WWW.IJRPR.COM

International Journal of Research Publication and Reviews

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

Plant Disease Detection using Deep Learning

Narmatha.R[1],Siva Ramani.S[2], Sarika Sri.P[3], Kanishka.R[4], Luvika.R[5]

[1-5]Department of Computer Science and Engineering, Government College of Engineering (Anna University), Dharmapuri, Tamil Nadu, India

ABSTRACT:

In response to the increasing demand for sustaining food supplies amidst growing populations, maintaining plant health is paramount. Detecting diseases in plants, often challenging even for seasoned farmers, has been facilitated by advancements in technologies like Deep Learning and Image Processing. This project introduces a system designed to detect leaf diseases, employing the RESNET9 architecture for enhanced efficiency. Leveraging deep learning techniques, our model achieves a commendable accuracy of 99%, contributing significantly to disease detection in plants. This approach, utilizing RESNET9 and PyTorch, represents a novel contribution to the field, offering improved capabilities in plant disease recognition and mitigation.

Index terms: Deep Learning, Plant leaf disease, Resnet9, Image Processing, PyTorch.

INTRODUCTION :

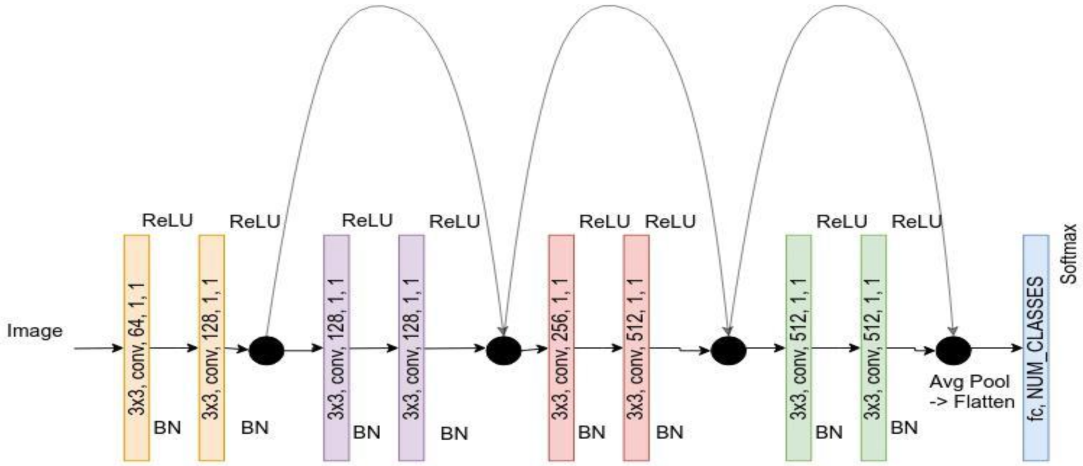
Agriculture is the backbone of India, with plants serving as a vital source for human sustenance. Consequently, safeguarding plant health is imperative for agricultural development. Detecting healthy and diseased plants is crucial, with leaf analysis being a primary method for identifying infections, as many disease symptoms manifest on leaves. Traditional detection methods, reliant on manual observation or basic image processing, are time-consuming and may lack accuracy. However, advancements in deep learning, particularly convolutional neural networks (CNNs), have revolutionized automated leaf detection and classification, offering efficiency and precision. In this project, we propose utilizing the ResNet9 architecture, an adaptation of the ResNet50 model, renowned for its deep layers and skip connections facilitating robust feature extraction and learning complex patterns in images. Our aim is to develop a proficient system for identifying and classifying plant leaves using ResNet9. The model will be trained on a diverse dataset comprising labelled images of healthy leaves and those afflicted by various diseases. Employing convolutional neural network architecture, the model may incorporate transfer learning techniques. The dataset will undergo pre-processing, and the model's performance will be assessed using training, validation, and testing sets. The goal is early disease detection in plant leaves to mitigate and prevent infections' spread. The project's objective is to distinguish between healthy and infected leaves using deep learning and image processing techniques. The dataset encompasses images of leaves with diverse diseases and healthy leaf samples to train the system effectively. The resultant system will facilitate the detection of infected leaves, aiding farmers and agricultural practitioners in disease management. The algorithm and methodology employed will be efficient and adaptable for execution on various platforms, including mobile devices. The system will prioritize user-friendliness and accuracy, serving as a versatile tool for plant disease detection in agriculture.

II. LITERATURE SURVEY

The literature survey offers a comprehensive overview of recent methodologies and advancements in the crucial domain of plant disease detection and classification, primarily leveraging deep learning techniques. Alok Kumar and Ankit Kumar (2023) introduced a sophisticated plant disease detection system utilizing the VGG16 architecture, yielding significant results, particularly in potato and tomato plant species. Md. Tariqul Islam (2020) proposed an image processing-based methodology coupled with CNN models for identifying diseases in key crops like grape, potato, and strawberry, aiming to streamline agricultural practices. Reshmi A.M. and Prameeja Prasidhan (2022) explored automatic leaf disease identification using a CNN algorithm, focusing on feature extraction and classification to facilitate accurate diagnosis and effective remedy implementation. LILI LI, SHUJUAN ZHANG, and BIN WANG (2021) provided a comprehensive review of plant leaf disease recognition using deep learning, emphasizing the importance of diverse datasets, data augmentation, and transfer learning in enhancing classification accuracy. Their analysis highlighted emerging trends such as hyper-spectral imaging for early disease detection. Rinu R. and Manjula S H (2021) leveraged CNN architectures for identifying thirteen distinct plant leaf diseases, achieving an impressive accuracy rate of 94.8% on the Plant Village dataset. Their integration of a user-friendly Graphical User Interface (GUI) enhanced accessibility and usability among farmers and stakeholders. These studies collectively underscore the significant progress made in plant disease detection through deep learning, while also indicating future research directions. The convergence of artificial intelligence and agriculture holds promise for revolutionizing farming practices, mitigating crop losses, and ensuring global food security amidst evolving challenges.

RESNET 9

ResNet9, a variant of the Residual Network (ResNet) architecture, has emerged as a promising solution for plant leaf disease detection tasks. Despite its smaller scale compared to ResNet50, ResNet9's architecture, comprising nine layers, proves effective in learning intricate features from high-resolution images, thereby facilitating the discernment of subtle signs of plant diseases. In the realm of plant pathology, ResNet9 demonstrates proficiency in capturing nuanced patterns and textures on leaf surfaces, enabling accurate classification of various diseases. Like ResNet50, the residual connections within ResNet9 mitigate the vanishing gradient problem, allowing for effective learning of complex disease symptoms while maintaining computational efficiency.



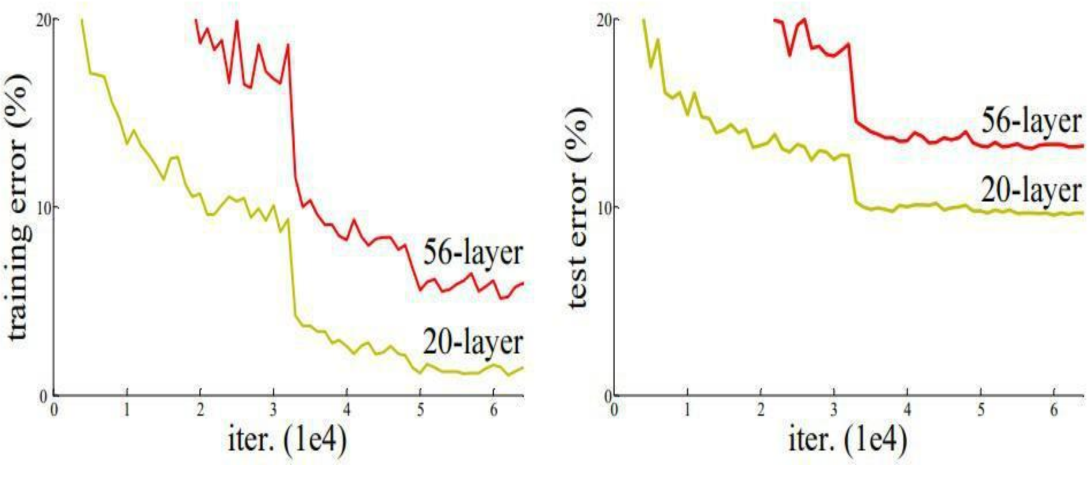
ResNet 9 Architecture

In practical applications, ResNet9 serves as a foundational architecture for feature extraction and classification in plant leaf disease detection pipelines. Researchers and practitioners fine-tune pre-trained ResNet9 models on domain-specific datasets of plant leaf images to leverage learned representations for accurate disease identification and classification across different plant species.

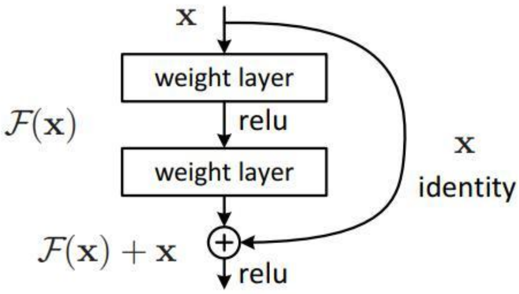
Furthermore, ResNet9's transfer learning capabilities enable efficient adaptation to new disease classes or emerging pathogens, enhancing its versatility for agricultural applications. With its commendable performance and scalability, ResNet9 contributes significantly to automating plant disease diagnosis, thereby advancing crop health management and agricultural sustainability.

Below are the benefits of using ResNet:

a) **Problems with Plain Network:** Conventional deep learning networks typically consist of convolutional layers interconnected with fully connected layers for classification, without skipping or altering connections. However, in deeper networks, the issue of vanishing or exploding gradients may arise. This problem occurs when gradients become extremely small or large during training, hindering effective learning.



b) **Skipping Connection in ResNet:** ResNet addresses the vanishing/exploding gradient issue by introducing skipping connections. These connections allow the raw input \(x\) to bypass several weight layers and directly reach subsequent layers. By doing so, ResNet mitigates the degradation problem associated with deep networks and facilitates the training of extremely deep models.



IV. EXPERIMENTAL RESULTS

The dataset used for experimentation consists of 54,306 labelled images representing 38 categories of plant types and diseases. Plant types include Apple, Tomato, and Corn, while diseases range from Apple_scab to Tomato_Yellow_Leaf_Curl_Virus. Categories vary in size, with the largest containing 2,527 images and the smallest 2,270. This diverse dataset offers ample variation for training machine learning models to detect and classify plant leaf diseases.

[8]:

	no. of images
Strawberry___healthy	1824
Grape___Black_rot	1888
Potato___Early_blight	1939
Blueberry___healthy	1816
Corn_(maize)___healthy	1859
Tomato___Target_Spot	1827
Peach___healthy	1728
Potato___Late_blight	1939
Tomato___Late_blight	1851
Tomato___Tomato_mosaic_virus	1790
Pepper,_bell___healthy	1988
Orange___Haunglongbing_(Citrus_greening)	2010
Tomato___Leaf_Mold	1882
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1722
Cherry_(including_sour)___Powdery_mildew	1683
Apple___Cedar_apple_rust	1760
Tomato___Bacterial_spot	1702
Grape___healthy	1692
Tomato___Early_blight	1920
Corn_(maize)___Common_rust_	1907
Grape___Esca_(Black_Measles)	1920
Raspberry___healthy	1781
Tomato___healthy	1926
Cherry_(including_sour)___healthy	1826
Tomato___Tomato_Yellow_Leaf_Curl_Virus	1961
Apple___Apple_scab	2016
Corn_(maize)___Northern_Leaf_Blight	1908
Tomato___Spider_mites Two-spotted_spider_mite	1741
Peach___Bacterial_spot	1838
Pepper,_bell___Bacterial_spot	1913
Tomato___Septoria_leaf_spot	1745
Squash___Powdery_mildew	1736
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	1642
Apple___Black_rot	1987
Apple___healthy	2008
Strawberry___Leaf_scorch	1774
Potato___healthy	1824
Soybean___healthy	2022

Fig.1 Dataset Description

Visualization of the dataset comprises bar charts representing different plant leaf disease categories, such as Apple_scab, Black_rot, and Cedar_apple rust, with bars indicating severity levels. Disease categories exhibit varying numbers of coloured bars, reflecting severity progression. Healthy categories like Apple_healthy feature a single bar denoting absence of disease. This visualization aids researchers in quickly comprehending disease severity within each category, facilitating targeted algorithm development and evaluation.

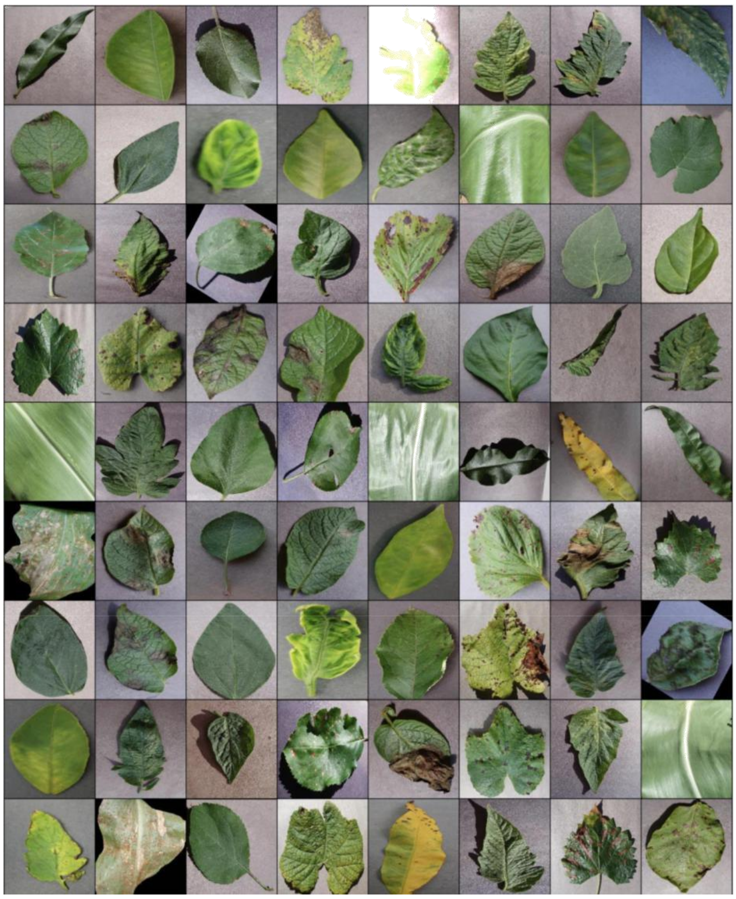


Fig.2 Data Visualization

Training and validation accuracies for the Plant Village dataset are presented in Figure 3. These accuracies provide insight into the model's performance during training and validation phases, indicating its ability to learn and generalize from the data.

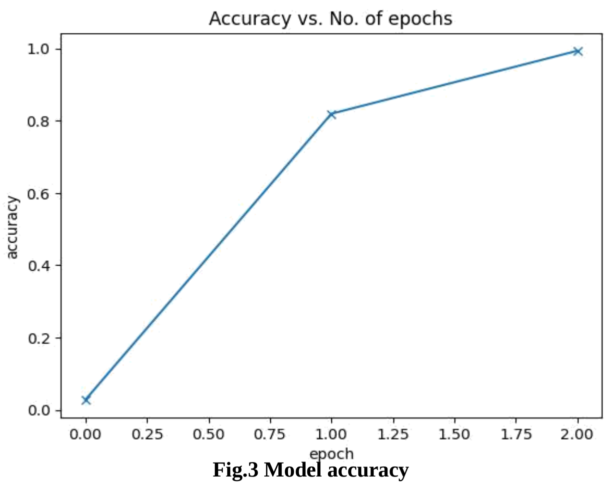


Fig.3 Model accuracy

Training and validation Losses for the Plant Village dataset are presented in Figure 4. These Losses provide insight into the model's performance during training and validation phases.

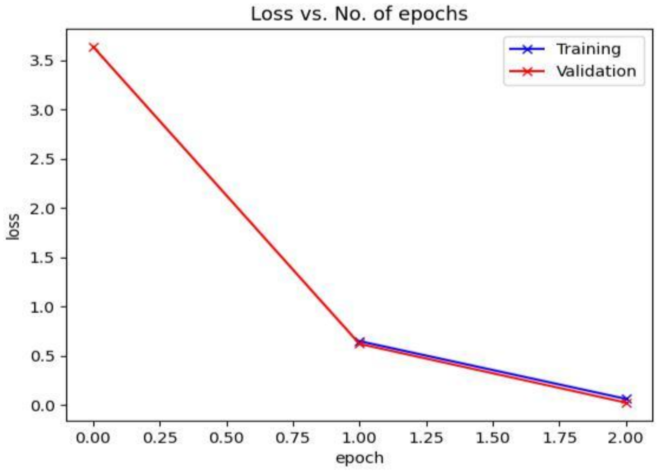


Fig.4 Training and validation accuracies

V. CONCLUSION

The implementation of ResNet50 for plant leaf disease detection represents a significant advancement in agricultural technology. Its deep architecture and pre-processing steps ensure accurate classification, enabling early diagnosis and intervention for improved crop yields. Objective evaluation metrics validate its reliability, promising a transformative impact on disease management and food security. Continued refinement and expansion of ResNet50-based solutions holds immense potential for sustainable agricultural practices.

REFERENCES :

1. Simonyan, Karen, Zisserman, Andrew. "Very Deep Convolutional Networks for Large-Scale Image Recognition", arXiv 2014.
2. Dubey, S. R., and Jalal, A. S. "Adapted approach for fruit disease identification using images", International Journal of Computer Vision and Image Processing, vol. 2, no. 3, pp. 44-58, Jul. 2012.
3. Barbedo, J. G. A. "Plant disease identification from individual lesions and spots using deep learning", Biosystems Engineering, vol. 180, pp. 96-107, Apr. 2019.
4. Lee, S. H., Goëau, H., Bonnet, P., and Joly, A. "New perspectives on plant disease characterization based on deep learning", Computers and Electronics in Agriculture, vol. 170, Mar. 2020.
5. Bi, C., Wang, J., Duan, Y., Fu, B., Kang, J.-R., and Shi, Y. "MobileNet based apple leaf diseases identification", Mobile Networks and Applications, vol. 10, pp. 1-9, Aug. 2020.
6. Zhang, X., et al. "A deep learning-based approach for automated yellow rust disease detection from high-resolution hyperspectral UAV images", Remote Sensing, vol. 11, no. 13, Jun. 2019.
7. Lu, J., Tan, L., & Jiang, H. "Review on Convolutional Neural Network (CNN) Applied to Plant Leaf Disease Classification", Agriculture, vol. 11, no. 8, 2021.
8. Monigari, Vaishnavi. "Plant Leaf Disease Prediction", International Journal for Research in Applied Science and Engineering Technology, vol. 9, pp. 1295-1305, 2021.