WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Exploring Convolutional Neural Networks for Effective Plant Disease Detection

Dekka Devi Pradeep

B.tech,GMR IT ,Rajam 532127 , India

ABSTRACT :

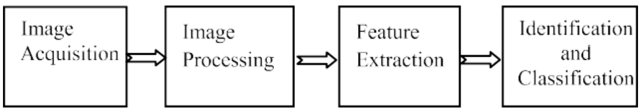
The prevalence of plant diseases has increased recently, which is very problematic for farmers. Among the many worries that farmers have are pest difficulties, decreased output value, and irrigation issues. Early detection and treatment of plant diseases are necessary to minimize output losses. In "Deep Learning" statistical machine learning techniques, neural network architecture is used to analyse data sets and identifies the plant diseases. Datasets were derived from the Plant Village collection, which included images of both healthy and damaged plant leaves. CNN is a deep learning system that can identify conditions based on inputs from leaf image databases. Until suitable patterns are found, several stages of image analysis is conducted. The performance of several CNN designs, including Inception V3 and Mobile Net, is evaluated, compared and examined in this work in relation to a specific data set. To detect infections and prevent crop losses farmers prefer accurate designs.

Keywords: Plant Disease Detection, Deep Learning , Convolutional Neural Networks, Mobile Net, Inception V3.

Introduction :

As a source of food for both people and animals, plants are essential to the survival of life on Earth. Establishing effective methods for early detection and research of plant diseases is therefore essential. Damage to agriculture can be significant due to natural disasters, pests, and delayed disease diagnosis that often affect crop output.The agriculture industry and farmers benefit in the future from improved crop quality, which can only be attained by early detection and investigation of plant diseases.Hand diagnosing diseases, however, can be a challenging and ineffective procedure.Deep learning has emerged as an efficient method for identifying plant diseases in order to address this problem. The general process of using traditional image recognition processing techonology to identify plant diseases is shown in Fig [1].

Figure 1-Traditional image recognition processing



In recent times, deep learning particularly convolution neural network (CNN) gained much attention in agricultural field such as plant detection. The reason behind the CNN-based model’s popularity is the automatic extraction of appropriate features from the data set. Several popular deep learning-based models such as AlexNet , GoogleNet , VGGNet , ResNet , DenseNet have been developed for identification of plant diseases.While preserving agricultural output and promoting sustainable farming methods, this approach ensures the early detection and treatment of plant diseases. With the use of deep learning technology, we can improve plant health monitoring and encourage the agriculture industry's continuous expansion. The process of identifying diseases in plants using deep learning is shown in Fig[2].

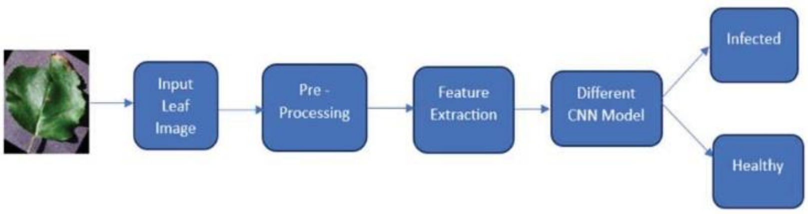


Figure 2-DeepLearning image recognition processing

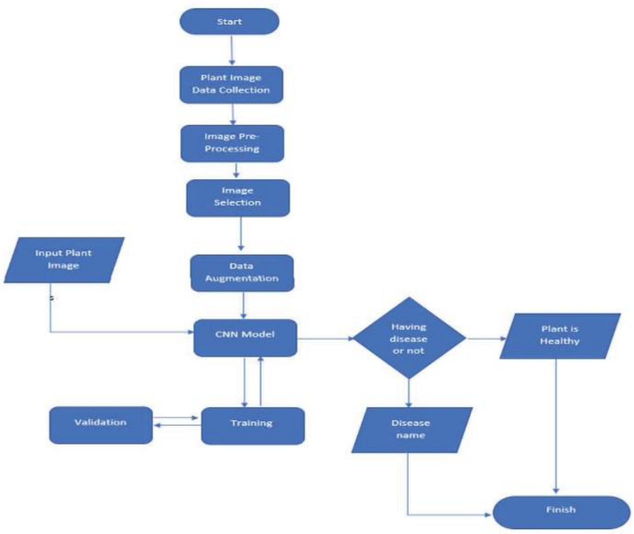
Literature Survey :

[1] The study suggests using Convolutional Neural Networks (CNN) to identify plant diseases from leaf photos. CNN outperforms other models like Support Vector Machines (SVM), Extreme Learning Machines (ELM), and Artificial Neural Networks (ANN) with an incredible 99.3% accuracy rate.
[2] Another work focuses on automating disease identification with CNNs and the PlantVillage dataset, with a 94% success rate, especially in crops like tomatoes and potatoes. This helps farmers increase crop yields and decrease crop losses.
[3] With a 99.3% accuracy rate, ResNet50 outperformed the other CNN models, including VGG16, ResNet34, and ResNet50, according to a comparative analysis. This model offers a reliable option for early disease diagnosis.
[4] In order to improve dataset variety, a 14-layer deep CNN (14-DCNN) model is presented, which uses sophisticated data augmentation techniques like BIM and DCGAN to attain an exceptional 99.96% accuracy.
[5] Although its complex background elements present challenges, resulting in lower accuracies for some models such as ResNetV2 (41.19%) and MobileNet (74.05%), the FieldPlant dataset, which consists of 5,170 annotated field images from actual plantations in Cameroon, provides a realistic benchmark for plant disease detection models.
[6] With 70% fewer parameters than Inception V3, a lightweight CNN architecture utilizing Inception modules and residual connections achieved 99.3% accuracy while drastically lowering processing needs.
[7] With a 13-convolution layer architecture optimized for performance, a refined CNN model trained on a Kaggle dataset achieved 98.7% accuracy.
[8] An additional lightweight 2D CNN architecture that was created for the classification of cotton and tomato diseases achieved 97.36% accuracy, proving to be more effective than models such as VGG16 and InceptionV3.
[9] Across the apple, tomato, and grape leaf datasets, a hybrid CNN-LBP model that combines deep and handmade features demonstrated a high accuracy of 98.03%, making it appropriate for edge computing and real-time applications.
[10] Plant disease detection has also made extensive use of transfer learning models such as DenseNet-121, ResNet-50, and Inception V4. Through fine-tuning, DenseNet-121 and ResNet-50 both achieved approximately 99.8% accuracy.
[11] The advantages of applying deep learning for automated disease management were highlighted by a study that used ResNet-34 for quick plant disease diagnosis and reported an accuracy of 98.7%.
[12] On big datasets, transfer learning models such as Inception V3 and AlexNet demonstrated efficacy in early disease identification, with accuracies of 99.57% and 99.17%, respectively.
[13] YOLOv3 offered a quick real-time solution with an accuracy of 82.69%, whereas EfficientDet-D2, which used multiscale feature fusion and compound scaling, attained an accuracy of 88.13%.
[14] An accuracy of 95.01% was attained by fine-tuning pre-trained models such as EfficientNetV2S to identify plant diseases in noisy environments.
[15] Lastly, by simplifying feature extraction and enabling high-accuracy classifications, CNN models continue to rule plant disease detection tasks, despite ongoing issues with generalization and dataset quality.

Methodology :

Convolutional neural networks, or CNNs, are specialized deep learning models made for tasks involving spatial data, such as object detection and classification, and picture analysis. They are constructed using layers that use filters to identify objects in pictures, gradually identifying details ranging from basic aspects like edges and colors to intricate shapes. CNNs primarily use convolutional layers, which create "activation maps" that emphasize important features in specific areas of an image by applying filters. Following these, pooling layers—which frequently employ max or average pooling—maintain important data, minimize spatial size, and improve the model's resistance to slight input changes. Lastly, the retrieved characteristics are integrated for classification or prediction by fully linked layers.
In order to detect plant diseases using CNNs, a variety of plant photos representing both healthy and diseased plants are systematically gathered from fields or agricultural databases. The program can more successfully and precisely identify between healthy and unhealthy plants when variation is ensured in these samples. Following collection, these photos undergo a number of pre-processing stages, including resizing them to a consistent size for batch processing and applying normalization to stabilize training by scaling pixel values, frequently to a range of 0 to 1. Additionally, noise reduction techniques are employed to eliminate superfluous data, enhancing the model's precision in recognizing patterns. The next step is a selection procedure that removes pictures that are imprecise or ambiguous in order to preserve data quality and avoid model confusion.

Figure 3- Architecture of CNN



By creating many versions of each image using methods including cropping, scaling, flipping, and rotating, data augmentation enhances the dataset even more. This increases the dataset's size and exposes the model to a wider range of viewpoints, which improves its ability to identify diseases from several perspectives. In order to repeatedly optimize the CNN model as it gains the ability to identify complex patterns linked to a variety of plant illnesses, the produced dataset is separated into training and validation sets. Once trained, the model can correctly categorize fresh photos of plants, detecting illnesses or verifying the health of the plants. By assisting with early disease detection, this automated diagnosis helps farmers and other agricultural professionals manage crops in a timely and informed manner.

3.1 RESNET 50

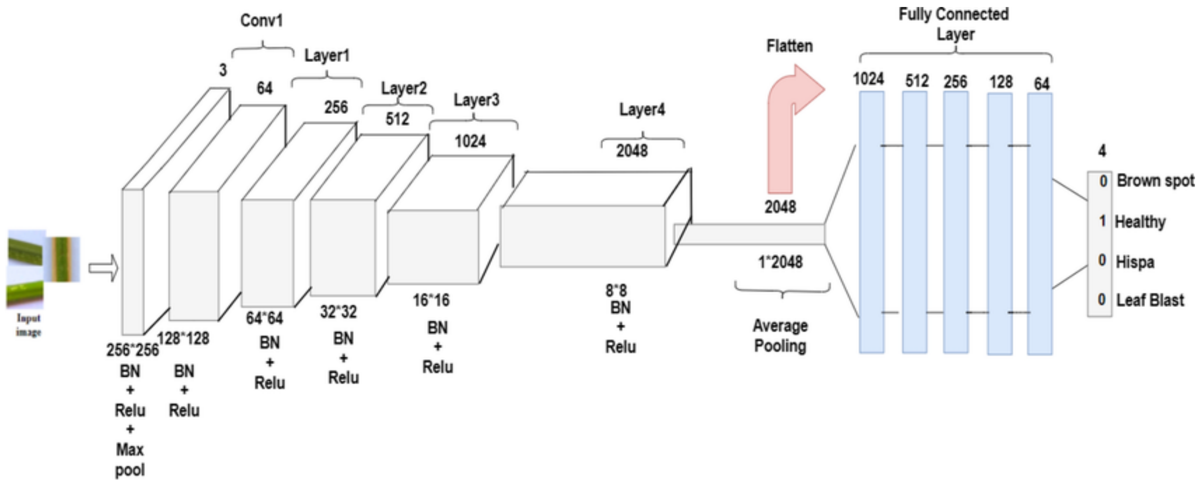


Figure 4- Architecture of ResNet-50

A deep convolutional neural network architecture called ResNet-50, or Residual Network with 50 layers, was created to solve the vanishing gradient issue in extremely deep networks. The utilization of residual connections, or shortcut paths, which enable some levels to bypass and link to succeeding layers, is its primary innovation. By facilitating training and enhancing gradient flow, this structure aids the network in learning identity mappings, enabling deeper and more intricate structures without sacrificing performance. Four major stages of bottleneck residual blocks make up ResNet-50, which starts with an initial convolution layer and gradually learns more abstract aspects of the input data.

Images of plant leaves are processed using ResNet-50 to determine if they are healthy or unhealthy in order to detect plant diseases. An initial convolution layer is used in this application to extract basic patterns from a leaf picture, which is typically 256x256 pixels in size. The image goes through a number of changes as it passes through the four primary stages, each of which is made up of several residual layers, capturing fine details like texture, color, and leaf structure. These changes aid the model in distinguishing between leaves that are disease-free and those that have brown spot, hispa, or leaf blast.

After the final residual layer, the output feature map is subjected to average pooling, reducing it to a single vector. This vector is then flattened and passed through fully connected layers, where the final classification occurs. Each node in the output layer corresponds to a specific disease class or the healthy class, with the model assigning a probability to each class. In the example you provided, the output layer has four nodes, representing different plant health statuses. By learning distinct patterns associated with each class, the ResNet-50 model can accurately classify the leaf images, assisting in early and precise disease diagnosis.

3.2 VGG 16

For image identification applications, the deep convolutional neural network architecture VGG-16 has been used extensively. VGG-16 was first presented by the Visual Geometry Group (VGG) at Oxford and was named for its 16 layers (three fully linked layers and thirteen convolutional layers). Finer details in photographs can be captured since it consistently applies smaller 3x3 filters across layers. In order to help the network understand intricate patterns, the architecture additionally incorporates ReLU activation functions following each convolutional layer, which introduce non-linearity. After downsampling the spatial dimensions with pooling layers, the model can perform classification tasks thanks to fully linked layers at the conclusion. The output layer creates class probabilities using a softmax algorithm.

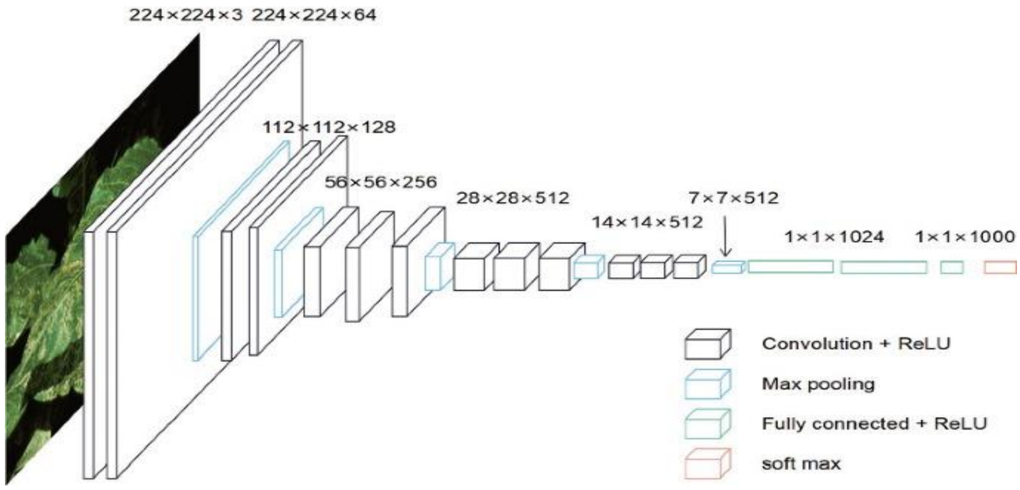


Figure 5- Architecture of VGG-16

VGG-16 helps with the diagnosis of plant diseases by examining plant photos and recognizing characteristics linked to different illnesses. Initially, a sizable library of plant photos is created, comprising both healthy and sick specimens. These pictures are adjusted to match the input dimensions of VGG-16, which are normally 224x224 pixels. Convolutional layers in the model recognize hierarchical elements as it processes these photos, ranging from simple edges and textures to more intricate forms and patterns linked to signs of plant diseases. The model can concentrate on important patterns without extraneous noise because to the pooling layers' reduction of the spatial scale.

By changing its weights through backpropagation during training, the model gains the ability to identify particular characteristics associated with various diseases. VGG-16 is capable of accurately identifying diseases or verifying the health of plants by classifying new photos using the patterns it has learned. Because of this, VGG-16 is an effective instrument for diagnosing plant diseases and provides a scalable and automated way to keep an eye on crop health.

4. Results and Discussion :

The results of this study show that ResNet-50 outperforms CNN, VGG-16, and VGG-16 in terms of accuracy, precision, F1-score, and error rate. Because of its high accuracy (94.1%), precision (94%), and F1-score (93.8%), ResNet-50 is a highly useful tool for diagnosing plant diseases due to its great generalization and prediction skills. ResNet-50's residual learning approach allows the model to capture minute details of disease symptoms for early identification while preserving important characteristics and resolving gradient concerns.

Table-1: Comparison among various methods

Model	Accuracy%	Precision%	F1-score%	Error Rate%
CNN	92.6	92.4	92.5	7.4
ResNet-50	94.1	94	93.8	5.9
VGG-16	91	90.5	90.7	9

Even if ResNet-50 performs better, VGG-16 comes in second, particularly in precision and F1-score, with 90.5% precision and 90.7% F1-score. This suggests that even though VGG-16 has a simpler architecture, it can still be a dependable choice, especially where computational economy is crucial. Conversely, CNN performs somewhat worse, particularly in error rate and F1-score, which raises the possibility that it may overlook or incorrectly identify some disease cases. Given that CNN's recall and precision are lower than those of the other models, it is therefore less appropriate for applications demanding high sensitivity and specificity.

All things considered, the results validate the efficacy and robustness of ResNet-50 for precise and prompt plant disease identification, establishing it as a useful instrument in precision farming. ResNet-50 supports attempts to prevent crop loss through prompt intervention because of its great generalization capabilities, which allow it to adapt to many plant species and disease kinds. To further improve model resilience, future studies could examine bigger, more varied datasets encompassing different plant species, disease stages, and environmental circumstances. Furthermore, overfitting might be reduced by using sophisticated regularization strategies like dropout and data augmentation, which would increase the model's flexibility when dealing with fresh data. In addition to enabling useful, real-time apps for farmers, efforts to optimize the model for mobile and edge devices through methods like pruning and lightweight architectures may also encourage sustainable farming practices by managing diseases early.

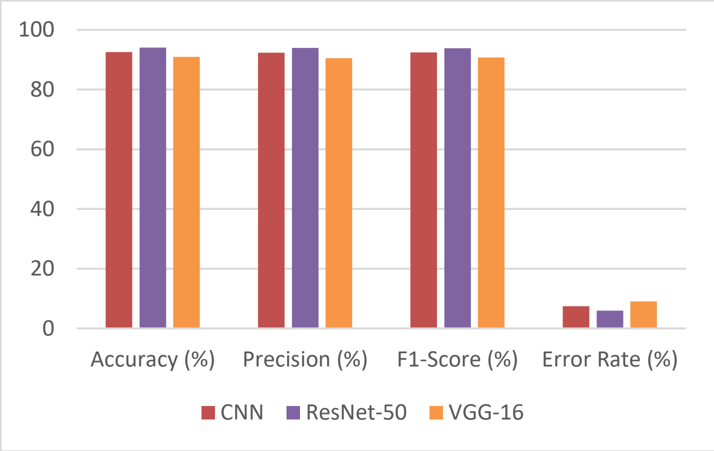


Figure 6- Graphical representation of various performance metrics

5. Conclusion :

The comparison of CNN, VGG-16, and ResNet-50 in the detection of plant diseases highlights how deep learning has the potential to revolutionize the agricultural industry. Conventional illness diagnosis techniques frequently rely on expert analysis and visual inspection, which can be laborious, arbitrary, and prone to mistakes. On the other hand, farmers can detect diseases early and stop more crop damage thanks to deep learning models, like ResNet-50, which provide automated, quick, and extremely accurate detection capabilities. Protecting crop yields requires more proactive disease management, which is made possible by this move toward AI-driven solutions.

ResNet-50 is unique because of its sophisticated residual learning architecture, which enables it to identify complex patterns and minute signs of plant illnesses. It is ideal for agricultural applications, where prompt and accurate disease diagnosis is crucial, due to its excellent accuracy and efficiency ratio. ResNet-50's greater accuracy and precision make it a favored option for applications needing high reliability, particularly in identifying a variety of early-stage signs of plant diseases, despite VGG-16's respectable performance and computational simplicity.

Disease management techniques in agriculture could be greatly enhanced by the use of ResNet-50 and related models. By using these tools, farmers can minimize crop losses and increase output by responding to disease threats more quickly. Deep learning models like ResNet-50 may be crucial to sustainable agriculture as technology develops further, ensuring that crops are shielded from disease outbreaks and enhancing a robust food supply chain.

6. REFERENCES :

1. T. Chaturya, Y. Swathi, V. Kumar, P. Karthik, A. Nayan and A. Yadav, "Detection of Plant Disease using Convolutional Neural Networks (CNN)," 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 2023, pp. 598-603, doi: 10.1109/ICSCDS56580.2023.10105099.
2. M.O. Lawrence and P.Ogedebe, "Detection of Image-based Plant Leaf Diseases Using Convolutional Neural Networks," 2024 International Conference on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG), Omu-Aran, Nigeria, 2024, pp. 1-6, doi: 10.1109/SEB4SDG60871.2024.10630105.
3. S. Gupta, S. Gilotra, S. Rathi, T. Choudhury, K. Kotecha and T. Choudhury, "Plant Disease Recognition Using Different CNN Models," 2024 14th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 2024, pp. 787-792, doi:10.1109/Confluence60223.2024.10463383.
4. J. Arun Pandian, V. Dhilip Kumar, Oana Geman , Mihaela Hnatiuc , Muhammad Arif & K Kanchanadevi (2022). "Plant Disease Detection Using Deep Convolutional Neural Network", Applied Sciences, 12, 6982.
5. E. Moupojou et al., "FieldPlant: A Dataset of Field Plant Images for Plant Disease Detection and Classification With Deep Learning," in IEEE Access, vol. 11, pp. 35398-35410, 2023, doi: 10.1109/ACCESS.2023.3263042.
6. S. M Hassan, A. K Maji (2021). "Plant Disease Identification Using Novel Convolutional Neural Network", in IEEE Access, vol. 10, pp. 5390-5401.
7. G. Singh, K. Guleria and S. Sharma, "A Deep Learning-based Fine-tuned Convolutional Neural Network Model for Plant Leaf Disease Detection," 2023 4th IEEE Global Conference for Advancement in Technology (GCAT), Bangalore, India, 2023, pp. 1-6, doi: 10.1109/GCAT59970.2023.10353487.
8. H I Peyal, M Nahiduzzaman, M A H Pramanik , M K Syfullah , S M Shahriar , A Sultana, M Ahsan , J Haider , A Khandakar & M E H Chowdhury (2023), "Plant Disease Classifier: Detection of Dual-Crop Diseases Using Lightweight 2D CNN Architecture", in IEEE Access, vol. 11, pp. 110627-110643.

9. K M Hosny , W M El-Hady , F M Samy , E Vrochidou & G A Papakostas (2023), "MultiClass Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern" , in IEEE Access, vol. 11, pp. 62307-62317.
10. Vasileios Balafas , Emmanouil Karantoumanis , Malamati Louta & N Ploskas (2023), "Machine Learning and Deep Learning for Plant Disease Classification and Detection", in IEEE Access , vol. 11, pp. 114352-114377.
11. K. Harshavardhan, P. J. V. A. Krishna and A. Geetha, "Detection of Various Plant Leaf Diseases Using Deep Learning Techniques," 2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), Chennai, India, 2023, pp. 1-6, doi: 10.1109/ACCAI58221.2023.10200031.
12. T. Gupta, Titunath and V. Jain, "Plant Disease Detection using Deep Learning," 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS), Coimbatore, India, 2023, pp. 202-206, doi: 10.1109/ICSCSS57650.2023.10169268.
13. R. Kavitha Lakshmi & Nickolas Savarimuthu (2021), "PLDD—" A Deep Learning-Based Plant Leaf Disease Detection", in IEEE Consumer Electronics Magazine, vol. 11, no. 3, pp. 44-49.
14. Bahaa S. Hamed , Mahmoud M. Hussein , Afaf M. Mousa (2023), "Plant Disease Detection Using Deep Learning", International Journal of Intelligent Systems and Applications (IJISA) , Vol.15 , No.6 , pp.38-50 .
15. E. Hirani, V. Magotra, J. Jain and P. Bide, "Plant Disease Detection Using Deep Learning," 2021 6th International Conference for Convergence in Technology (I2CT), Maharashtra, India, 2021, pp. 1-4, doi: 10.1109/I2CT51068.2021.9417910.