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# Improving Precision Agriculture by Utilizing Resnet152 for Cassava Plant Disease Detection and Enhanced Crop Health Monitoring.

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MobileNetv2, Image Classification, deep learning, Resnet, Transfer learning, Resnet152, Convolutional Neural Network (CNN)

**ABSTRACT:**
Manihot esculenta, a crucial crop, provides millions of people in many parts of the world with their primary source of food. However, the presence of plant diseases, which can considerably limit yields and result in financial losses for farmers, poses a serious challenge to the sustainable cultivation of cassava. Identification of these illnesses as soon as feasible is crucial in order to take prompt mitigation steps and stop extensive out breaks. In this paper, a brand-new method for detecting diseases in cassava plants is proposed. The aim of the study is to create a powerful computer vision model that can automatically recognize and categorize several illnesses affecting cassava plants from photographs of their leaves. Resnet-152, a deep learning model, was utilized to effectively identify and understand patterns related to various diseases improving crop health monitoring and cassava plant disease detection using ResNet-152 is a promising approach in modern agriculture. ResNet-152 is a deep learning model known for its exceptional performance in image recognition tasks. By leveraging this powerful neural network, we can enhance the accuracy and efficiency of cassava disease detection. ResNet-152 is a convolutional neural network that can effectively classify and detect various diseases in cassava plants based on input images, helping farmers identify and mitigate infections to protect their crops this offers numerous benefits to farmers and agricultural experts, as it enables them to monitor crop health on a large scale and detect diseases at an early stage.

## I. INTRODUCTION

A crucial tropical root crop is cassava. When compared to stable crops, it provides abundant dietary carbohydrates. It is a type of underground plant part, and it is commonly consumed as a food source and utilized for medicinal purposes. Additionally, it is employed to alleviate fatigue, combat dehydration in individuals suffering from diarrhea, manage sepsis, and even stimulate labor. In India, it is mainly found in the southern states; in Tamil Nadu and Kerala .There are some products that include food, flour, animal feed, alcohol, and biodegradable products. Industrially, it is used to produce sago, starch, and chips. Improving crop health monitoring and cassava plant disease detection using ResNet-152 is a promising approach in modern agriculture. ResNet-152 is a deep learning model known for its exceptional performance in image recognition tasks. By leveraging this powerful neural network, we can enhance the accuracy and efficiency of cassava disease detection. ResNet-152 is a convolutional neural network that can effectively classify and detect various diseases in cassava plants based on input images, helping farmers identify and mitigate infections to protect their crops this offers numerous benefits to farmers and agricultural experts, as it enables them to monitor crop health on a large scale and detect diseases at an early stage. By promptly identifying and addressing infections, farmers can take appropriate measures, such as targeted treatments or crop rotation, to minimize the spread of diseases and optimize crop yields. Overall, integrating ResNet-152 into cassava plant disease detection systems holds great potential for advancing agricultural practices, promoting sustainable farming, and contributing to global food security. The presence of satellite molecules known as Cassava Mosaic Begomovirus-Associated Satellites (CMAS) makes the effect of CMB on cassava output even worse. Small, circular, single-stranded DNA molecules known as these satellites rely on the helper virus (CMB) for reproduction and movement inside of plants. Understanding the epidemiology of CBSD will help with disease awareness campaigns and the creation of management plans in areas where cassava is grown. Cassava leaves are prone to a number of bacterial, viral, and fungal diseases. Yellowing, withering, spotting, and distortion of the leaves are just a few of the signs that might result from these illnesses. The most common diseases of cassava leaves include the following: Different begomovirus species produce the virus known

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as cassava mosaic disease (CMD), which results in mosaic patterns and leaf yellowing. CMD can drastically inhibit cassava plant development and output. Symptoms of the viral ailment called cassava brown streak disease (CBSD) manifest as brown streaks and tissue death on the leaves. This disease adversely affects both the leaves and the roots, leading to a decline in root quality and yield. Cassava bacterial blight (CBB): Xanthomonas axonopodis pv. Manihotis bacteria are the cause of CBB. It can lead to considerable defoliation and produce angular leaf lesions with wet borders. Despite not being a disease in and of it, cassava green mite (CGM) infection can seriously harm cassava leaves. As a result of the mites feeding on the leaves, they become dis-colored, dry out, and eventually fall off. The most common disease among those reported is cassava mosaic virus disease (CMD), which significantly reduces crop yields and damages crops.

## II.RELATED WORK

[1] Manual examination is required to determine the severity and type of viral or fungal illness. However this is time-consuming, expensive, and lacks the information to catch the disease early. This lowers yields and forces farmers to use preventative measures on cassava plants that aren't diseased. It causes a lag in accurately forecasting the cassava sickness. We must therefore create a model to automatically anticipate the cassava illness based on the periodic growth and time. [2]The difficult problem of automating the identification of several illnesses in cassava plants using convolutional neural networks (CNN) is addressed in this research study. Cassava as a security crop in Sub-Saharan Africa is highlighted in the article, as is the demand for a reliable identification model to aid farmers in spotting plant illnesses. With an AUC value of 96%, the suggested CNN model successfully identified the illnesses shown in the plant photos. The management of the class imbalance issue is also covered in the paper, along with a method for creating an effective identification CNN model that can be applied in the real world. Making a model that can identify more illnesses affecting the leaves of the cassava plant is a future research project and determining precisely where on the plant leaves the disease has affected. Overall, this study offers a potential answer to the difficulties farmers in Sub-Saharan Africa encounter when producing cassava plants, and it has the potential to have a big impact on the sector. [3] Proposes the purpose of early diagnosis and crop disease control, the suggested model seeks to increase the precision of disease identification in cassava plants. The authors stress the significance of automating agricultural disease detection and classification, particularly in Sub-Saharan Africa, where cassava is a primary food crop for more than 500 million people. Traditional machine learning techniques have problems in properly diagnosing illnesses in crops. The use of this model has substantial implications for food security in Sub- Saharan Africa since it can assist farmers in more successfully monitoring their crops and preventing crop losses due to illnesses. Overall, this research offers a viable method for applying deep learning to enhance crop disease detection and prevention. [4] In this study, deep neural networks and transfer learning are used to provide a novel technique for identifying Huanglongbing (HLB) in orange trees. HLB is a terrible disease that kills citrus trees all over the world and results in substantial financial losses. On a short dataset of HLB images, transfer learning is used to improve the classification accuracy of a pre-trained CNN model. The outcomes demonstrate that the suggested method outperforms existing methods in detecting HLB in orange trees with high accuracy. By proposing a CNN-based technology option to identify HLB, this work has the potential to lessen the financial losses suffered by small citrus producers in low-income areas. Orange trees are afflicted by other diseases and inadequacies. In summary, this innovative approach has the potential to dramatically lessen the financial harm that HLB causes throughout the world and increase the viability of the citrus business. [5]In order to distinguish between healthy tomato leaves and the four diseases powdery mildew, blight, leaf mold fungus. This paper suggests an enhanced Faster RCNN model. The suggested model employs the k-means clustering algorithm for enhanced anchoring and a depth residual network for extracting picture features. Traditional agricultural disease detection techniques primarily rely on manual observation, which has a low detection effectiveness and low dependability. These problems are addressed by the suggested model, which also offers a quicker and more accurate way to identify crop diseases. In conclusion, the suggested model considerably increases the accuracy of the crop disease recognition model, Leaves and identifying sick leaves. A depth residual network and the k-means clustering technique are used to enhance anchoring and speed up identification. The experimental findings show how well the suggested approach for detecting crop leaf disease works. [6] This study employs the EfficientNet-B0 model to investigate the early identification of leaf diseases in cassava plants. The study emphasizes how crucial image recognition is for detecting plant illnesses, especially in the agriculture sector. The cassava plant is susceptible to a number of ailments, which could result in substantial financial losses and jeopardize food security in Africa. The suggested model reduces parameter size and FLOPS while outperforming current CNNs in terms of accuracy and efficiency. Early disease detection allows farmers to increase crop yields while saving time and money. Four different forms of cassava

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leaf diseases were classified by the model with a 92.6% accuracy rate. The outcomes show how well the EfficientNet-B0 model performs in correctly identifying and categorizing plant diseases. This study makes a contribution to the creation of dependable and effective disease detection techniques for the agricultural industry, which will ultimately help farmers and increase food security. [7] Explores the use of various convolutional neural networks (CNNs) to classify cassava leaf diseases, compares the performance of different CNN models, including VGG16, ResNet50, InceptionV3, and MobileNetV2 when measured by classification precision, confusion matrix, and F1 score. The results show that InceptionV3 achieved the highest accuracy followed by ResNet50.demonstrates the potential of using CNNs for cassava disease recognition, which could help farmers detect and manage diseases more effectively and shows that InceptionV3 and ResNet50 are effective models for cassava disease classification, with InceptionV3 achieving the highest accuracy. Suggests that future research could explore the use of other CNN models or ensemble methods to improve classification performance. lkin cj demonstrated the CNN method for implementing deep learning is a promising strategy for categorizing illness photos on cassava leaves in Indonesia. The model underwent81 iterations, completed an epoch consisting of 80 cycles, and employed a learning rate of 0.0001 and an input size of 224* 224 results demonstrates that the CNN method can help farmers identify and treat diseased plants more efficiently, which can ultimately improve crop yields and quality. [8] The study's goal is to provide a method for spectral data- based cassava disease diagnosis. Matrix Relevance Learning (MRL) is the name of the technique that is suggested in this study. To extract pertinent features from spectrum data, MRL, a machine learning approach, combines matrix factorization with relevance learning. The results of the study demonstrate how successful the MRL method is at detecting illnesses in cassava. Based on spectral data, the MRL model distinguished between healthy and unhealthy plants with great accuracy. The accuracy of MRL beat that of other machine learning algorithms that were also extensively employed for spectral data analysis, according to the authors' comparison. The results of this study have applications for diagnosing cassava illness, in people who suffer from CMD and CBSD. When employing a smaller feature set, the findings indicated enhanced classification accuracy, especially when PCA was used to reduce dimensionality. Future research will examine spectral data obtained in a more controlled setting where plants can be vaccinated and data can be gathered before they exhibit obvious symptoms. [9] In this study, a deep learning-based pre- training model is employed to identify cassava leaf disease. Densenet169 was the deep learning model employed in this investigation. A collection of 21397 photos with 5 classes of cassava leaf was used to create the model. In terms of performance metrics like loss, accuracy, specificity, and sensitivity, the model has been assessed. The Kaggle platform has been used to run the model. The data set has undergone data augmentation, improving its accuracy and utility. The Adam optimizer was used to run the model with stack sizes of 32 and 28 epochs. Loss, accuracy, specificity, and sensitivity are just a few of the performance qualities that are the subject of the experimental investigation. [10] Paper presents an illness detection technique in cassava leaf photos produced using deep learning methods. Farmers and other stakeholders can use the technique to diagnose illnesses swiftly and easily in their crops because it is applied in a web environment and reviews the related work on disease detection in cassava leaf images. Discuss the different deep learning architectures that have been used for this task, as well as the different datasets that have been created. The cassava leaf images are pre-processed to remove noise and improve the contrast. The attributes are derived from the pre-processed images through the utilization of a deep learning framework. The features are classified using a machine learning algorithm, used the ResNet50 and MobileNetV2 deep learning architectures for feature extraction. The development of accurate and efficient methods for detecting diseases in cassava leaf images is important for improving the productivity of cassava crops. Deep learning methods have shown promise for this task.

## III.PROPOSED METHODOLOGY

The utilization of Convolutional Neural Networks (CNNs) in deep learning is common for the classification of images, particularly well-suited for identifying diseases in cassava plant leaves due to their ability to autonomously grasp and identify intricate visual patterns within images. The model underwent 81 iterations, completed an epoch of 80 cycles, and used a learning rate of 0.0001, for the combined CNN and MobileNetV2 architecture. The model employs the Rectified Linear Unit (ReLU) as its activation function, SoftMax as the classifier function, and utilizes categorical cross-entropy as the loss function [11],[12],[13],[14]. The following fig.1 gives us an idea about input sample provided.

1. **Real-time Processing**: Once trained, CNN models can perform inference on new images in real time, making them suitable for applications that require quick disease Detection and response. It is fast and can process images quickly, no need of human intervention work process.

2. **Data collection**: A dataset of cassava leaf images was collected, including images of healthy leaves and leaves with different types of diseases.

3. **Data preprocessing**: The images were preprocessed to standardize their size and color, and to remove any background noise or artifacts that could interfere with disease detection.

4. **Model selection**: Several well-known CNN models were selected for evaluation, including VGGs, ResNet, DenseNet, and Inception.

5. **Model training**: The selected models were trained on the cassava leaf image dataset utilizing a validation set and a training set. The validation set was used to monitor the model's performance while the training set was utilized to refine the model's parameters, and prevent overfitting.

6. **Model evaluation**: Trained models were evaluated on a test set of cassava leaf images to measure their classification accuracy and F1-score

7. **Model optimization**: By adding brightness augmentation to the input photos, the top-performing model was chosen and further refined. The architecture of the CNN models used in this study consisted of several layers of convolutional, pooling, and fully connected layers, which were intended to learn and extract information from the input photos. The output layer of the model was a SoftMax layer, which produced a probability distribution over the different disease categories. [15],[16],[17] Utilizing the Adam optimizer and a cross-entropy loss function, the model was tuned during training

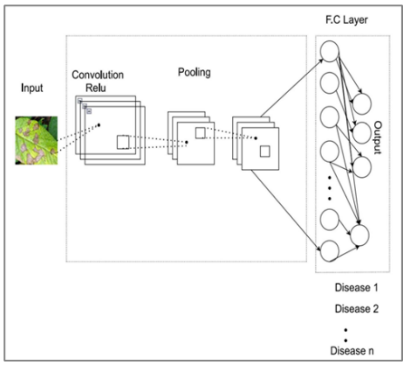


**Fig-1: Input Sample**

ResNet152 is the name of a deep convolutional neural network employed for the task of image classification and the following fig.2 gives the steps. It is a residual network, which means that it has skip connections between layers. ResNet152 is used to overcome the vanishing gradient problem. The architecture contains residual blocks, which helps for the training of deeper networks without suffering from diminishing performance gains. In cassava plant leaf disease detection ResNet-152 can be used as a feature extractor and classifier to differentiate between healthy and diseased plant leaves.[17].

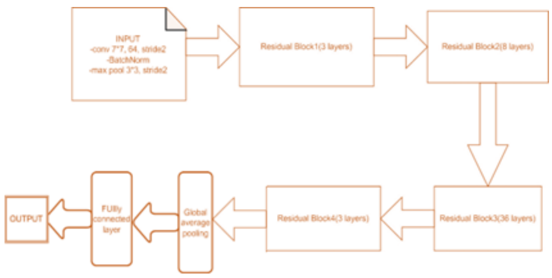


**Fig-2: ResNet152 steps**

## IV. RESULTS & DISCUSSION

| S.NO | AUTHOR NAME | TECHNIQUES USED | ADVANTAGES | DISADVANTAGES | ACCURACY |
|---|---|---|---|---|---|
| 01 | [18] J.F.Tusubira .et | Resnet 101. | The paper focuses on Improving surveillance of cassava white fly pests using machine learning techniques Enabling timely intervention and pest management strategies. | The provided citation does not offer detailed insights with out further information,it is challenging assess the robustness and effectiveness of proposed approach | F1-score=0.89 |

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| | | | | | |
|---|---|---|---|---|---|
| 02 | [19] Li, L.et al. | VGG-16<br>VGG-19<br>Resnet<br>InceptionV3<br>Mask RNN | Simplicity<br>Deep Representation<br>High Accuracy | Large number of parameters<br>High Memory Usage<br>Lack of Attention Mechanisms | Classification Accuracy-96.25fc |
| 03 | [20] Lodhi.S.et.al | Convolution neural network | Accurate disease detection Scalability<br>Timely intervention | Data preprocessing takes more time. Model construction is difficult due to various layers | CNN-84.3% |
| 04 | [21] Methil,A.et.al | Efficient net B4 | High accuracy Parameter efficiency Robust features | Computational Resource requirements<br>Model size Resource Imbalance | Efficient net B4-85.64% |
| 05 | [22] Satoto.B.D.et.al | Convolution Neural Network | Improved Accuracy<br>Efficiency<br>Generalizability | Overfitting<br>Complexity<br>Sensitivity to Augmentation | MSE-0.0080<br>MAE-0.0063<br>RMSE-0.0935 |
| 06 | [23] Sambasivam,G.A.O.G.D.et.al | Convolution Neural Networks | Improve disease detection | Scalability issues<br>Resource constraints | F1 score=0.92 for healthy |
| 07 | [24] Sharma,p.et.al | Image Segmentation | Open-source Models<br>Performance Analysis<br>Image segmentation | Real worldvalidation Ethical Considerations<br>Validation metrices | S-CNN=98.6% |
| 08 | [25] Moupojou,E.et.al | Mobile NetV2<br>YOLOv3<br>Mask R-CNN<br>Faster R-C-NN<br>Inception ResNetV2<br>InceptionV3 | Data Diversity<br>Training and Education<br>Dataset<br>creation: creating ourown dataset | Data quality<br>Data Annotation | Mobile NetV2-99.69% |

## V.CONCLUSION

Convolutional neural networks (CNNs) and residual networks (ResNet), in particular, are deep learning models that are used, for detecting cassava leaf disease shows enormous promise in resolving the issues that cassava production is now facing. These models have the ability to identify complex patterns and variances in images of cassava leaves, allowing for accurate and early disease identification. These illnesses significantly affect crop productivity and food security. The use of the ResNet architecture increases the efficiency with which these models can learn from various datasets and get around the difficulties of disease detection in agricultural contexts. Deep learning for the diagnosis of cassava leaf disease has a variety of advantages. Early detection of diseases including cassava mosaic disease (CMD), cassava brown streak disease (CBSD), and cassava bacterial blight (CBB) enables farmers and stakeholders to put interventions into place quickly, avoiding crop losses and guaranteeing sustainable agricultural practices.

## REFERENCES

[1] Dharani, M. K., Thamilselvan, R., Rajdevi, R., Logeshwaran, M. K., & Arunesh, J. (2022, October). Analysis on Cassava leaf disease prediction using pre-trained models. In *2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT)* (pp. 1-6). IEEE.’

[2] John, A. A. (2022, July). Identification of Diseases in Cassava Leaves using Convolutional Neural Network. In *2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT)* (pp. 1-6). IEEE.

[3] Ahishakiye, E., Mwangi, W., Muriithi, P., Kanobe, F., Owomugisha, G., Taremwa, D., & Nkalubo, L. (2023). Deep Gaussian convolutional neural network model in classification of cassava diseases using spectral data. *The Journal of Supercomputing*, 1-23.

[4] Gómez-Flores, W., Garza-Saldaña, J. J., & Varela-

Fuentes, S. E. (2022). A Huanglongbing Detection Method for Orange Trees Based on Deep Neural Networks and Transfer Learning. *IEEEAccess*, *10*, 116686-116696.

[5] Zhang, Y., Song, C., & Zhang, D. (2020). Deep learning-based object detection improvement for tomato disease. *IEEE access*, *8*, 56607-56614.

[6] Vijayalata, Y., Billakanti, N., Veeravalli, K., Deepa, A., & Kota, L. (2022, February). Early Detection of Casava Plant Leaf Diseases using EfficientNet-B0. In *2022 IEEE Delhi Section Conference (DELCON)* (pp. 1-5). IEEE.

[7] Surya, R., & Gautama, E. (2020, October). Cassava leaf disease detection using convolutional neural networks. In 2020 6th international conference on science in information technology (ICSITech) (pp. 97-102). IEEE.

[8] Owomugisha, G., Melchert, F., Mwebaze, E., Quinn, J. A., & Biehl, M. (2021). Matrix relevance learning from spectral data for diagnosing cassava diseases. *IEEE Access*, *9*, 83355-83363.

[9] Singh, R., Sharma, A., Sharma, N., & Gupta, R. (2022, December). Automatic detection of cassava leaf disease using transfer learning model. In *2022 6th International Conference on Electronics, Communication and Aerospace Technology* (pp. 1135-1142). IEEE.

[10] METLEK, S. (2021). Disease detection from cassava leaf images with deep learning methods in web environment. *International Journal of 3D Printing Technologies and Digital Industry*, *5*(3), 625-644.

[11] Q Noon, S. K., Amjad, M., Qureshi, M. A., & Mannan, A. (2022). Handling severity levels of multiple co-occurring cotton plant diseases using improved YOLOX model. *IEEE Access*, *10*, 134811-134825.

[12] Rani, K. A., & Gowrishankar, S. (2023). Pathogen-based Classification of Plant Diseases: A Deep Transfer Learning Approach for Intelligent Support Systems. *IEEE Access*.

[13] Torkpo, S. K., Amponsah, E., Arhin, C. D., & Offei, S. K. (2021). Occurrence of cassava mosaic begomovirus-associated satellites on cassava in Ghana. *Cogent Food &Agriculture*, *7*(1), 1963929.

[14] Muhindo, H., Yasenge, S., Casinga, C., Songbo, M., Dhed'a, B., Alicai, T., ... & Monde, G. (2020). Incidence, severity and distribution of Cassava brown streak disease in northeastern Democratic Republic of Congo. *Cogent Food & Agriculture*, *6*(1), 1789422.

[15] Raji, S. N., Subhash, N., Ravi, V., Saravanan, R., Mohanan, C. N., Nita, S., & Kumar, T. M. (2015). Detection of mosaic virus disease in cassava plants by sunlight-induced fluorescence imaging: a pilot study for proximal sensing. *International Journal of Remote Sensing*, *36*(11), 2880-2897

[16] Magadum, S., Srikar, S., Hattikal, S., Yuvaraj, M., & Badrinath, P. (2023, May). Identification of Disease in Cassava Leaf using Deep Learning. In *2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)* (pp. 298-304). IEEE.

[17] Rani, K. A., & Gowrishankar, S. (2023). Pathogen-based Classification of Plant Diseases: A Deep Transfer Learning Approach for Intelligent Support Systems. *IEEE Access*.

[18] Tusubira, J. F., Nsumba, S., Ninsiima, F., Akera, B., Acellam, G., Nakatumba, J., ... & Oyana, T. (2020). Improving in-field cassava whitefly pest surveillance with machine learning.In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops* (pp. 68-69).

[19] Li, L., Zhang, S., & Wang, B. (2021). Plant disease detection and classification by deep learning—a review. *IEEE Access*, *9*, 56683-56698.

[20] Lodhi, S., & Kukreja, V. (2022, October). Deep Learning Based Method To Detect Diseases In Leaves Of Cassava Plant. In *2022 International Conference on Data Analytics for Business and Industry (ICDABI)* (pp. 128-134). IEEE.

[21] Methil, A., Agrawal, H., & Kaushik, V. (2021, July). One-vs-all methodology based cassava leaf disease detection. In *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)* (pp. 1-7). IEEE.

[22] Satoto, B. D., Syarief, M., & Khotimah, B. K. (2021, December). Region Proposal Convolutional Neural Network with augmentation to identifying Cassava leaf disease. In *2021 4th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)* (pp. 74-79). IEEE.

[23] Sambasivam, G. A. O. G. D., & Opiyo, G. D. (2021). A predictive machine learning application in agriculture: Cassava disease detection and classification with imbalanced dataset using convolutional neural networks. *Egyptian informatics journal*, *22*(1), 27-34

[24] Sharma, P., Berwal, Y. P. S., & Ghai, W. (2020). Performance analysis of deep learning CNN models for disease detection in plants using image segmentation. *Information Processing in Agriculture*, *7*(4), 566-574.

[25] Moupojou, E., Tagne, A., Retraint, F., Tadonkemwa, A., Wilfried, D., Tapamo, H., & Nkenlifack, M. (2023). FieldPlant: A Dataset of Field Plant Images for Plant Disease Detection and Classification With Deep Learning. *IEEE Access*, *11*, 35398-35410.