ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

https://zenodo.org/records/11632090

Vol 18, Issue 2, 2024

Automated Plant Disease Detection using Deep Learning with DenseNet-121

Mohammed Rafi Nizami[1]
rafinizami01@gmail.com
Dept. of IT
ISL Engineering College
Hyderabad, Telangana, India

Syed Ateeq[2]
syedatee3@gmail.com
Dept. of IT
ISL Engineering College
Hyderabad, Telangana, India

Syed Mohd Malik Ali[3]
syedmohdmalikali786@gmail.com
Dept. of IT
ISL Engineering College
Hyderabad, Telangana, India

Syed Mujeeb Ul Hassan[4]
syedmujeebulhassan@gmail.com
Associate Professor
ISL Engineering College
Hyderabad, Telangana, India

ABSTRACT:

Plant diseases are a major danger to global food security, generating huge agricultural losses and damaging crop productivity and economic stability around the world. In order to reduce these losses and raise the production of crops overall, timely and effective detection of these diseases is essential. However, human mistake is common, and traditional manual techniques of identifying diseases are frequently challenging and time-consuming. Research show that valuable primary production losses (26%) and much higher secondary yield losses (38%), are caused by disease and pests. Considering these difficulties, automating the disease identification procedure through the use of deep learning techniques presents a feasible choice. In order to identify plant diseases, this project uses a deep learning strategy with the DenseNet121 architecture.The machine learning algorithm uses a dataset of labelled plant leaf images to classify photos into one of fifteen disease categories with high accuracy. The suggested method discusses the potential of deep learning techniques to transform agricultural operations by enabling precise and rapid disease identification. Farmers can minimize output losses and increase agricultural productivity by efficiently identifying and addressing diseases through the simplification of the detection procedure. This project highlights how cutting-edge technologies can be used to ensure sustainable farming practices and protect global food security.

Keywords: Plant disease, Convolutional neural network, DenseNet121, leaf image.

INTRODUCTION:

In India, where agriculture supports over 70% of the population to generate income, identifying and managing plant diseases is critical for maintaining food security and supporting rural livelihoods. But most Indian agricultural laborers—many of whom are smallholder farmers—lack formal schooling and plant pathology-specific expertise. Handling plant diseases by hand is already a difficult undertaking; this educational gap makes it even moredifficult.

Plant disease detection and observation conducted manually are extremely difficult tasks, especially in areas with limited access to agricultural extension services and knowledge.The signs of plant diseases include wilting, spotting (necrosis), mold, pustules, rot, hypertrophy and hyperplasia (overgrowth), deformation, mummification, discoloration, and destruction of the affected tissue. [1] Additionally, depending too much on outdated approaches like chemical analysis or visual inspection can be expensive and ineffective, particularly for small-scale farmers with little or no resources.

In this sense, the use of sophisticated technologies such as image processing and machine learning has a potential to narrow the skills divide and support automatic disease diagnosis. Through image processing techniques, important details are extracted from images including leaf colour, texture and damage extent without necessarily requiring specialized knowledge.

Artificial intelligence in particular machine learning offers automated ways through which diseases can be categorized and predicted minimizing dependence on expert judgment and manual work. Machine learning models are therefore capable of distinguishing between healthy plants and those that are diseased by looking at several image parameters for timely intervention and management practices. The importance of automated disease detection in agriculture cannot be emphasized, especially among smallholder farmers without access to formal education and agricultural extension services. In areas with limited access to expert's knowledge, automated systems provide a scalable and affordable alternative that can monitor large agricultural fields and accurately detect illnesses.With the ability to diagnose diseases quickly and accurately, computationally assisted disease identification systems have become important tools for farmers, even those without professional training or education in plant pathology. Plant diseases can be accurately classified and predicted by these systems, which use machine learning techniques such convolutional neural networks (CNNs), decision trees, random forests, Naïve Bayes, and support vector machines (SVMs).

In this project, we present an approach for detecting plant diseases using leaf photos that is specifically adapted to the needs of India's smallholder farmers. Our goal is to show how effective our strategy is in managing diseases that farmers with low levels of education and experience encounter through indirect evaluation and validation. Through utilizing technology to improve methods for disease identification and management, we aim to empower smallholder farmers and assist them in achieving food security and rural development.

LITERATURE SURVEY:

In 2015, S. Khirade et Al. tackled the problem of plant disease detection using digital image processing techniques and back propagation neural network (BPNN) [2]. The authors of the paper describe a comprehensive method for identifying plant diseases using leaf photos. For precise contaminated region segmentation, they utilize Otsu's thresholding, boundary detection, and spot detection techniques. They take the segmented images and extract various elements including color, texture, morphology, and edges, then feed those features into a Backpropagation Neural Network (BPNN) to classify diseases. This integrated approach demonstrates how machine learning may simplify farming procedures and reduce crop losses.

In an innovative study, Sharath D. M. et al. developed an advanced method for detecting a bacterial disease in pomegranate trees. In order to detect illness symptoms, this unique method precisely extracts a wide range of data from plant photos, including color, mean, homogeneity, standard deviation, variance, correlation, entropy, and edges. Authors have implemented grab cut segmentation for segmenting the region of interest in the image [3]. The system is able to detect subtle disease signs because it uses advanced segmentation techniques like grab cut segmentation and edge detection algorithms like Canny edge detector to reliably isolate regions of interest and extract fine-grained edge characteristics. Notably, the method predicts the fruit's level of infection, going beyond simple detection and offering important information about the severity and course of the disease.

A novel two stage neural networkarchitecture was proposed to classify the plant disease. The traditional augmentation and state of the art style generative adversarial networks were used to augment the images in the database [14]. The Random Forestclassifier was used to distinguish disease plant and healthy plant. The leaf of the plant is used for classification [15]. Image-processingbased study was presented for plant disease detection [14].

IMPLEMENTATION:

A) *Dataset*

In this project, we utilized the PlantVillage dataset, which was curated by Sharada P. Mohanty and colleagues. The dataset comprises 87,000 RGB images of plant leaves, featuring both healthy and diseased specimens, across 38 categories. For our algorithm's testing, we selected a subset of 25 specific classes.

B) *Preprocessingand Feature Extraction*

First, the original image, which contains all its original colors and details, is converted to grayscale. This step simplifies the image by using shades of gray to represent intensity, which can be useful when color isn't necessary for the analysis and might even cause inconsistencies. Next, the grayscale image is smoothed using a Gaussian filter. This filter reduces noise and unwanted variations by applying a bell-shaped curve that assigns higher importance to central pixels and less to those further away, resulting in a smoother image with softened edges. Finally, Otsu’s thresholding method is used to transform the grayscale image into a binary image, which consists only of black and white pixels. Otsu's method calculates

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

https://zenodo.org/records/11632090

Vol 18, Issue 2, 2024

an optimal threshold to effectively distinguish the foreground, or the object of interest, from the background, enhancing the image for further analysis.

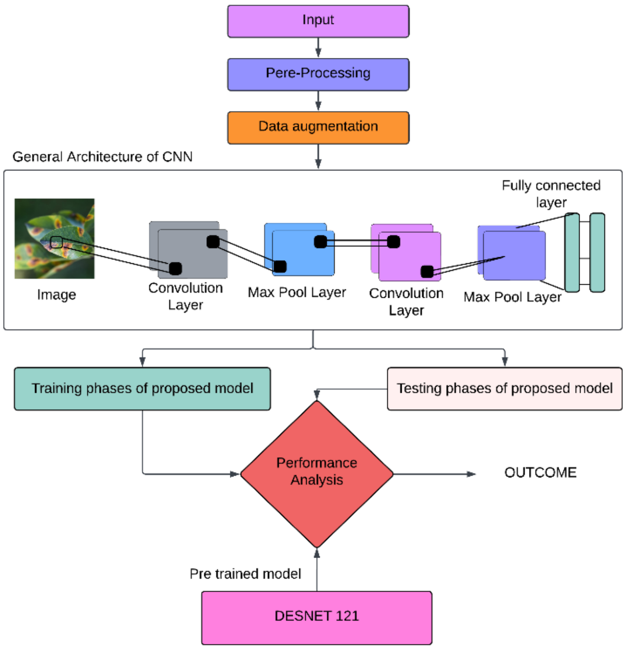

Fig. 1 DenseNet-121 Workflow Architecture

C) *FeatureSelection*

Feature selection is essential to this project since it helps to improve the quality of the dataset and the performance of our machine learning model. In order to accurately anticipate diseases, our method depends on evaluating the association between several variables and the target variable. We look at the correlation matrix shown in Fig. 3 to find examples of variables that show strong correlation, indicating redundancy, such as the green portion of the leaf feature (F1) and another (F2). We exclude one of the highly associated variables in order to simplify our dataset. Less correlated characteristics are also eliminated since they are thought to be less relevant, such as the correlation (f8), dissimilarity (f5), red channel standard deviation, blue channel standard deviation, and green channel mean. We refine the dataset using this rigorous feature selection approach, concentrating on the most significant

D) *ClassificationAlgorithm*

In our project, we use the DenseNet-121 architecture, a type of deep convolutional neural network, to identify plant leaf diseases in images. DenseNet-121 establishes dense connectivity between layers to enhance feature reuse and reduce the problem of gradients vanishing. Every layer pass along its own feature maps to all other layers after receiving inputs from all previous layers. Because of its extensive connectedness, the network can learn and reuse features more effectively, requiring fewer parameters and improving training stability. The network is organized into dense blocks, with transition layers positioned between each to minimize the feature maps' spatial dimensions. The model gains knowledge of progressively complicated

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

https://zenodo.org/records/11632090

Vol 18, Issue 2, 2024

aspects as images move through these steps. Upon the network's conclusion, a global average pooling layer. After which the result is calculated based on confusion matrix.

RESULTS AND DISCUSSION

We assessed the effectiveness of our proposed method by utilizing a 70:30 split of the data to train and test the DenseNet-121 model on the PlantVillage dataset. Our approach was also benchmarked against other state-of-the-art methods for identifying tomato leaf diseases, and the results demonstrated that our method provided superior accuracy. Remarkably, the model achieved an overall accuracy of 98.3% on the testing set.

To illustrate the efficacy of our proposed method for detecting diseases in tomato leaves using the DenseNet-121. It is important to recognize that different pre-processing methods and the selection of datasets can significantly impact the F1 score, recall, and precision of each class. Despite these variables, our findings consistently indicate that the DenseNet-121 architecture is a highly effective strategy for disease detection in tomato plants.

In summary, the DenseNet-121 model, when trained and tested on a well-curated dataset such as PlantVillage, exhibits exceptional performance in identifying and classifying tomato leaf diseases. The model's high accuracy and reliable classification capabilities make it a valuable asset for agricultural applications, helping to ensure healthy crop yields and effective disease management practices.

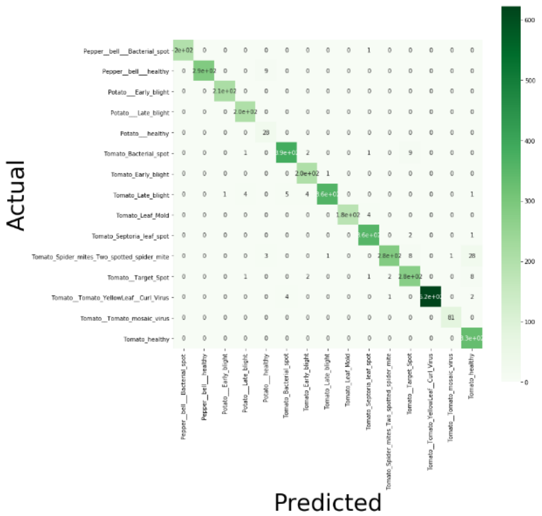

Fig 2: Confusion Matrix of actual vs prediction results.

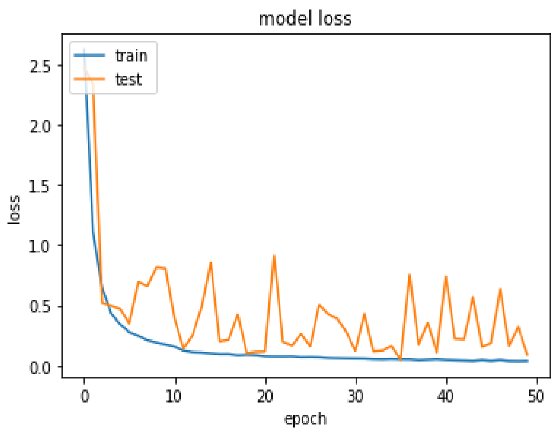

Fig 3. Model loss visualization showing the decrease in loss over training epoch

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN2454-9940
www.ijasem.org
https://zenodo.org/records/11632090
Vol 18, Issue 2, 2024

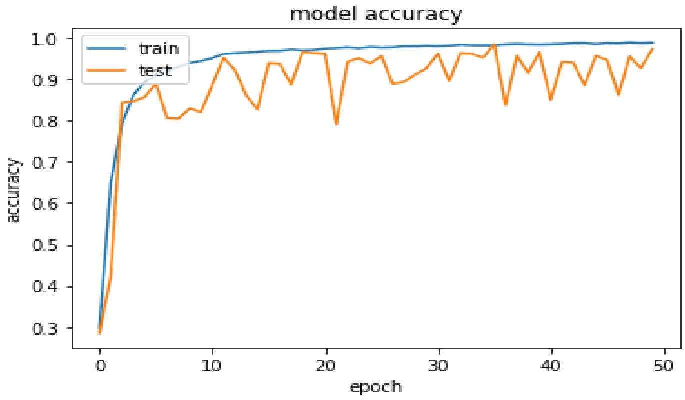

Fig 4. Model accuracy plot indicating the increasein correct predictions over training epochs.

Fig 5. Screenshot of the homepage

CONCLUSION:

In conclusion, our project demonstrates the effectiveness of using the DenseNet-121 architecture for accurate disease identification in plant leaves. Through rigorous experimentation and evaluation, we achieved an impressive overall accuracy of 98.3% on the testing set, outperforming state-of-the-art approaches in tomato leaf disease identification. Our method showcases the robustness and reliability of DenseNet-121 in distinguishing between various types of leaf diseases in tomatoes.

The success of our approach underscores the importance of leveraging advanced neural network architectures like DenseNet-121 for complex image classification tasks. By harnessing the power of dense connectivity and transfer learning, we have developed a model

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN2454-9940
www.ijasem.org
https://zenodo.org/records/11632090
Vol 18, Issue 2, 2024

capable of accurately detecting diseases in tomato plants, which has significant implications for crop management and agricultural sustainability.

In the future, we aim to expand our dataset with more types of plant diseases and refine our model's settings for better performance. We also plan to develop user-friendly applications for farmers to use our model in real-time plant disease detection. Continuous testing and validation will ensure our model remains effective across various environments and agricultural scenarios, further contributing to crop protection and food security efforts.

REFERENCES:

[1] Cerda, R., Avelino, J., Gary, C., Tixier, P., Lechevallier, E., &Allinne, C. (2017). Primary and Secondary Yield Losses Caused by Pests and Diseases: Assessment and Modeling in Coffee. *PloS one*, *12*(1), e0169133. https://doi.org/10.1371/journal.pone.0169133

[2] S. D. Khirade and A. B. Patil, "Plant Disease Detection Using Image Processing," 2015 International Conference on Computing Communication Control and Automation, 2015, pp. 768-771, doi: 10.1109/ICCUBEA.2015.153.

[3] S. D.M., Akhilesh, S. A. Kumar, R. M.G. and P. C., "Image based Plant Disease Detection in Pomegranate Plant for Bacterial Blight," 2019 International Conference on Communication and Signal Processing (ICCSP), 2019, pp. 0645-0649, doi: 10.1109/ICCSP.2019.8698007.

[4]Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A., & Stefanovic, D. (2019). Solving current limitations of deep- learning based approaches for plant disease detection. Symmetry, 11(7), 939, 2019.

[5] Ramesh, S., Hebbar, R., Niveditha, M., Pooja, R., Shashank, N., & Vinod, P. V. Plant disease detection using machine learning. In 2018 International conference on design innovations for 3Cs computer communicate control (ICDI3C) (pp. 41-45). IEEE, 2018

[6] Mohanty SP, Hughes DP and Salathé M (2016) Using Deep Learning for Image-Based Plant Disease Detection. Front. Plant Sci. 7:1419. doi: 10.3389/fpls.2016.01419

[7] R. M. Haralick, K. Shanmugam and I. Dinstein, "Textural Features for Image Classification," in IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-3, no. 6, pp. 610-621, Nov. 1973, doi: 10.1109/TSMC.1973.4309314.

[8] Zhu, J., et al. "Tomato leaf disease recognition using deep learning algorithms." Journal of Physics: Conference Series. Vol. 1619. No. 5. IOP Publishing, 2020.

[9] Sharma, D., et al. "Tomato Leaf Disease Detection and International Journal of Intelligent Systems and Applications in Engineering Classification using Deep Learning." International Journal of Advanced Research in Computer Science 11.5 (2020): 50-57

[10]Zhang, L., et al. "Tomato leaf disease recognition based on deep convolutional neural network." Information Processing in Agriculture 7.3 (2020): 399-408.

[11]Liu, Y., Wang, L., & Deng, H. (2019). Tomato Leaf Disease Recognition Based on Deep Convolutional Neural Network. In 2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC) (pp. 1811-1815). IEEE.

[12]Pandey, R., & Kumar, A. (2020). Tomato leaf disease detection using convolutional neural networks. Journal of Crop Science and Technology, 4(1), 1-6.

[13]Zaman, S., Raza, S., & Khan, M. U. (2021). Tomato leaf disease detection and classification using transfer learning. Neural Computing and Applications, 1-14.

[14]Sharma, V., & Dutta, S. (2021). Tomato leaf disease detection using deep learning: A comparative study. Computers and Electronics in Agriculture, 88, 106463.

[15]Moradi, P., & Hossein Zadeh, M. (2021). Tomato leaf disease detection using a novel CNN-based model with high efficiency and accuracy. Computers and Electronics in Agriculture, 182, 106026