grad-cam for model explainability	leafy	3058	• Early leaf spot • Late leaf spot, • Rust Disease • Nutrition Deficiency • Health leaf	99.02%
Anbumozhi and Shanthini (2024).	CNN	leafy	4670	• Early Leaf Spot • Late Leaf Spot • Rust • Rosette • Health leaf	99.73% on training 96% on testing
Anbumozhi and Shanthini (2023)	Progressive CNN	leafy	619	• Healthy • Unhealthy	97.58%
Patayon and Renato (2022)	pre-trained 16, VGG16, VGG19, InceptionV3, MobileNet, DenseNet, Xception, InceptionResNetV2, and ResNet50	leafy	1,000	• Leaf Spot	98% accuracy with DenseNet-169 -

From Table 1 it is evident that most of the previous research on groundnut disease detection and classification concentrated on grouping the diseases into various categories but does not provide information about the severity of the disease, which is very essential to the farmers in deciding on appropriate mitigation measures as soon as possible. At the same time, these models are computationally expensive and do not support real-time object detection on resource-constrained handheld devices (Chen *et al*., 2020). It is worth noting that timely disease identification and diagnosis, and control are the most critical actions in crop growth monitoring for optimal yield expectation. Therefore, this research aimed at developing a machine learning model that assesses the severity of groundnut rosette in a farm setting and provides recommendations for disease management.

YOLO (You Only Look Once) Family. Unlike the CNNs that perform multiple object detection in two stages, the YOLO (You Only Look Once) models define a class of deep learning algorithms that efficiently and accurately detect multiple objects in a single image frame (Du *et al*., 2018; Chen *et al*., 2020; Fan *et al*., 2023). The YOLO algorithm provides an innovative approach to object recognition and detection in the field of computer vision as it facilitates real-time object recognition and detection in both images and video streams within a single phase (Zong *et al*., 2023). Different researchers have used YOLO and its variants in the detection of plant diseases such as for hell paper diseases (Mathewand and Jyoti, 2022); Leafy Tomato disease and pests (Liu and Wang, 2020); Eggplant disease (Nasution and Kartika, 2022); Mulberry leaf disease orange by year (Padma Reddy, 2021). These models have provided good results in the recognition and classification of crop diseases in real-time.

STUDY METHODS

Data collection and dataset description. Image data of groundnut rosette disease were collected from two national groundnut research centers within Uganda. These two research centers were National Semi-Arid Resources Research Institute (NaSARRI), located in the Eastern Agro-ecological zone in Serere District, 21 km south of Soroti Town, and the Nakabango Technology Verification Centre in Jinja. NaSARRI is the base station responsible for the development of improved high-yielding groundnut varieties that are resistant/ tolerant to pests/diseases, while Nakabango is a technology verification center that is in charge of conducting adaptive research. Both sites are recognized a hotspots for Rosette and leafspot diseases (Okello *et al*., 2010b, 2021). The data collection process was guided by groundnut rosette disease research experts from the two hotspot centers. Field tours were conducted with the experts, and this included observing groundnuts at different growth stages. Groundnut images of groundnut crops infected with groundnut rosette were taken using a digital camera with 2268x4032 pixels resolution. The severity level of the groundnut rosette virus disease in the captured images was scored by the experts using a scale of 1 to 9, where a scale of 1 represents a healthy crop and 9 severely infected crops (Kayondo *et al*., 2014). A total of 192 images were collected from the field, capturing various environmental conditions to represent the actual field conditions where the model is expected to be deployed. Table 2 and Figure 1 show the raw dataset and the scale distribution of the groundnut rosette disease while Figure 2 shows a sample of raw images of groundnut rosette at different severity scales.

Table 2. Number of Groundnut rosette virus disease images at different Scales

Rosette Scale	1	2	3	4	5	6	7	8	9	Total number of images
Number of images	42	27	8	9	7	11	15	16	57	192

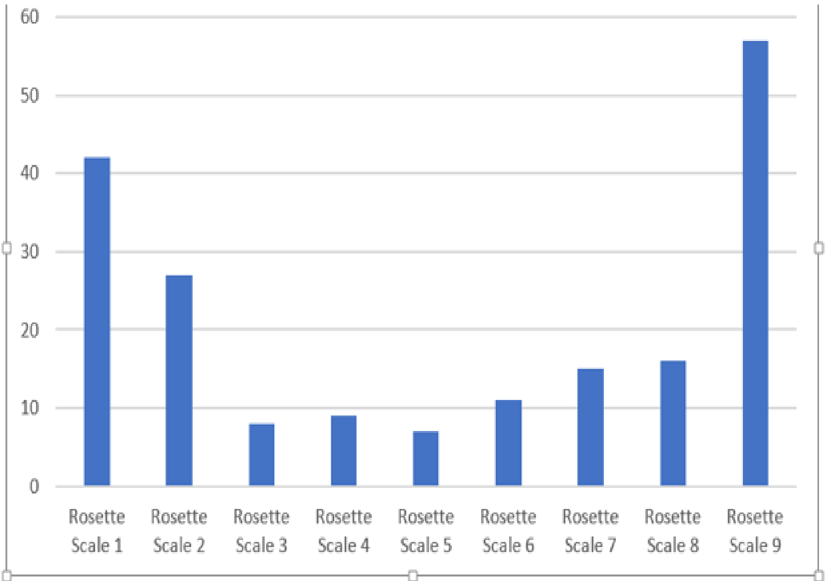
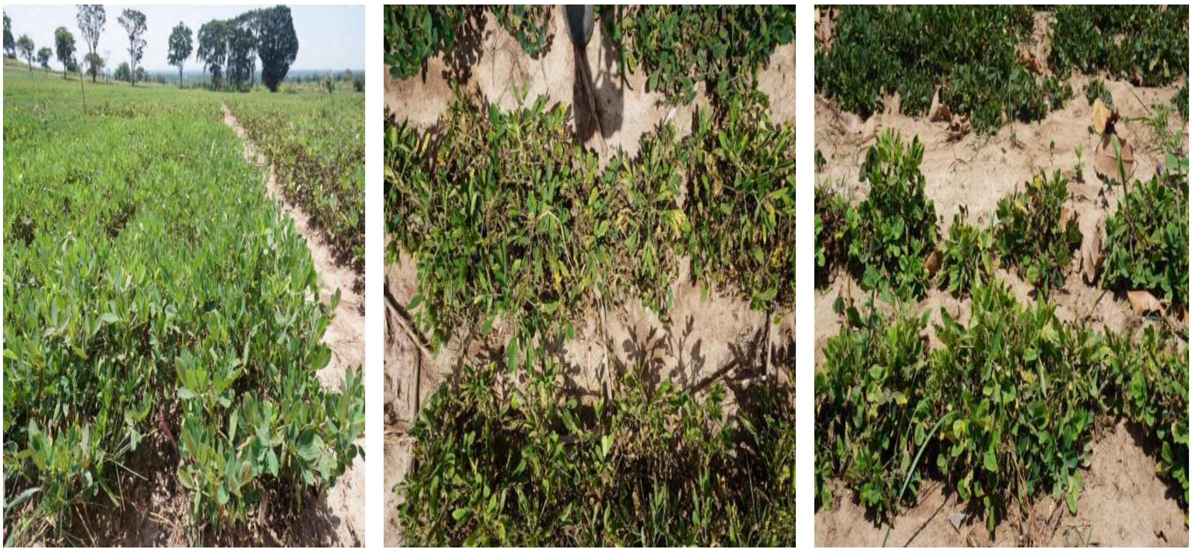


Figure 1. Distribution of the groundnut Rosette Severity Scale



(a) Rosette Scale 1 (b) Rosette Scale 5 (c) Rosette Scale 9

Figure 2. Sample Images of Groundnut Rosette at different Scales from NaSARRI, Serere

Data cleaning and preprocessing. Data preprocessing techniques that included image resizing and annotation were used to ensure that the data were clean, relevant, and in a suitable format for model training and evaluation. We did data cleaning on the collected images and created a labeled dataset that was used to train the CNN model and validate the performance of the model. Figure 3 provides a block diagram that shows the processes involved in the classification of the groundnut rosettes into the different severity levels.

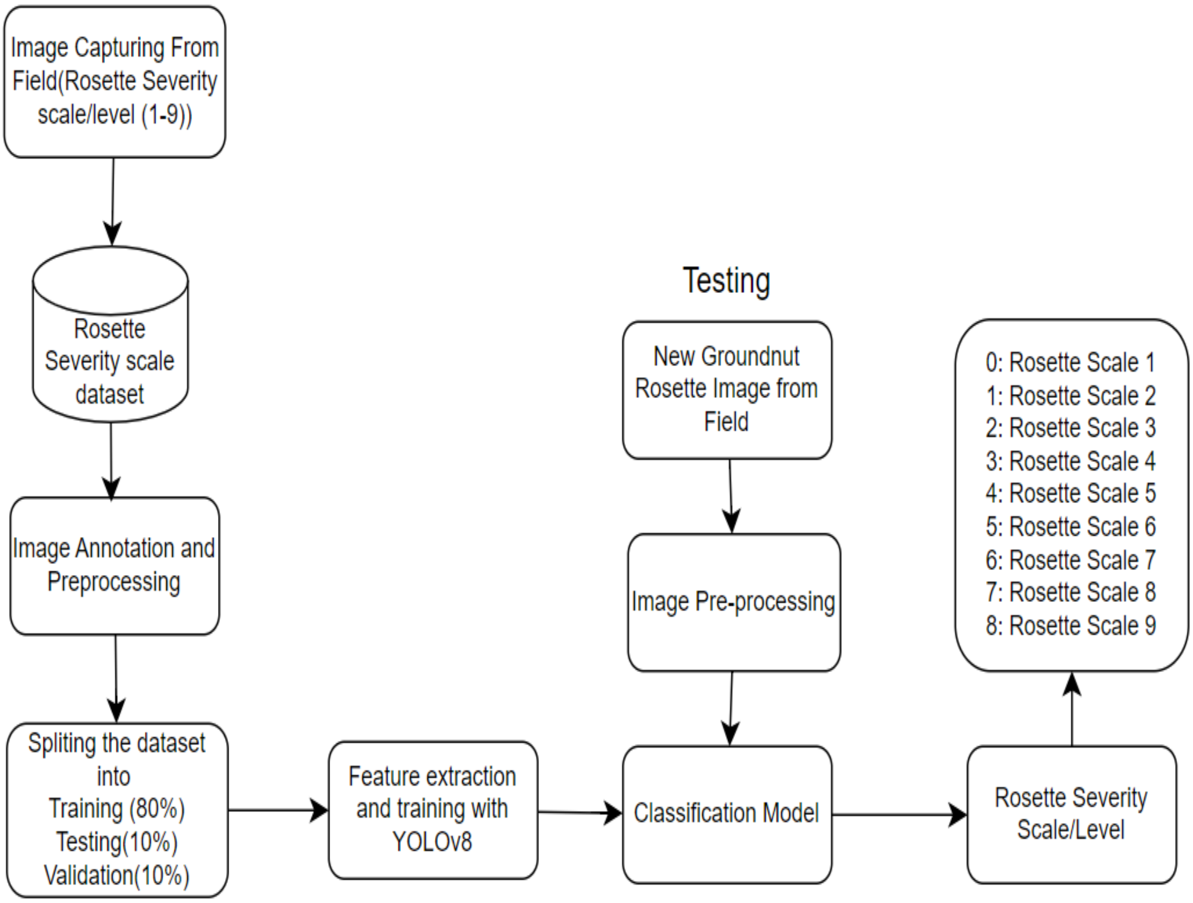


Figure 3-Block diagram for Groundnut Rosette disease severity level classification using CNN

Data annotation. Since the images were captured to mimic the field environment where the model would be operating, there was a lot of background noise that was introduced during the image-capturing process. To reduce the background noise, data annotation (explaining the meaning) was necessary. Data annotation was carried out manually using the LabelMe image annotation tool (Torralba *et al*., 2010). Using this tool, polygons were drawn around areas of interest in the image. For each of the bounding boxes, a class label was assigned to it that corresponded to the rosette severity level of the image being annotated. Since some of the rosette scale disease images appear the same due to the state of the infection that was present, the knowledge of the experts in rosette disease was employed to help in the detection of the class of the images and diseased parts of the plant. Figure 4 shows a sample of the annotated image of groundnut rosette scale 5.

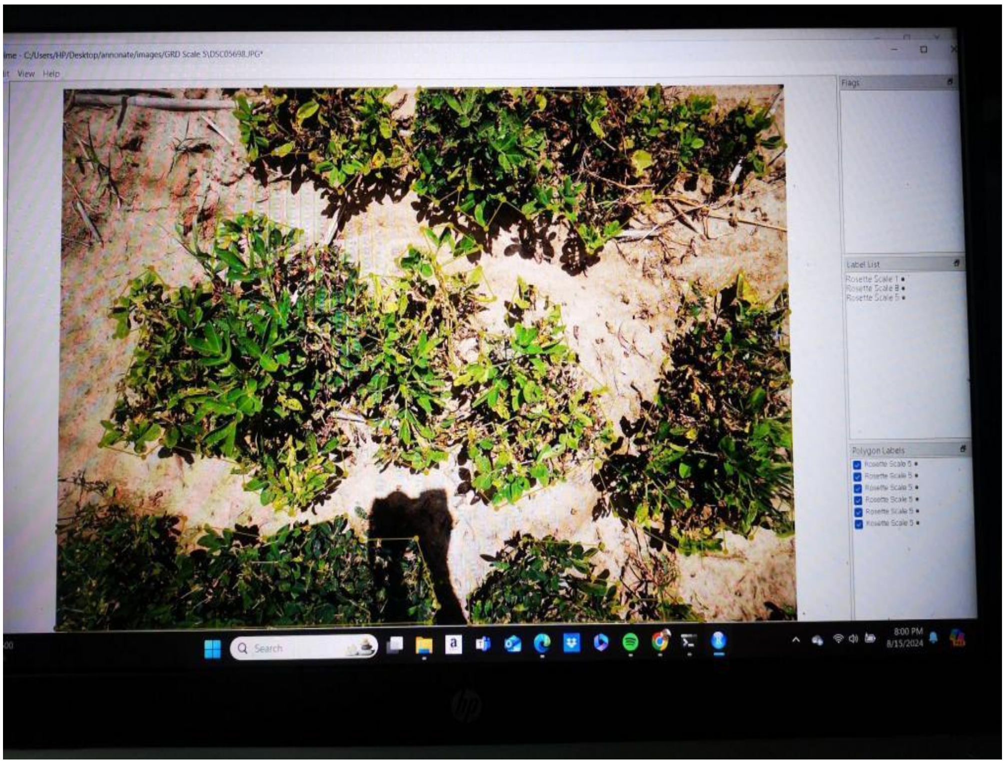


Figure 4. Sample of groundnut rosette scale 5 annotated image

Model architecture. In this work, the YOLOv8 (the 8th version within the YOLO family of deep learning models) object detection algorithms were employed during the training of custom groundnut rosette disease severity detection and classification. The model was developed by Ultralytic (Vijayakumar and Vairavasundaram, 2024) and released in January 2023. YOLOv8 is built on the same backbone architecture as YOLOv5 but with some modifications. YOLOv8 utilizes the C2f (cross-stage partial bottleneck with two convolutions) module for visual feature extraction and the spatial pyramid pooling fast (SSPF) layer for pooling features into a fixed-size feature map, which enables the expedition of model computation. Within the YOLOv8 model architecture, every convolution was complemented by a batch normalization and SiLU (Sigmoid Linear Unit) activation. Using this implementation, the head of the model was decoupled to handle object-oriented tasks independently (Terven *et al*., 2023). YOLOv8n, which is ideal for customization, detecting very small objects, and is easily supported on edge devices, was used. A range of five scaled versions of YOLOv8 were offered and included: YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large), and YOLOv8x (extra-large).

Model training. In the training, the dataset was split into 80% training, 10% testing set, and 10% validation set. To retain information present in the images as the training progresses, the distinct block processing technique was applied. The technique was employed due to its previous successes in retention of information and has been used successfully for various previous disease classification tasks, such as Cassava mosaic disease classification (Oyewola *et al.*, 2021). We utilized the Adam optimizer with a decay of 1e-5 for training the YOLOv8 model. The image sizes used for training and validation were set at 640. The YOLOv8 model was implemented using Ultralytics

YOLOv8.0.137, Python-3.10.12. The training process consisted of 100 epochs. Each batch size was set at 4.

RESULTS and DISCUSSION

Model performance is assessed based on precision, recall, and F1-score, providing a comprehensive appreciation of its reliability and usefulness. High precision scores imply that when the model detects the disease, there's a strong likelihood that the detection is correct, minimizing false alarms. Precision represents the reliability of the model in identifying groundnut rosette diseases. The results, as shown in Figure 5, summarize the effectiveness of the groundnut rosette disease detection model evaluated using precision, recall, and mean Average Precision (mAP).

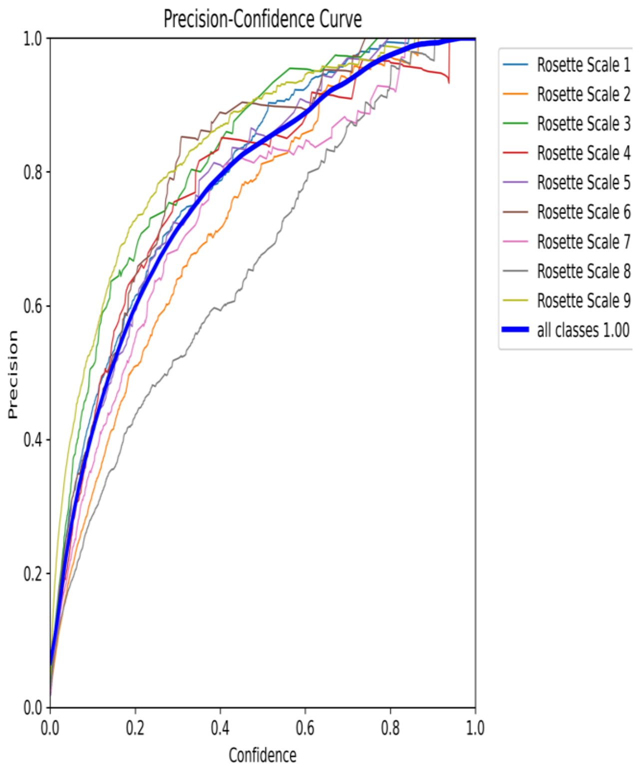
Precision score as shown in Figure 5(a) ensures minimal false alarms by measuring the proportion of true positives in detections, reflected by a consistently high precision curve. Precision represents the reliability of the model in identifying groundnut rosette diseases. Recall that as shown in Figure 5(b) measures the model's capability to identify all groundnut rosette diseases reflects the comprehensiveness of the model in recognizing the complete set of diseases.

The Recall Precision curve (Figure 5(c)) is plotted with Recall as the horizontal axis and Precision as the vertical axis, making it particularly effective in evaluating the performance of a classifier on imbalanced datasets. Precision represents the proportion of samples predicted as positive by the classifier that are positive, while Recall represents the proportion of actual positive samples that are correctly predicted as positive by the classifier. The closer the curve is to the top-right corner, the better the performance of the classifier, indicating its ability to accurately identify diseased samples while minimizing misclassification of non-diseased samples. As can be seen from Figure 5, the recognition accuracy of each category is relatively good. By analyzing the PR curve and the accuracy legend, we can effectively evaluate the performance of the classifier on the datasets, providing strong support for the performance of the algorithm.

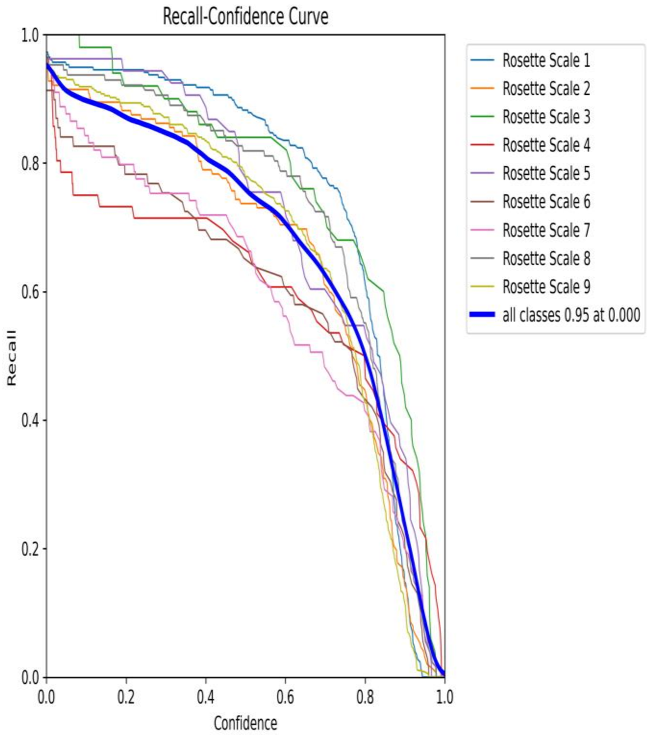
Figure 5(d) shows the F1-confidence curve, which combines precision and recall and is a measure of balanced performance at different confidence levels. The peak indicates the confidence level where the model achieves the best balance between precision and recall for this specific dataset.

Performance of the model for the various groundnut rosette scales was evaluated using the confusion matrix. Figure 5 shows the confusion matrix of the model with 9 groundnut rosette scales. The diagonal elements represent the number of correctly classified samples for each class, while the off-diagonal elements represent misclassifications. The vertical axis (Y-axis) stands for the predicted values, which the model outputs actually and the horizontal axis (X-axis) stands for the true labels, which are ground truth values. From the confusion matrix, we can see that the model has the highest accuracy in classifying Rosette scale 1 and Rosette scale 5.

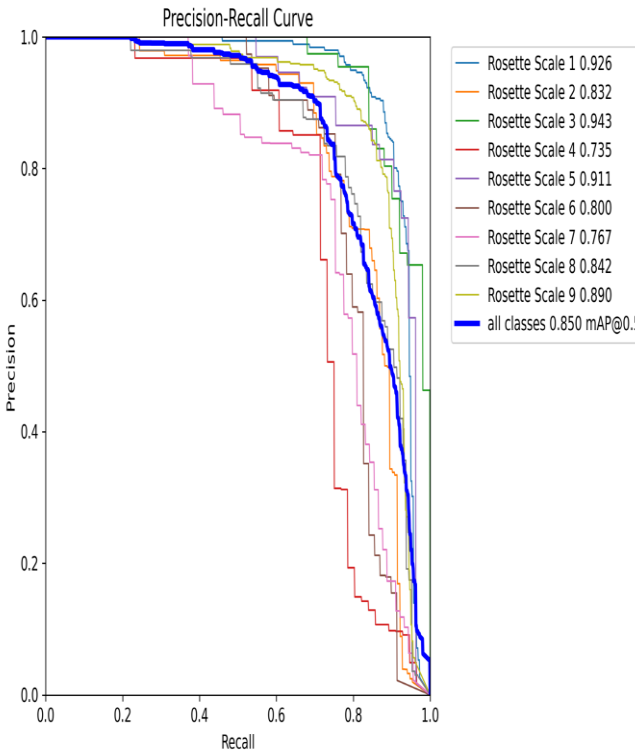
Confusion Matrix. In the task of groundnut rosette disease identification, the confusion matrix is an important evaluation tool that can visually present the comparison between the model's prediction results and the actual labels. The confusion matrix in Figure 6 shows the model's performance at different groundnut rosette disease scales.



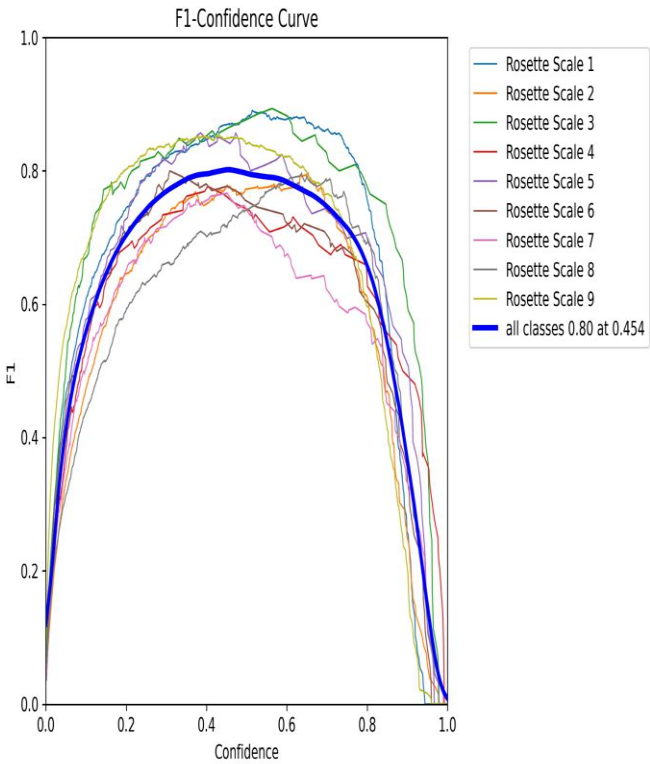
(a) Precision-confidence



(b) recall-confidence



(c) Precision-recall Curve



(d) F1-Confidence Curve

Figure 5. The Groundnut Rosette disease detection results on the dataset

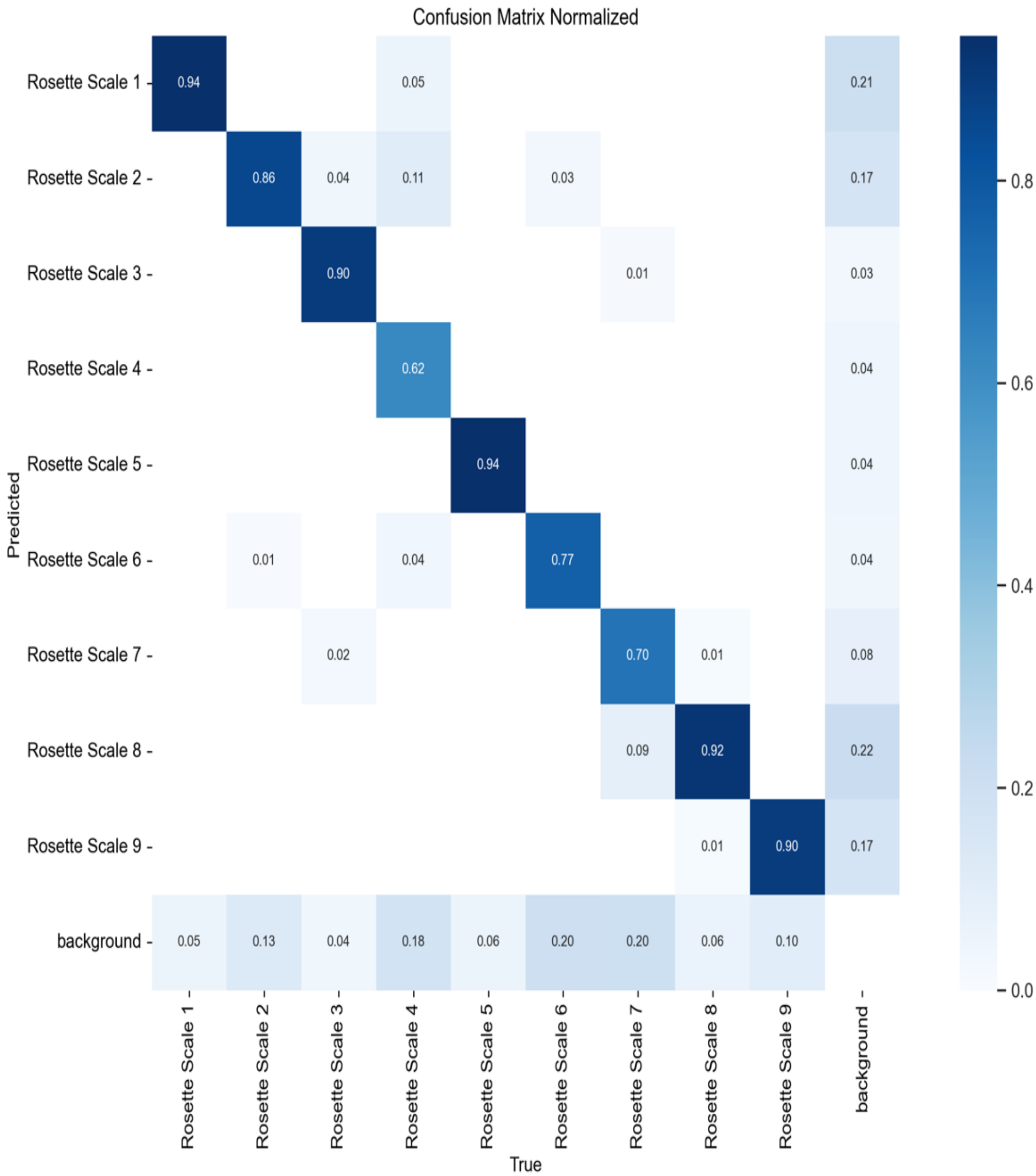


Figure 6. Confusion matrix normalized visualization

By examining the normalized confusion matrix, we can identify which groundnut rosette disease scale category the model performs well in. Each cell shows how often the model confused one groundnut rosette disease scale for another, or correctly identified it. Each cell in the normalized confusion matrix represents the proportion of the true category being predicted as a certain category. For example, 0.94 "Rosette scale 1" instances were correctly identified, while 0.26 were misclassified. In general, the model achieved high accuracy across all groundnut rosette scales, and this indicates that the YOLOv8 groundnut rosette disease diagnosis model possesses high accuracy in feature extraction and classification. Table 3 illustrates the precision, recall, and mean Average Precision (mAP) of each class in the model.

Table 3. Performance Evaluation Metrics on Dataset

Rosette Scale	1	2	3	4	5	6	7	8	9
Precision	0.836	0.776	0.889	0.847	0.834	0.904	0.809	0.634	0.895
Recall	0.906	0.776	0.84	0.69	0.851	0.681	0.712	0.85	0.81
mAP50	0.926	0.832	0.942	0.736	0.908	0.8	0.767	0.845	0.89
mAP50-95	0.498	0.481	0.533	0.471	0.518	0.388	0.454	0.49	0.566

In order to verify the accuracy of the groundnut rosette disease diagnosis model in this study in recognizing groundnut rosette in the groundnut fields in the season of planting groundnuts under natural conditions, two images Figure 7(a) and Figure 8(a), were randomly selected for target detection. The detection effect is shown in Figure 7(b) and Figure 8(b), in which it can be seen that the model exhibits a good recognition ability in the groundnut field. In summary, the model in this study shows good recognition ability and can effectively detect groundnut rosette disease in groundnut fields in the natural environment.

Deployment. After training the model, we converted it to TFLite format so that it can be imported into a mobile application, which can run on both Android and iOS devices. Figure 9 shows the results of the integrated model into the mobile application, and the model exhibited a reliable diagnosis result with corresponding confidence values. TensorFlow Lite is a lightweight solution for mobile and embedded devices, derived from TensorFlow. It enables on-device machine learning inference with low latency and a small binary size. TensorFlow Lite also supports hardware acceleration with the Android Neural Networks API. This Tflite model can then be integrated into mobile applications for use by farmers or agricultural extension workers in mobile devices such as smartphones to be used for real-time monitoring and early warning of groundnut rosette disease so that necessary prevention methods be applied. In addition, with the ability of the mobile App to detect groundnut rosette disease, farmers can easily select healthy cultivars that are resistant to this disease.

Figure 7(a). Original Image.

Figure 8(a). Original Image.

Figure 7(b). Image Prediction.

Figure 8(b). Image Prediction.

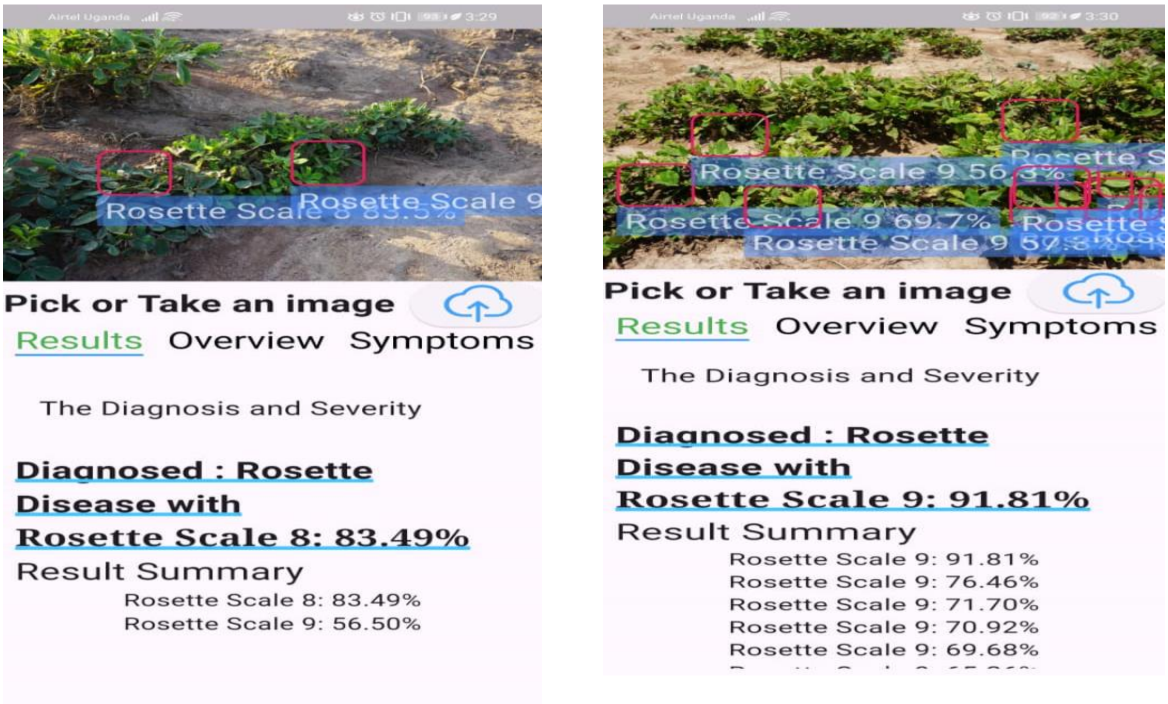


Figure 9. Model Deployment on Mobile application

CONCLUSION

This paper details opportunities artificial intelligence has for diagnosing groundnut rosette disease which is the main purpose of the model. It is worth noting that agriculture remains a critical sector for the African context. The results show a valuable approach that supports accurate detection of the diseased leaf. The groundnut rosette disease was classified into different scales from scale 1 through scale 9. An image processing technique was applied to detect the affected part of the leaf from the input image. This model can be integrated into mobile applications for use by farmers or agricultural extension workers in mobile devices such as smartphones to be used for real-time monitoring and early warning of groundnut rosette disease recognition, so that necessary prevention methods can be applied. The deployed model on the mobile phone exhibited reliable diagnosis results on the test field image data.

STATEMENT OF CONFLICT OF INTEREST

The authors declare no conflict of interest

REFERENCES

Abed, S. H., Al-Waisy, A. S., Mohammed, H. J. and Al-Fahdawi, S. 2021. A modern deep learning framework in robot vision for automated bean leaves diseases detection. *International Journal of Intelligent Robotics and Applications* 5 (2): 235–251.https://doi.org/10.1007/S41315-02100174-3/FIGURES/13

Anbumozhi, A. 2023. Leaf Diseases Identification and Classification of Self-Collected Dataset on Groundnut Crop using Progressive Convolutional Neural Network (PGCNN). *IJACSA) : International Journal of Advanced Computer Science and Applications* 14 (2) 2023. Retrieved October 18, 2024, from www.ijacsa.thesai.org

Anusha, P., Reddy, K.G., Anirudh, K., Varshini, M. and Chaitra, R. 2024. Cassava Leaf Disease Prediction Using Efficientnet-B0 Model. *International Research Journal on Advanced Science Hub* 6 (1) : 6-13. https://doi.org/10.47392/IRJASH.2024.002

Chen, T., Yang, W., Zhang, H., Zhu, B., Zeng, R., Wang, X., Wang, S., Wang, L., Qi, H., Lan, Y. and Zhang, L. 2020. Early detection of bacterial wilt in peanut plants through leaf-level hyperspectral and unmanned aerial vehicle data. *Computers and Electronics in Agriculture* 177: 105708. https://doi.org/10.1016/J.COMPAG.2020.105708

Du, P., Qu, X., Wei, T., Peng, C., Zhong, X. and Chen, C. 2018. Research on Small Size Object Detection in Complex Background. *Proceedings 2018 Chinese Automation Congress CAC* 2018 : 4216–4220. https://doi.org/10.1109/CAC.2018.8623078

Fan, Z., Cheng, M., Wang, L., Li, C., Wu, D., Li, J., Cheng, Z., Zhang, H. and Li, W. 2023. Feasibility evaluation of fermented peanut meal to replace soybean meal in the diet of common carp (*Cyprinus carpio*): Growth performance, serum biochemistry, intestinal health and microflora composition. *Aquaculture Reports* 31: 101675. https://doi.org/10.1016/J.AQREP.2023.101675

Gomez, N., Yousefi, M., Pollard, D., DeConto, R. M., Sadai, S., Lloyd, A., Nyblade, A., Wiens, D. A., Aster, R. C. and Wilson, T. 2024. The influence of realistic 3D mantle viscosity on Antarctica's contribution to future global sea levels. *Science Advances* 10 (31): 1470. https://doi.org/10.1126/SCIADV.ADN1470/SUPPL_FILE/SCIADV.ADN1470_MOVIES_S1_TO_S8.ZIP

Gopi, A., Sudha, L. R. and Iwin Thanakumar Joseph, S. 2024. Disclosing the Potential of Deep Learning in Cassava Leaf Disease Analysis by using CNN and Neural Networks Approach. *7th International Conference on Inventive Computation Technologies, ICICT 2024* 188–193pp. https://doi.org/10.1109/ICICT60155.2024.10544880

Mpirirwe, H., Mirembe, D.P., Lubega, J. and Agaba, J.E. 2021. E-learning platforms and security mechanisms used by educational institutions in Kampala, Uganda. *International Journal of Information Technology, Communications and Convergence* 4 (1): 47-62. 10.1504/IJITCC.2021.119110

Jagan Mohan, D. and Mohammed Nazer, D. 2022. A Comparative CNN Based Deep Learning Model Investigation for Identifying and Classifying the Leaf Diseases of *Arachis hypogea* (Groundnut Crop) grown in the Semi-Arid Landscapes of Villupuram District of Tamil Nādu. *Journal of Algebraic Statistics* 13 (2): 232–249. https://www.publishoa.com/index.php/journal/article/view/161

Kayondo, S. I., Rubaihayo, P. R., Ntare, B. R., Gibson, P. T., Edema, R., Ozimati, A. and Okello, D. K. 2014. Genetics of resistance to groundnut rosette virus disease. *African Crop Science Journal* 22 (1): 21–30. https://www.ajol.info/index.php/acsj/article/view/101369

Kukadiya, H., Meva, D., Arora, N. and Srivastava, S. 2024. Effective Groundnut Crop Management by Early Prediction of Leaf Diseases through Convolutional Neural Networks. *International Research Journal of Multidisciplinary Technovation* 6 (1) :17–31. https://doi.org/10.54392/IRJMT2412

Kursun, R., Yasin, E.T. and Koklu, M., 2023, August. The effectiveness of deep learning methods on groundnut disease detection. In 11th International conference on advanced technologies (ICAT'23) Istanbul, Turkiye 4-20pp. https://doi.org/10.58190/icat.2023.11

Laixiang, X., Cao, B., Zhao, F., Ning, S., Xu, P., Zhang, W. and Hou, X. 2023. Wheat leaf disease identification based on deep learning algorithms. *Physiological and Molecular Plant Pathology* 123: 101940. https://doi.org/10.1016/j.pmpp.2022.101940

Liu, J. and Wang, X. 2020. Tomato Diseases and Pests Detection Based on Improved Yolo V3 Convolutional Neural Network. *Frontiers in Plant Science* 11: 521544. https://doi.org/10.3389/FPLS.2020.00898/BIBTEX

Mathew, C. and Joseph Kristu Jyoti, C. 2022. Object Identification using *YOLO Algorithm*. 10 (7): 2320–2882. www.ijcrt.org

Mirembe, D.P, Kizito, J, Tuheirwe, D. and Muyingi, H.N. 2008. A model for electronic money transfer for low re-sourced environments: M-cash. In: Third International Conference on Broadband Communications, Information Technolo-gy and Biomedical Applications. 389–393 pp

Mirembe, D. P., Obaa, B. and Ebanyat, P. 2016. Developing and piloting a multi-channel ICT-enabled model to en-hance university engagement with smallholder farming communities in Uganda. *African Journal of Rural Development* 1(1) :13–21

Mirembe, D.P., Lubega, J.T. and Kibukamusoke, M. 2019. Leveraging social media in higher education: A case of universities in Uganda. *EURODL*. 22(1): 70-84.

Mugisa, I. O., Karungi, J., Akello, B., Ochwo-Ssemakula, M. K. N., Biruma, M., Okello, D. K. and Otim, G. 2016. Determinants of groundnut rosette virus disease occurrence in Uganda. *Crop Protection* 79 :117–123. https://doi.org/10.1016/J.CROPRO.2015.10.019

Mugisha, J., Lwasa, S. and Mausch, K. 2014. Value chain analysis and mapping for groundnuts in Uganda, Socioeconomics Discussion Paper Series Number 14.

Mugisa, I.O., Karungi, J., Akello, B., Ochwo-Ssemakula, M.K., Biruma, M., Okello, D.K. and Otim, G. 2015a. Assessing the effect of farmers practices on the severity of groundnut rosette virus disease in Uganda. *African Journal of Agricultural Research* 10 (9):995-1003. ttps://doi.org/10.5897/AJAR2014.9171

Mugisa, I.O., Karungi, J., Akello, B., Ochwo-Ssemakula, M.K., Biruma, M., Okello, D.K. and Otim, G. 2015b. Assessing the effect of farmers practices on the severity of groundnut rosette virus disease in Uganda. *African Journal of Agricultural Research* 10 (9):995-1003.

Mwesigwa, E., Tulinayo, F.P. and Mirembe, D.P. 2016. Enhancing agricultural knowledge sharing among smallholder farmers in Uganda: An evaluation of mobile and web technologies. Regional Universities Forum for Capacity Building in Agriculture.

Nasution, S. W. and Kartika, K. 2022. Eggplant Disease Detection Using Yolo Algorithm Telegram Notified. *International Journal of Engineering, Science and Information Technology* 2 (4) :127–132. https://doi.org/10.52088/IJESTY.V2I4.383

Noviyanto, Sunyoto, A. and Ariatmanto, D. 2024. Innovative Solutions for Bean Leaf Disease Detection Using Deep Learning. *International Conference on Artificial Intelligence and Mechatronics System, AIMS 2024*.https://doi.org/10.1109/AIMS61812.2024.10512726

Okello, D. K., Biruma, M. and Deom, C. M. 2010. Overview of groundnuts research in Uganda: Past, present and future. *African Journal of Biotechnology* 9 (39): 6448–6459. https://doi.org/10.4314/AJB.V9I39

Okello, D. K., Biruma, M. and Deom, C. M. 2010b. Overview of groundnuts research in Uganda: Past, present and future. *African Journal of Biotechnology* 9 (39): 6448–6459. https://www.ajol.info/index.php/ajb/article/view/92294

Okello, D. K., Deom, C. M. and Puppala, N. 2021. Registration of 'Naronut 2T' groundnut. *Journal of Plant Registrations* 15 (1): 62–67. https://doi.org/10.1002/PLR2.20086

Oyewola, D. O., Dada, E. G., Misra, S. and Damaševičius, R. 2021. Detecting cassava mosaic disease using a deep residual convolutional neural network with distinct block processing. *PeerJ Computer Science* 7: 1–15. https://doi.org/10.7717/PEERJ-CS.352/SUPP-1

Padma Reddy, M. 2021. Mulberry leaf disease detection using YOLO. *International Journal of Advance Research, Ideas and Innovations in Technology*. https://www.ijariit.com

Paramanandham, N., Sundhar, S. and Priya, P. 2024. Enhancing Disease Detection with Weight Initialization and Residual Connections Using LeafNet for Groundnut Leaf Diseases. *IEEE Access* 12: 91511–

91526. https://doi.org/10.1109/ACCESS.2024.3422311

Patayon, U. B. and Crisostomo, R. V. 2022. Peanut leaf spot disease identification using pre-trained deep convolutional neural network. *International Journal of Electrical and Computer Engineering (IJECE* 12 (3): 3005–3012. https://doi.org/10.11591/ijece.v12i3.pp3005-3012

Rajmohan, P., Gopinathan, U. U., Parvin Ashraf Saudha, N., Jose, M., Raphael, L. and Thomas, J. 2022. Effectiveness of ChAdOx1 nCoV-19 coronavius vaccine in preventing severe disease and mortality during the second wave of pandemic. *Journal of Acute Disease* 11 (5): 188–193. https://doi.org/10.4103/2221-6189.357457

Rakholia, R. M., Tailor, J. H., Saini, J. R., Kaur, J. and Pahuja, H. 2022. Groundnuts Leaf Disease Recognition using Neural Network with Progressive Resizing. *International Journal of Advanced Computer Science and Applications* 13 (6) : 83–88. https://doi.org/10.14569/IJACSA.2022.0130611

Ramcharan, A., Baranowski, K., McCloskey, P., Ahmed, B., Legg, J. and Hughes, D. P. 2017. Deep learning for image-based cassava disease detection. *Frontiers in Plant Science* 8 :293051. https://doi.org/10.3389/FPLS.2017.01852/BIBTEX

Reddy, T. Y., Reddy, V. R. and Anbumozhi, V. 2003. Physiological responses of groundnut (*Arachis hypogea* L.) to drought stress and its amelioration: a critical review. *Plant Growth Regulation* 41 (1): 75–88. https://doi.org/10.1023/A:1027353430164

Sangeetha, K., Lakshmi Devi, R., Ananya, A., Harinishrii, V. S. and Nithyasree, V. 2024. A Machine Learning Approach To Detect And Treat Groundnut Leaf Disease(Nut-O-Care). *2024 International Conference on Communication, Computing and Internet of Things, IC3IoT 2024 - Proceedings*. https://doi.org/10.1109/IC3IOT60841.2024.10550237

Sapre, S., Gontia-Mishra, I., Thakur, V. V., Sikdar, S. and Tiwari, S. 2021. Molecular techniques used in plant disease diagnosis pp. 405–421.In: *Food Security and Plant Disease Management* https://doi.org/10.1016/B978-0-12-821843-3.00001-5

Tambe, U. Y., Shanthini, A. and Hsiung, P. A. 2024. Integrated Leaf Disease Recognition Across Diverse Crops through Transfer Learning. *Procedia Computer Science* 233 :22–34. https://doi.org/10.1016/J.PROCS.2024.03.192

Terven, J., Córdova-Esparza, D. M. and Romero-González, J. A. 2023. A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS. *Machine Learning and Knowledge Extraction 2023.* 5 (4): 1680–1716. https://doi.org/10.3390/MAKE5040083

Torralba, A., Russell, B. C. and Yuen, J. 2010. LabelMe: Online image annotation and applications. *Proceedings of the IEEE* 98 (8) :1467–1484. https://doi.org/10.1109/JPROC.2010.2050290

Vaishnnave, M. P., Suganya Devi, K. and Ganeshkumar, P. 2020. Automatic method for classification of groundnut diseases using deep convolutional neural network. *Soft Computing* 24 (21): 16347–16360. https://doi.org/10.1007/S00500-020-04946-0/METRICS

Vijayakumar, A. and Vairavasundaram, S. 2024. YOLO-based Object Detection Models: A Review and its Applications. *Multimedia Tools and Applications* 83 (35): 83535–83574. https://doi.org/10.1007/S11042-024-18872-Y/METRICS

Zong, C., Meng, K., Sun, J. and Zhou, Q. 2023. Real Time Object Recognition Based on YOLO Model. *2023 International Conference on Electronic Information Engineering and Computer Science, EIECS 2023* 197–202pp. https://doi.org/10.1109/EIECS59936.2023.10435392

Zhou, J., Wang, G. and Chen, X. 2024. Deep learning-based image recognition for crop disease classification using convolutional neural networks. *Computers and Electronics in Agriculture* 205:107456. https://doi.org/10.1016/j.compag.2024.107456