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Disease diagnosis in Cassava leaves using CNN design and ResNet algorithm

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Abstract:

Introduction: Growth rate of crops is significantly lowered by illnesses that affect plants. It is impossible for anyone to eat the crops since they are tainted with various diseases. Farmers may suffer enormous losses as a consequence. Since cassava is an important food source in several countries, the financial system might be seriously damaged by the issue at hand.

Objectives: Traditional plant pathogen detection is labour-intensive and error-prone. It is not typically a dependable strategy to identify and stop the spread of plant viruses. Innovative technologies like deep learning as well as machine learning might aid in the early detection of plant diseases as an approach to get around these problems.

Methods: The main goal of the work is to employ deep learning to image classification in order to accurately identify diseases that especially impact cassava plants.

Results: This recognition may make it possible to implement preventative measures like the specific application of chemical pesticides or confinement of contaminated crops. Each and every training and testing image comes from a rural area in the natural world. Using a specific collection of information, the simulation has been verified to ascertain its true results.

Conclusions: The installation of a precise disease identification and mitigation model has the potential to significantly increase the durability of the cassava crop, improving food production and the quality of life for millions of people who are dependent upon this valuable crop.

Keywords: Cassava leaves, Deep learning, Disease, Identification, Testing, Training.

1. Introduction

Despite the fact that more obscure than the plant's appetizing roots, thousands of individuals of people in South America, Asia, and Africa consume a lot of cassava leaves [3]. These nutritious veggies are an important source of nutrition since they are nutrient-rich, particularly for those areas wherein the availability of a wide variety of foods is restricted [6]. Cassava leaves are packed with protein, iron, calcium, vitamin A as well as vitamin C, and other nutrients that support overall wellness and help fight hunger in communities who are currently at jeopardy.

The abundant protein content of cassava leaves serves as one of their most notable qualities; this is especially welcome in areas wherein animal-based protein is unreliable. Furthermore, they are an outstanding source of antioxidants and dietary fiber, which promote digestive function and cement resilience [11]. Nevertheless these health advantages, cyanogenic compounds—which, when served raw or cooked erratically, can emit poisonous hydrogen cyanide—must be avoided while handling cassava leaves. One typical way to assure quality is to simmer or ferment the foliage.

Cassava leaves are valued for their gastronomic diversity in alongside their health perks [5]. They give taste and nourishment to meals by being utilized as accompaniments, in meals, and in recipes throughout many civilizations [7]. The leaves of cassava are a common component in many regional cuisines, as seen in the countries of the Democratic Republic of the Congo, Indonesia, and the Philippines, demonstrating its socioeconomic relevance [12].

Problem statement:

Cassava disease outbreaks are a major threat to agricultural production because they lower crop yields and cause farmers to suffer large financial losses. The current techniques for diagnosing plant diseases are unsatisfactory for controlling extensive crop pathogens because they are labour-intensive, error-prone, and ineffective. A more precise and effective method of early cassava disease detection is vitally required. Utilizing cutting-edge technology for picture categorization, such as deep learning, is a viable solution to this problem. Creating an effective framework for swift detection and action is the goal in order to maintain the integrity of the growing of cassava and enhance the quality of life for the people that depend on this vital crop.

2. Materials and Proposed methods

Dataset

The dataset used for cassava disease detection consists of labelled photos of cassava leaves, divided into several disease classifications and healthy leaves. This dataset is essential for both training and evaluating the performance of in distinguishing between various cassava diseases. The dataset was sourced from the publicly available Kaggle Cassava Leaf Disease Dataset. It includes high-resolution images of cassava leaves labelled with specific types of diseases.

(a) Sample set -1

(b) Sample set -2

Figure 1 Dataset of cassava leaves (a) Sample set -1 (b) Sample set -2

Every image provides complex visual clues that aid in the development of machine-learning models for accurate sickness identification, as seen in sample datasets (a), (b) in Fig 1.

Data Preprocessing

Plant disease classification relies heavily on the preprocessing of the cassava dataset [13]. To standardize input for the model, the images are first resized to a consistent dimension (e.g., 224x224 pixels). After that, normalization is applied to scale pixel values to the range of [0, 1], aiding in training convergence. Data augmentation techniques, such as rotation, flipping, and brightness adjustment, are employed to improve dataset diversity and reduce overfitting [17]. Additionally, images may be filtered to reduce noise or unnecessary background elements, ensuring that the model focuses on the key aspects of the cassava leaves [22]. This comprehensive preprocessing procedure optimizes the dataset for subsequent classification tasks.

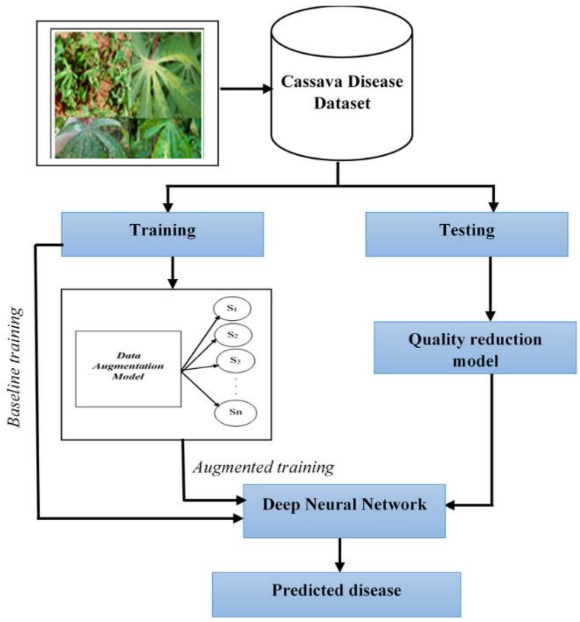

Figure 2 Flowchart of process for disease detection

The steps involved in identifying cassava leaf disease are depicted in Fig. 2. Subsequently, these features are used to build a machine learning model that will categorize the leaves. If a disease is present, the model determines what kind of sickness it is and predicts if the leaf will be sick or healthy.

Algorithms

A plant disease detection algorithm is a computational process used to automatically detect and categorize plant illnesses by examining photos of leaves, stems, or other plant components [19]. These algorithms look for patterns that indicate disease using machine learning, deep learning, or conventional image processing methods. Several methods have been used to identify cassava disease, taking advantage of advancements in image processing and machine learning [21]. Convolutional Neural Networks (CNNs) are at the forefront when it comes to automatically extracting spatial characteristics from leaf images to identify disease trends. Strong classification capabilities are provided by Random Forest methods and Support Vector Machines (SVMs), which generate decision boundaries and combine predictions from several decision trees, respectively [8]. Furthermore, K-Nearest Neighbors (KNN) offers a simple way to conduct fast evaluations based on proximity to labelled samples [4]. Deep Belief Networks (DBNs) and Gradient Boosting Machines (GBM) improve prediction accuracy through layered feature extraction or by correcting errors in successively constructed trees.

ResNet Algorithm

A particular kind of deep learning architecture called ResNet, or Residual Network, was created to overcome the challenges involved in training extremely deep neural networks [17]. ResNet has established itself as a foundational model in the field of computer vision, especially for tasks like semantic segmentation, object detection, and image classification. Because it can learn complex features and address fundamental deep learning issues like the vanishing gradient problem, the ResNet algorithm is unique in the field of cassava disease detection. In contrast to conventional algorithms, which may struggle to extract features from deeper networks, ResNet employs residual connections that facilitate the easier flow of gradients during training [1]. With this architecture, the model can identify more intricate patterns from images of cassava leaves, improving its ability to distinguish between healthy and diseased leaves. Additionally, ResNet can leverage the knowledge it has gained from large datasets through its transfer learning capability, which is particularly useful when working with smaller datasets.

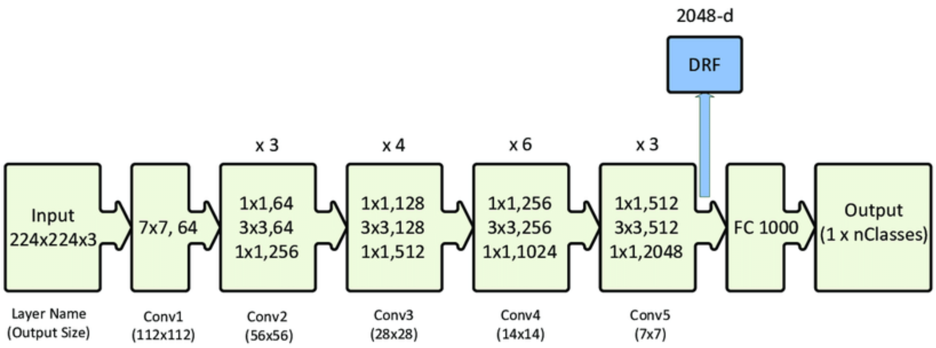

Figure 3 Architecture of ResNet 50 Algorithm

With many residual blocks, the network may effectively acquire deeper features, which is apparent in Fig. 3 for challenging tasks like picture categorization.

Implementation of ResNet 50 Algorithm

ResNet-50, a well-known deep learning architecture, can effectively learn complicated characteristics through residual learning, it provides a potent solution for cassava disease detection [2]. To guarantee consistency and improve the dataset, the following preprocessing tasks must be completed before training the ResNet-50 model:

Resizing: To ensure equal input size, as stated in eq(1), each picture D in the dataset is scaled using the interpolation function size() to a given dimension i×j (e.g., 224x224 pixels).

$$D' = size(D,i,j) \quad - \quad (1)$$

Where:

- D is the original image with dimensions i ×j,
- i×j is the target size (e.g., 224x224 pixels),
- D' is the resized image.

Normalisation: The pixel values of each picture are scaled, as stated in eq (2), to fall inside a specified range, typically [0,1] [0,1], by dividing them by the maximum pixel value p_mn that may be produced (typically 255 for 8-bit images):

$$P'_{mn} = \frac{p_{mn}}{255} \quad - \quad (2)$$

P'_{mn} = normalized pixel value

Data augmentation: Utilize the formula to rotate a picture by an angle θ, as stated in eq (3), to apply arbitrary rotations to images for augmentation.

$$\begin{pmatrix} q' \\ p' \end{pmatrix} = \begin{pmatrix} cos(\theta) - sin(\theta) \\ sin(\theta)\, cos(\theta) \end{pmatrix} \begin{pmatrix} q \\ p \end{pmatrix} \quad - \quad (3)$$

Training Model: The last layer of the model is altered to categorise the particular diseases in the cassava dataset once it has been trained on the prepared dataset.

Loss Function: The categorical cross-entropy loss function is used to calculate the degree to which the projected probability and the actual target labels, t, coincide, as shown in eq (4). For a multi-class classification problem with M classes, the loss S is given by:

$$s(t,\hat{t}) = -\sum_{m=1}^{M} t_m\, log(\hat{t}_m) \quad - \quad (4)$$

Evaluation of Model: Following training, the model's performance in actual scenarios is assessed using the test set. The model's accuracy in classifying healthy and diseased leaves is evaluated using metrics like accuracy, precision, recall, and the F1-score.

Algorithm:

Input : d_im

Input : set_i

Output : result

1: procedure RNDETECTION(d_im, set_i)

2: output vector's initial value is an empty list with d_im length.

3: int try[length(d_im)];

4: combine = random.random()

5: for i in range(0, length(d_im)) do

6: combine in the event that the random number exceeds the combine constant

7: if combine >= combine_ part then

8: try[i] ← d_im[i]

9: else

10: try[i] ← set_i[i]

11: s_trial = fitness(try)

12: s_target = fitness(d_im)

13: if s_trial >= sc_target then

14: occupants[j] = try

15: result.append(s_trial)

16: else

17: result.append(s_target)

18: return result

3. Results

The model demonstrates its strongest performance when classifying healthy plants, achieving remarkable precision values of 95.8% and 96.3%, along with an impressive accuracy of 96.5%. These results indicate the model's effectiveness in reliably identifying healthy plants, suggesting that it is well-tuned for this category. Conversely, the Cassava Brown Streak Virus shows the weakest performance, with accuracy recorded at only 88.7% and precision values of 87.6% and 90.8%. This significant drop in metrics highlights the challenges faced by the model in accurately identifying this disease, which may stem from factors such as overlapping symptoms with other conditions or insufficient training data.

The performance for Green Mite Damage and Cassava Mosaic Disease is more moderate, with accuracy levels at 91.1% and 92.4%, respectively. While these results are respectable, they indicate that there is room for improvement, especially compared to the performance on healthy plants. The precision values for these two categories remain relatively stable, both exceeding 89%, suggesting that the model maintains a consistent ability to correctly identify true positives among these plant conditions. Overall, while the model excels in detecting healthy plants, enhancements are necessary to improve the detection of the Cassava Brown Streak Virus, as well as to bolster performance for other diseases like Green Mite Damage and Cassava Mosaic Disease. These findings underscore the need for ongoing research and potential adjustments to the model to achieve higher classification accuracy and reliability across all plant categories.

Table 1 Performance metrics for Cassava

Disease Class	Accuracy (%)	Precision (%)	Recall (%)
Cassava Mosaic Disease	92.4	91.6	91.8
Cassava Brown Streak Virus	88.7	87.6	90.8
Green Mite Damage	91.1	89.9	90.7
Healthy	96.5	95.8	96.3

In the above table 1, the Cassava Brown Streak Virus has the lowest accuracy (88.7%) among the classification performance indicators, highlighting cassava illnesses and healthy plants. Healthy plants, on the other hand, attain the highest levels of accuracy (96.3%) and precision (96.5%).

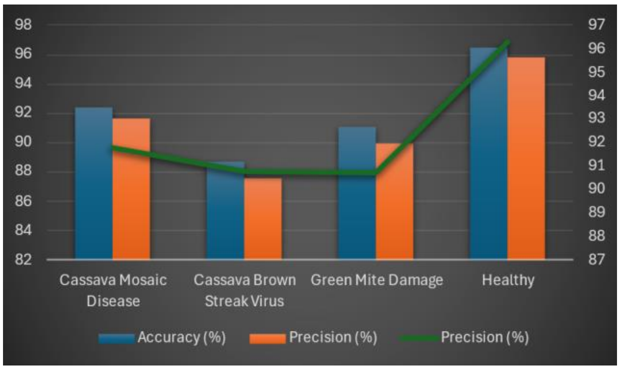

Figure 4 Combination chart depicting activity measures

The above Fig 4, shows the four categories—Cassava Mosaic Disease, Cassava Brown Streak Virus, Green Mite Damage, and Healthy Plants—accuracy and two precision measures are available. Cassava Brown Streak Virus plants have the lowest accuracy and precision across all measures, while healthy plants have the greatest levels. The accuracy measure (blue) varies more than the precision meter (orange and green), which are similar in all categories.

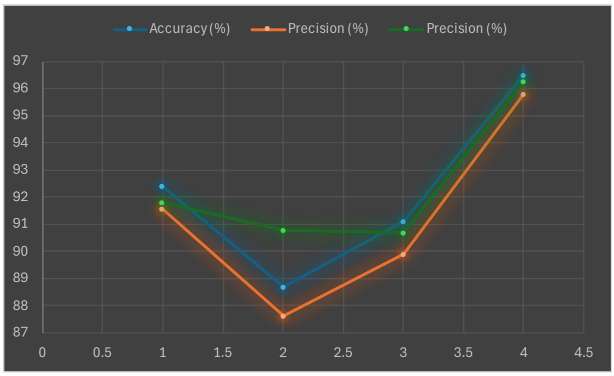

Figure 5 Accuracy and Precision (%) trends for Cassava disease classification.

In the above fig 5, the lines that represent the four plant categories are coloured blue for accuracy, orange for precision 1, and green for precision 2. Point 4 (healthy plants) has the best precision and accuracy, whereas Point 2 (the Cassava Brown Streak Virus) displays the lowest numbers. The precision measurements show a discernible decline at point 2, but otherwise stay pretty steady across the categories. More variation occurs in accuracy. The categorization performance is compared across various plant environments in the graph.

4. Discussion

The application of deep learning architectures to agricultural crop disease diagnosis has drawn a lot of interest lately [9]. Among these architectures, ResNet and VGG-16 have become well-liked options for image classification applications, such as diagnosing illnesses in cassava leaves [14]. Recognized for its simplicity and efficiency, VGG-16 has a simple architecture with 16 layers, mostly pooling layers after convolutional layers. By examining features at different dimensions, this deep network can diagnose a variety of diseases by identifying complex patterns in photos of cassava leaves. But as depth increases, VGG-16's deep design may cause problems like vanishing gradients, which reduces its effectiveness when learning from bigger datasets [10]. Notwithstanding these difficulties, the VGG-16 model has demonstrated efficacy in detecting cassava leaf diseases, especially when paired with data augmentation methods to boost the model's resilience [15].

ResNet (Residual Network), on the other hand, presents a novel idea of residual learning via skip connections, allowing gradients to move more freely during backpropagation [18]. With this approach, the vanishing gradient problem is avoided and considerably deeper structures can be built, circumventing the drawbacks of conventional deep networks [5]. Because ResNet can learn residuals, it can efficiently extract complicated information from photos of cassava leaves, which improves its accuracy in tasks involving the categorization of diseases. In terms of accuracy and generalization, ResNet frequently outperforms VGG-16 in the detection of illnesses like bacterial blight and cassava mosaic disease, especially when trained on large, diverse datasets.

In the end, there are advantages and disadvantages for both VGG-16 and ResNet when it comes to detecting cassava leaf disease [20]. ResNet provides a more complex framework that can achieve higher accuracy on larger datasets because of its deep architecture and novel residual learning, while VGG-16 offers a straightforward method that can produce good results with smaller datasets and less complexity [21]. The application's particular needs, such as the size of the dataset, the availability of computational power, and the demand for accurate illness detection, should be taken into consideration while selecting between these models.

5. Conclusion

ResNet-50's strong feature extraction capabilities have made it a successful deep learning model for disease detection in cassava leaves. It solves the vanishing gradient issue by utilizing residual connections in its deep design, which makes deep network training more effective. especially well-suited for detecting minute variations in leaf texture, color, and shape, which are crucial indications of illnesses in cassava plants because to its capacity to learn complicated patterns from huge datasets.

ResNet-50 offers a number of benefits over conventional image processing methods, including simpler convolutional networks and higher accuracy in cassava leaf disease diagnosis. Its pretrained weights can be adjusted for this particular job, minimizing training time and enhancing generalization. These weights are frequently obtained from huge image datasets such as ImageNet [18]. Consequently, it has the ability to accurately discriminate between a variety of cassava disorders, including Cassava Mosaic Disease and Brown Streak Disease, which are frequently difficult to discern with the untrained eye.

ResNet-50 has many advantages, but because of its deep structure, it also needs a lot of computational power, which can make it difficult to use in places with limited resources, like to use in places with limited difficult rural, like rural cassava farming areas [22]. Although the model performs exceptionally well in controlled environments, it is still difficult to optimize it for real-time detection in the field, on mobile devices, or on low-powered systems. Overall, ResNet-50 continues to be the best option for detecting cassava leaf disease; however, additional work must be done to improve its usability before it can be widely applied in agriculture.

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References

[1] V. N, M. Chinta, K. E and S. V. L, "Classification of Pneumonia using InceptionNet, ResNet and CNN," 2022 6th International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS), Bangalore, India, 2022, pp. 1-6, doi: 10.1109/CSITSS57437.2022.10026402.

[2] H. C. Choi and T. -C. Hsiao, "Image Classification of Cassava Leaf Disease Based on Residual Network," 2021 IEEE 3rd Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (ECBIOS), Tainan, Taiwan, 2021, pp. 185-186, doi: 10.1109/ECBIOS51820.2021.9510414.

[3] W. Hou, S. Wen, P. Li and S. Feng, "Surface Defect Detection of Fabric Based on Improved Faster R-CNN," 2023 IEEE International Conference on Sensors, Electronics and Computer Engineering (ICSECE), Jinzhou, China, 2023, pp. 600-604, doi: 10.1109/ICSECE58870.2023.10263522.

[4] G. Owomugisha, F. Melchert, E. Mwebaze, J. A. Quinn and M. Biehl, "Matrix Relevance Learning From Spectral Data for Diagnosing Cassava Diseases," in IEEE Access, vol. 9, pp. 83355-83363, 2021, doi: 10.1109/ACCESS.2021.3087231.

[5] P. Roshini, S. Khajavali, M. L. S. Snigdha, B. D. Harsha, B. Srilakshmi and A. Gopi, "CNN Design with AlexNet Algorithm for Diagnosis of Diseases in Cassava Leaves," 2024 International Conference on Expert Clouds and Applications (ICOECA), Bengaluru, India, 2024, pp. 1-8, doi: 10.1109/ICOECA62351.2024.00129.

[6] M. Amanatulla, G. Swathi, M. Pallavi and K. P. Bindu, "MRI Scans for Deep Learning-Based Chronic Nephropathy Detection: A Comparison of CNN, MobileNet, VGG16, and ResNet-50 Models," 2024 5th International Conference for Emerging Technology (INCET), Belgaum, India, 2024, pp. 1-6, doi: 10.1109/INCET61516.2024.10593144.

[7] J. J. Joseph, J. V. George, K. M. Manoj, M. M. Reji and J. Mathew, "Fusing Deep CNN and Local Binary Pattern for Accurate Plant Disease Diagnosis," 2023 Annual International Conference on Emerging Research Areas: International Conference on Intelligent Systems (AICERA/ICIS), Kanjirapally, India, 2023, pp. 1-6, doi: 10.1109/AICERA/ICIS59538.2023.10420071.

[8] M. C. Loo, R. Logeswaran and Z. A. A. Salam, "CNN Aided Surface Inspection for SMT Manufacturing," 2023 15th International Conference on Developments in eSystems Engineering (DeSE), Baghdad & Anbar, Iraq, 2023, pp. 328-332, doi: 10.1109/DeSE58274.2023.10099694.

[9] S. Mehta, V. Kukreja and R. Gupta, "Decentralized Detection of Cassava Leaf Diseases: A Federated Convolutional Neural Network Solution," 2023 International Conference on Circuit Power and Computing Technologies (ICCPCT), Kollam, India, 2023, pp. 381-386, doi: 10.1109/ICCPCT58313.2023.10245357.

[10] R. Somkunwar, A. K. Gupta, A. Anand, G. Gawali, A. Hiralkar and D. Shinde, "CNN-based Soil Image Analysis for Enhanced Crop Prediction in Smart Agriculture," 2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSoCiCon),Pune,India,2024,pp.1-5,doi: 10.1109/MITADTSoCiCon60330.2024.10575651.

[11] S. M. Riaz, M. Ahsan and M. U. Akram, "Diagnosis Of Cassava Leaf Diseases and Classification Using Deep Learning Techniques," 2022 16th International Conference on Open Source Systems and Technologies (ICOSST), Lahore, Pakistan, 2022, pp. 1-8, doi: 10.1109/ICOSST57195.2022.10016854.

[12] S. Endargiri and K. Laabidi, "Automatic Healthcare Diagnosis and Prediction Assessment based on AI Multi-Classification Algorithm," 2020 16th International Computer Engineering Conference (ICENCO), Cairo, Egypt, 2020, pp. 112-117, doi: 10.1109/ICENCO49778.2020.9357385.

[13] P. A, S. Kumar and S. Pundeer, "Performance Assessment of Data Centric and Model Centric Approach for Premature Detection of Leaf Disease," 2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE), Gautam Buddha Nagar, India, 2024, pp. 172-176, doi: 10.1109/IC3SE62002.2024.10593510.

[14] Y. Liang, L. Lu, Q. Xiao and S. Yan, "Evaluating Fast Algorithms for Convolutional Neural Networks on FPGAs," in IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, vol. 39, no. 4, pp. 857-870, April 2020, doi: 10.1109/TCAD.2019.2897701.

[15] S. Lodhi, Sakshi and V. Kukreja, "Deep Learning Based Method To Detect Diseases In Leaves Of Cassava Plant," 2022 International Conference on Data Analytics for Business and Industry (ICDABI), Sakhir, Bahrain, 2022, pp. 128-134, doi: 10.1109/ICDABI56818.2022.10041484.

[16] G. B. Alghanimi, H. K. Aljobouri and K. A. Al-shimmari, "CNN and ResNet50 Model Design for Improved Ultrasound Thyroid Nodules Detection," 2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS), Manama, Bahrain, 2024, pp. 1000-1004, doi: 10.1109/ICETSIS61505.2024.10459588.

[17] R. Pillai, N. Sharma, R. Gupta and A. Sharma, "Classification of Plant Diseases using DenseNet 121 Transfer Learning Model," 2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), Chennai, India, 2023, pp. 1-6, doi: 10.1109/ACCAI58221.2023.10200401.

[18] A. Li, R. Gao, J. Fu and F. Yang, "Research on the target cargo identification method based on CNN," 2021 14th International Symposium on Computational Intelligence and Design (ISCID), Hangzhou, China, 2021, pp. 32-35, doi: 10.1109/ISCID52796.2021.00015.

[19] P. R. Jeyaraj, E. R. Samuel Nadar and B. K. Panigrahi, "ResNet Convolution Neural Network Based Hyperspectral Imagery Classification for Accurate Cancerous Region Detection," 2019 IEEE Conference on Information and Communication Technology, Allahabad, India, 2019, pp. 1-6, doi: 10.1109/CICT48419.2019.9066215.

[20] J. Zhang and W. Liu, "Predicting and Analyzing IoT Performance Based on Improved Resnet," 2023 IEEE 2nd Industrial Electronics Society Annual On-Line Conference (ONCON), SC, USA, 2023, pp. 1-6, doi: 10.1109/ONCON60463.2023.10430561.

[21] G. Yogapriya, R. S. Kumari, S. Suganthi, K. Agalya, T. Elangovan and D. S. Pandian, "Crop Yield Identification Using CNN," 2023 International Conference on Artificial Intelligence and Knowledge Discovery in Concurrent Engineering (ICECONF), Chennai, India, 2023, pp. 1-4, doi: 10.1109/ICECONF57129.2023.10084304.

[22] J. Zhao, A. Wu, B. Jiang and Q. Zhang, "ResNet-Based Fast CU Partition Decision Algorithm for VVC," in IEEE Access, vol. 10, pp. 100337-100347, 2022, doi: 10.1109/ACCESS.2022.3208135.

[23] M. K. Dharani, R. Thamilselvan, S. P. Gudadhe, M. A. Joshi and V. Yadav, "Leaf Disease Detection using Deep Learning Models," 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS), Tashkent, Uzbekistan, 2022, pp. 646-650, doi: 10.1109/ICTACS56270.2022.9988660.