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Plant Disease Detection Using Transfer Learning and Generative Adversarial Networks

G. Santhi Kumari, Ph.D. Research Scholar, Department of Mathematics, Shri Jagdishprasad Jhabarmal Tibrewala University, Jhunjhunu, Rajasthan, India
Dr. Vineeta Basotia, Department of Mathematics, Shri Jagdish Prasad Jhabarmal Tibrewala University, Jhunjhunu, Rajasthan, India

Abstract

Digital image processing is a crucial part of the information technology department as nearly all the multimedia data are captured, processed, presented and transmitted with the help of this technology. Prompt and accurate detection of plant infections is necessary for successful farming. Early diagnosis has been the most effective way of preventing waste of resources, which will then lead to more efficient and sustainable agriculture. The real problem is the detection and determination of the diseases within the countless plants in the different environmental conditions. The current study presents a plant disease detection model using a technique called transfer learning, which involves integrating VGG16 with CNN. Specifically, the system is implemented in Python, and the effectiveness of the model is examined through metrics, such as accuracy, precision, and recall.

Keywords: Plant Disease, Apple, VGG16, GAN, CNN

1. Introduction

The global yield of fruits and crops is significantly impacted by numerous plant diseases, which in turn contribute to the economic decline of the agricultural sector worldwide. Apple cultivation is widespread and apples rank among the most consumed fruits across the globe. In 2018 alone, global apple production is estimated at 86 million tons, with both production and consumption steadily increasing since then. Nevertheless, the actual yield per nation remains considerably below the potential productivity levels [1][2]. Various critical factors contribute to this shortfall, such as unfavorable ecological conditions, outdated post-harvest handling techniques, limited investment in foundational agricultural research, insufficient availability of high-quality planting materials and many socio-economic challenges faced by farmers. Despite their high demand and recognized health benefits, apple trees remain highly susceptible to numerous diseases caused by insects and microbial pathogens including bacteria and fungi. Prominent among these are anthracnose (caused by *Neofabraea* spp.), cedar apple rust (*Gymnosporangium juniperivirginianae*), fire blight (*Erwinia amylovora*), apple scab (*Venturia inaequalis*) and powdery mildew (*Podosphaera leucotricha*). Effective disease management necessitates timely care of the trees, such as the use of appropriate fertilizers. Early identification of disease symptoms [3][4], particularly those manifesting in the leaves is important for farmers to take corrective action and mitigate crop losses. However, traditional diagnostic techniques are time-consuming and reliant on manual observation, which often results in farmers missing the critical window for intervention. These conventional approaches also frequently require expert guidance, making them impractical for frequent or widespread use. The absence of automated systems for early detection contributes to inefficient use of resources and results in a decline in both the quantity and quality of produce. Recent technological advancements, however, steer the agricultural sector toward intelligent solutions. Machine learning and other soft computing methodologies emerge as powerful tools for the automated detection and classification of plant diseases, providing more accurate, timely and scalable alternatives to traditional practices [5][6]. Image processing and ML (machine learning) provide significant potential to assist farmers and orchardists by allowing intelligent, automated detection of plant diseases, moving beyond traditional manual inspections. ML offers a strong foundation for decision-making by systematically incorporating expert knowledge, showing great promise in many agricultural applications. Commonly used ML techniques for plant disease detection and identification include KNN (k-nearest neighbor), ANN (artificial neural networks) and SVM (support vector machines). Although these machine learning methods enhance the efficiency of plant disease analysis, their accuracy can be affected by factors including varying lighting conditions in crop images and the diversity of disease symptoms [7][8]. A clear advantage of deep learning compared to traditional ML is its ability to work directly with raw data in formats such as .csv or .jpg, whereas machine learning typically requires an extra preprocessing step involving feature extraction. Traditional machine learning algorithms including SVMs, decision trees and Bayesian networks are considered flat models. In these conventional methods, the accuracy of disease detection heavily depends on the quality of manually crafted features extracted from images. This feature extraction process is not only labor-intensive and resource-demanding but also susceptible to human bias and inconsistency, which limits the overall effectiveness of disease identification. With the continuous evolution of artificial intelligence, deep learning increasingly proves its capacity to rival and even surpass human intelligence in certain domains. It excels at autonomously learning intricate features that often exceed the precision and depth of those identified by human experts, capturing semantic details that manual feature engineering cannot match [9][10]. In recent years, deep learning becomes widely adopted in the field of plant disease identification, outperforming traditional methods that rely on handcrafted features. This technology revolutionizes plant disease detection by enabling highly accurate and automated classification directly from visual data, including images of leaves, stems, or fruits. Unlike conventional machine learning methods that require labor-intensive feature extraction, deep learning streamlines the process by learning directly from raw image data, thus providing greater efficiency and scalability. These models train on extensive image datasets that encompass both healthy and diseased specimens, enabling them to recognize many diseases across a wide array of crops [11][12]. Deep learning also stands out for its effectiveness in real-time applications, like mobile-based diagnostic tools and drone-assisted field monitoring, allowing farmers to take swift and informed action. Furthermore, deep learning algorithms remain uniquely capable of handling vast and complex datasets, making them specifically suited for large-scale agricultural implementations. Deep learning, especially through the use of CNNs (Convolutional Neural Networks), allows the automation of plant disease detection with remarkable accuracy. CNNs are specifically adept at recognizing spatial structures and visual patterns within images, making them well-suited for differentiating subtle variations between healthy and infected crops. These networks autonomously identify indicators including lesions, discoloration, fungal growth, and spots eliminating the need for manual feature extraction [13][14]. Training typically involves feeding the model a large, annotated dataset of plant images, enabling it to classify a variety of diseases such as bacterial blight, powdery mildew, early blight and mosaic viruses across crops including tomatoes, potatoes, rice, wheat and maize. To boost performance and efficiency, specifically when data is scarce, architectures including ResNet, VGGNet, Inception and MobileNet are used either from the ground up or via transfer learning techniques. Furthermore, recent advancements such as attention mechanisms and ensemble methods are used to improve classification accuracy further. These deep learning solutions integrate into mobile apps, drones and IoT-driven platforms to facilitate real-time disease monitoring directly in agricultural fields, supporting prompt responses and minimizing crop damage. One of the main strengths of deep learning is its scalability. Once a model is trained, it deploys globally and continuously enhances through the incorporation of new data [15][16]. Nonetheless, problems persist, such as the need for high-quality, balanced datasets, variability in environmental conditions, and the visual similarity between certain plant diseases. Even so, deep learning remains a powerful tool for precision agriculture, advancing sustainable farming and strengthening food security by equipping farmers with intelligent, automated diagnostic systems.

2. Literature Review

Z. Yin et al. (2025) explored the distribution traits of Watercore and implemented a slice stacking method based on RIFE interpolation to reconstruct three-dimensional representations of individual Watercore regions an outcome that traditional techniques had previously failed to deliver [17]. These 3D reconstructions unveiled unique internal configurations, notably a central hollow area and surrounding column-like structures. The research further integrated this 3D visualization method with near-infrared spectroscopy and a GAF-ConvNeXt classification algorithm to non-destructively categorize Watercore severity into five distinct levels. The proposed approach attained a high MIoU (mean intersection over union) score of 0.826 when comparing interpolated features with actual ones, validating its precision. The classification model achieved a detection accuracy of 98.10% across the five severity levels, establishing it as a robust and accurate technique for evaluating the internal quality of apples.

H. Li, et al. (2025) used NIRS (near-infrared spectroscopy) to allow fast and non-invasive detection of mildly mold-infected apple cores, with a particular emphasis on evaluating the influence of light source spot diameter [18]. Researchers examined spectral responses and employed analysis of variance (ANOVA), many classification models and optical simulation techniques to identify the most effective spot sizes. Findings indicated that a 20 mm light spot offered optimal detection performance for small to medium-sized apples, whereas a 50 mm spot was more suitable for larger fruits. Among the models tested, the CARS-QDA model delivered high levels of sensitivity, specificity, and overall classification accuracy across different apple sizes, with detection accuracy reaching as high as 94.44%. The findings demonstrated that carefully selecting the appropriate spot diameter significantly improved the effectiveness of moldy core detection.

B. Liu, et al. (2024) developed MCDCNet, a Multi-scale Constrained Deformable Convolution Network, aimed at improving the detection of apple leaf diseases in natural, uncontrolled environments [19]. This model incorporated a dual-branch convolutional structure to effectively capture features at multiple scales and strategically applied varied offset intervals to better adapt to the irregular and deformable shapes of disease lesions without increasing the model's parameter count. A dedicated feature fusion module was implemented to integrate the outputs from both branches, thereby strengthening classification performance. When assessed on five prevalent apple leaf diseases, MCDCNet achieved an accuracy of 66.8%, outperforming previous state-of-the-art models by 3.85%. These results reflected its better ability to extract complex features and maintain reliable detection performance in real-world settings.

Z. Liu, et al. (2024) presented new approach that integrated acoustic vibration analysis with visible/near-infrared (Vis/NIR) spectroscopy to significantly enhance the accuracy of moldy core detection in apples [20]. Utilizing a specially designed micro-LDV (micro laser Doppler vibrometer) in conjunction with an online Vis/NIR spectroscopy system, the researchers gathered both vibrational and spectral data to construct robust classification models. At the core of their methodology was the DMLPT (Dual-input MLP-Transformer) model, which effectively merged the two data modalities. This fused model consistently outperformed those relying on individual data sources, achieving an impressive overall accuracy of 99.31% and delivering near-perfect identification of moldy core across many progression stages. The results underscored the powerful role of multimodal data fusion in allowing precise, non-destructive evaluation of internal apple quality.

V. K. Vishnoi, et.al (2023) developed CNN (convolutional neural network) algorithm characterized by a reduced number of layers, effectively minimizing computational overhead [21]. To expand the training dataset without acquiring additional real-world images, they used many data augmentation techniques, such as shifting, shearing, scaling, zooming and flipping. The PlantVillage dataset was used to train the proposed model for identifying various plant diseases, including scab and black rot. The experimental results revealed that the algorithm achieved a high classification accuracy of 98%. Furthermore, the model demonstrated low memory requirements, fast execution times and minimal demand on computational resources, making it specifically well-suited for deployment on mobile devices.

X. Song, et.al (2023) designed an innovative disease diagnosis model by integrating an attention mechanism into a ResNet50 architecture [22]. To solve the problem of limited image samples in datasets related to apple tree disorders, they applied TL (transfer learning), which improved the training process of the network. A carefully designed training strategy was implemented to optimize both convergence speed and model accuracy. The experimental outcomes showed that the proposed mechanism significantly outperformed conventional methods, delivering enhanced diagnostic efficiency and reliability.

K. Zhao, et.al (2022) designed a hybrid framework named IResNet50-PSO-ELM, which leveraged a pre-trained IResNet50 network to automatically extract sensitive features from pixel-level images across time, frequency, and spatial domains [23]. An adaptive weighting model was used to fuse these multi-domain deep features effectively. Two shallow machine learning classifiers, Support Vector Machine) and ELM (Extreme Learning Machine), were then used to categorize diseases affecting apple plants based on the fused features. Moreover, PSO (Particle Swarm Optimization) was applied to fine-tune the parameters of both classifiers. The framework achieved an overall classification accuracy of approximately 96.7%. Recall rates reached 100% for identifying healthy fruit, 94.1% for sub-healthy fruit and 96.2% for unhealthy fruit, showing high diagnostic precision.

R. Ding, et.al (2022) focused on improving the performance of models used for identifying apple leaf diseases by integrating two improved methods with the ResNet18 architecture [24]. The researchers implemented ResNet-CBAM, which incorporated a convolutional block attention module and ResNet18 with random clipping branches (ResNet18-RC), both aimed at boosting classification accuracy. Experimental findings demonstrated that ResNet-CBAM achieved an accuracy of 95.2%, while ResNet18-RC attained a higher accuracy of 97.2%, thereby significantly improving the effectiveness of the original ResNet18 network. These enhanced versions of ResNet18 contributed to more accurate classification of apple leaf diseases. Consequently, the improved network showed strong potential as an automated and precise tool for disease detection, providing valuable support for the prevention and control of apple leaf disorders.

P. Karpyshev, et.al (2021) presented an autonomous system designed to inspect apple orchards and detect diseases at an early stage [25]. The method used 2D LiDAR sensors and RTK GNSS receivers to localize infections and determine obstacles within the orchard environment. This system aimed to reduce the reliance on insecticides while simultaneously improving crop yield. Built upon NNs (Neural Networks), the mechanism facilitated both plant segmentation and disease diagnosis. Advanced localization techniques, integrated with RTK GNSS, were used to pinpoint individual infected trees accurately. As a result, the need for widespread fungicide application was minimized and mass spraying was avoided. The proposed system proved to be a valuable decision-support tool for farmers, allowing targeted treatment and helping prevent the further spread of infections.

3. Research Methodology

This research work is based on the plant disease detection using transfer learning models. The proposed model has various phases which include pre-processing, segmentation and classification. The steps of proposed model are explained below: -

1. **Input image and pre-processing:** The dataset used in this study comprises apple images sourced from the PlantVillage repository, a widely used collection of agricultural image data. However, the raw images obtained from PlantVillage often suffer from limitations in terms of resolution, lighting conditions, and overall visual clarity. These quality constraints can adversely affect the performance of downstream computer vision tasks such as disease

classification or object detection. To address this issue, a Generative Adversarial Network (GAN) model is employed to enhance the visual quality of the images. GANs are a class of deep learning models capable of generating high-resolution, realistic images by learning the underlying data distribution. In this context, the GAN is trained to perform image super-resolution or enhancement, effectively improving the sharpness, contrast, and detail of the original apple images. This preprocessing step ensures that the improved image quality leads to better feature extraction and more accurate performance in subsequent deep learning models.

2. Segmentation: - To change the default, adjust the template as follows. This work makes use of snake segmentation to isolate specific parts of the image. Inspired by the raster scan approach, this method ensures extensive coverage of the image's edges. The active contour model, integral to this technique, initializes a parameterized contour curve within the image space and defines an energy functional. This functional characterizes the region's shape through a combination of internal and external energy. Internal energy is influenced by properties of the curve, such as curvature and length, while external energy is derived from the image's features. By minimizing this energy functional, the initial contour curve $C(s) = (x(s), y(s), s \in [0,1])$ progressively adapts to align with the target area's boundary under the interplay of internal and external constraints.

$$E(C) = \int_0^1 \alpha E_{int}\big(C(s)\big) + E_{img}\Big(C(s) + \gamma E_{con}\big(C(s)\big)\Big)\, ds \qquad (1)$$

The energy function in the Snake active contour model consists of three components: E_{int}, E_{img}, E_{con}. The internal energy (E_{int}) ensures the curve's smoothness and regularity. The image energy (E_{img}) is defined based on specific target features, such as edges, to guide the curve towards the desired region. The constrained energy (E_{con}) accounts for geometric factors like curve length and curvature. A key advantage of this model is its ability to effectively integrate geometric constraints, enabling the extraction of smooth and closed boundaries, even with lower-quality images. However, the method has limitations, particularly its sensitivity to the initial contour. The position, shape, and number of control points in the initial contour must be appropriately chosen to achieve optimal results.

3. Classification : - To predict the type of disease, this work applies transfer learning approach, combining VGG16 and ConvNet models. VGG16 serves as the base architecture, providing foundational feature extraction, while the ConvNet model is applied on top for training and fine-tuning.

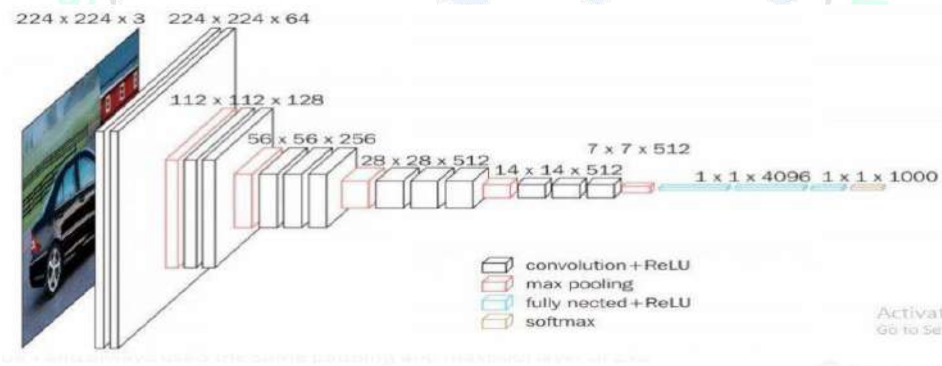

Figure 1: VGG16 Model Architecture

Below are the key specifications of the VGG16 model:

- The VGG16 signifies the 16 layers with learnable weights. The architecture includes thirteen convolutional layers, five max-pooling layers, and three dense layers, totalling 21 layers, of which only 16 are weight layers with trainable parameters.
- VGG16 accepts an input tensor of size 224×224 with 3 RGB channels.
- A distinctive feature of VGG16 is its simplicity, achieved by utilizing 3x3 convolutional

filters with a stride of 1 and consistent padding. Max-pooling layers use 2x2 filters with a stride of 2

- The convolutional and max-pooling layers are systematically arranged throughout the architecture.
- The Conv-1 layer contains 64 filters, Conv-2 has 128 filters, Conv-3 includes 256 filters, and Conv-4 and Conv-5 each have 512 filters.
- After the convolutional layers, there are three fully connected (FC) layers: the first two contain 4096 channels each, while the third layer, designed for 1000-way classification in ILSVRC, has 1000 channels. The output classification is performed by the final layer known as SoftMax layer.

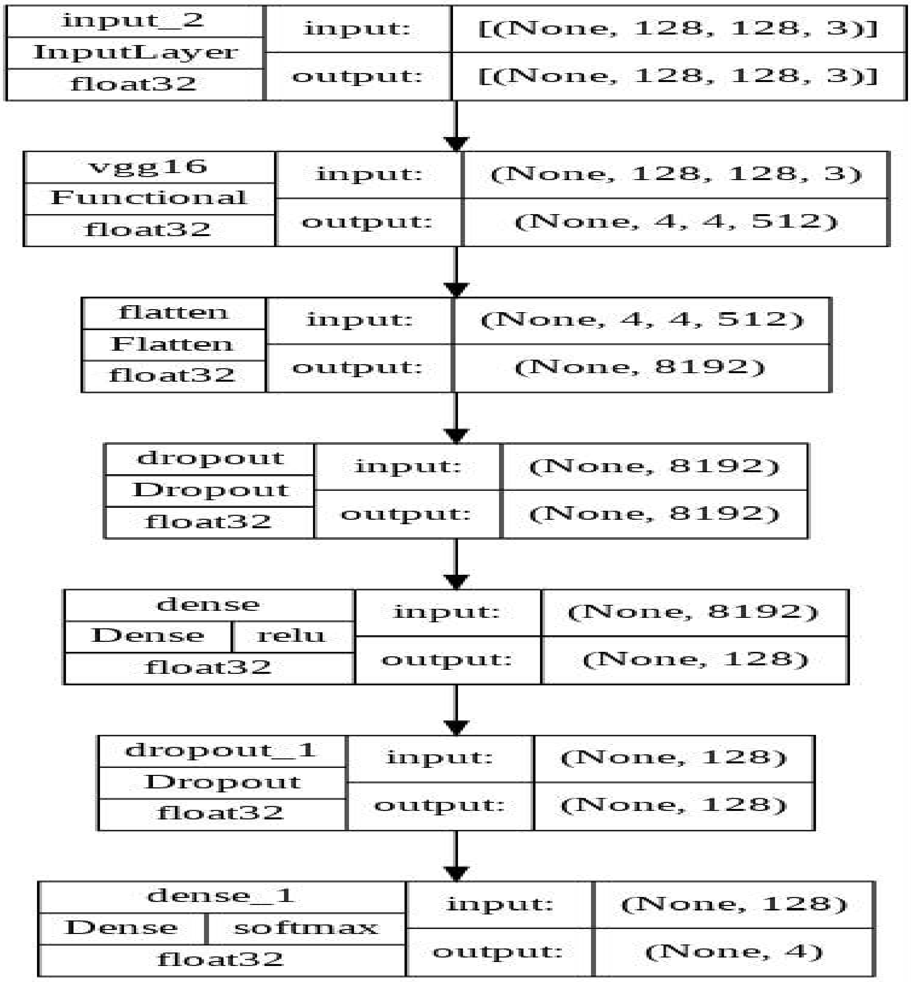

Figure 2: Proposed Transfer Learning Model

3. Result and Discussion

Python is a versatile software that emphasizes ease of reading, dynamic semantics, and object-oriented traits. Python, as a scripting language, integrates different elements and accelerate the development of applications. With its straightforward syntax, Python promotes modularity and code reuse through support for modules and packages, which helps reduce maintenance costs. Additionally, the Python interpreter and its comprehensive standard library are freely available in both source and binary formats across most major platforms. Applications like GIMP, Inkscape, Blender, and Autodesk Maya leverage the Python API to extend their utility.

3.1. Dataset description

The model that has been developed is assessed with the Plant Village dataset, a publicly accessible resource that provides detailed information about several plants and their connected diseases. The dataset covers the images where each is labelled one for a specific disease type.

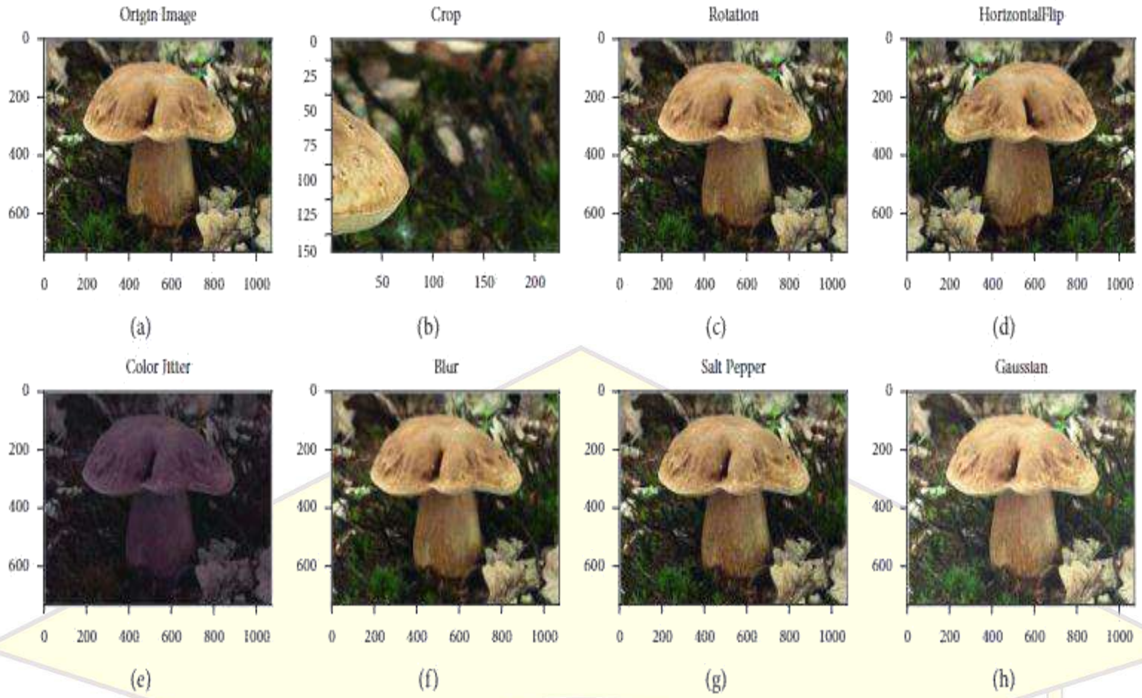

Figure 3: Dataset Images

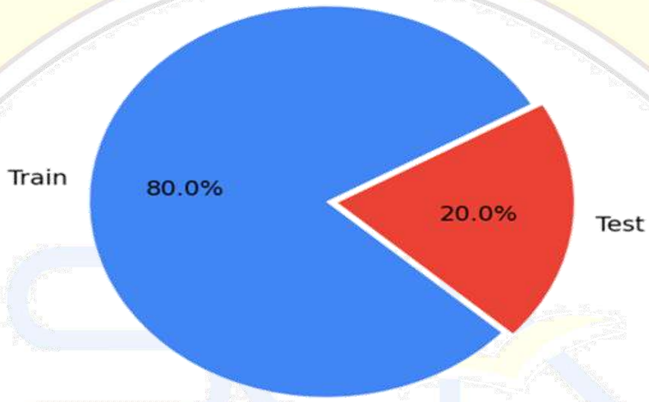

Figure 4: Training and test data

Figure 4 depicts the distribution of test and train data in percentage. The training data accounts for 80%, while the test data makes up 20%.

Figure 5: Model training information

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Figure 5 depicts the model's training and loss. As per this figure, the devised framework obtains 96% of training accuracy.

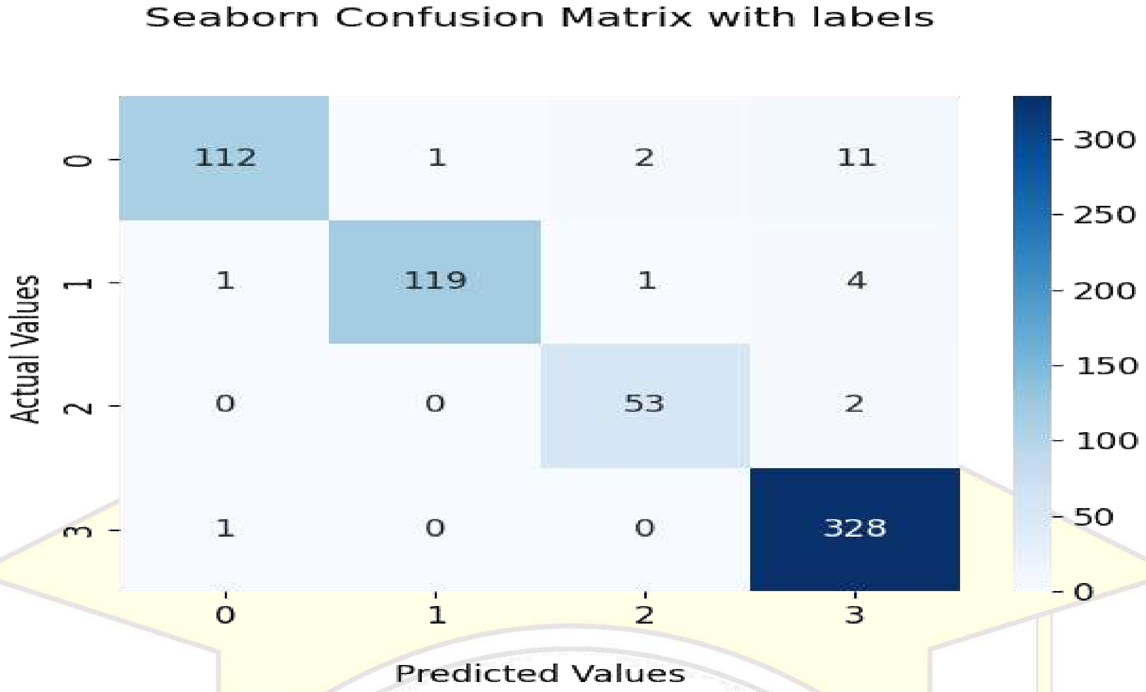

Figure 6: Confusion Matrix

Figure 6 depicts the testing the devised framework on the test data. There are four values (true positive, true negative, false positive and false negative) plotted on the confusion matrix.

3.2. Results

The performamnce analysis parameters are discussed :-

- Accuracy: One metric that is very commonly used to judge how good a program is accuracy. It is the number of correctly classified samples from the whole number of the samples. In the form of a mathematical equation, it is expressed as follows:

$$A_i = \frac{t}{n} \cdot 100$$

Here, t refers to the number of samples that have been correctly classified, and n denotes the overall samples.

- Precision: Precision defines how many true positive cases have been accurately predicted among the overall predicted positive cases

Precision= TP/TP+FP

- Recall: Recall is a performance metric that measures the proportion of actual positive cases correctly identified as positive by the model. It indicates how effectively the positive prediction rule (+P) captures all the true positive cases.

Recall= TP/TP+FN

Table 1 represents a comparison of the CNN, Resnet 50, Bidirectional LSTM and Proposed model in th perspective of accuracy, precision, and recall. The values for these measurements are provided as a percentage of the whole.

TABLE I. PERFORMANCE ANALYSIS

Model	Accuracy	Precision	Recall
CNN Model	90 Percent	90 Percent	89 Percent
Resnet50	92.5 Percent	92 Percent	93 Percent
Bidirectional LSTM	88 Percent	88 Percent	88 Percent
Proposed Model	98.5 Percent	97 Percent	97 Percent

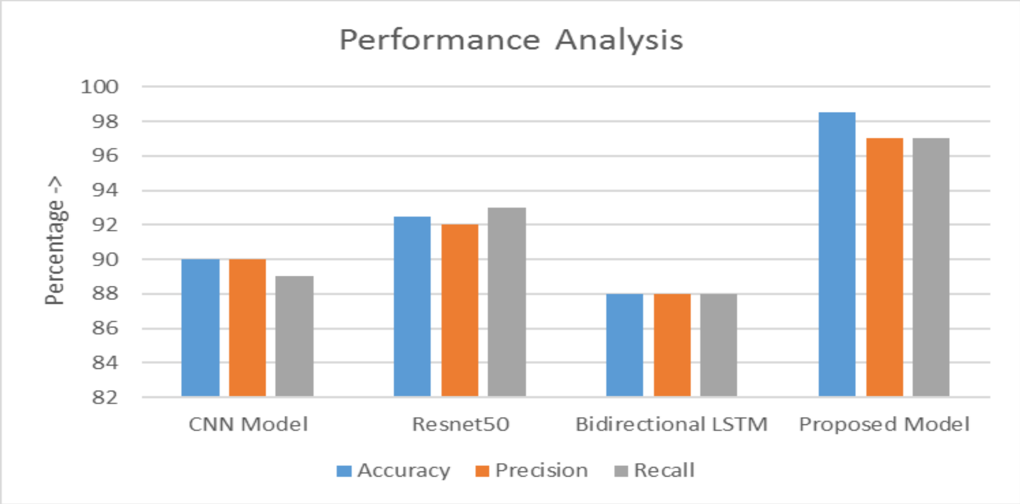

Figure 8: Performance Analysis

Figure 8 shows a comparison of the proposed model with the existing CNN, Resnet50 , Bidirectional LSTM with proposed model. It is analyzed that proposed model achieves accuracy of 98 percent which is approx. 5 percent higher than existing models.

3.3. Discussion

This research work focuses on the detection of diseases in mushroom plants using deep learning-based image classification models. To evaluate the effectiveness of different models, several architectures were tested and their performance was measured using accuracy, precision, and recall as key evaluation metrics. The standard Convolutional Neural Network (CNN) model achieved 90% accuracy, 90% precision, and 89% recall. While these results are promising, the CNN model showed some variability, particularly in recall, which indicates that it might miss some diseased cases during classification. The ResNet50 model, a well-known deep residual learning framework, performed better with an accuracy of 92.5%, precision of 92%, and recall of 93%. Its deeper architecture and use of residual connections enabled it to learn more complex and abstract features from the images, resulting in improved performance compared to the basic CNN. The Bidirectional Long Short-Term Memory (BiLSTM) model, although powerful for sequential data processing such as text or time-series data, was included to explore its applicability to image classification. It demonstrated a consistent but comparatively lower performance, with 88% across accuracy, precision, and recall. This result suggests that BiLSTM may not be ideally suited for this image-based task, especially when compared to convolution-based architectures designed specifically for visual feature extraction. The proposed model, which integrates a transfer learning approach with a pre-processing step using Generative Adversarial Networks (GANs), showed the most remarkable performance. It achieved an outstanding 98.5% accuracy, 97% precision, and 97% recall. The transfer learning strategy leverages a pre-trained deep neural network, which allows the model to benefit from knowledge gained from large-scale image datasets and adapt it effectively to the domain of mushroom disease detection. More importantly, the use of a GAN model for image enhancement played a crucial role in boosting the overall performance. Since the original images sourced from the Plant Village dataset were of relatively low quality, with issues like poor resolution and suboptimal lighting, the GAN was employed to enhance these images by improving texture, contrast, and sharpness. This enhancement enabled the model to extract more meaningful and discriminative features, which significantly contributed to better classification performance. The experimental results clearly indicate that the proposed combination of GAN-based image enhancement and transfer learning provides a highly effective framework for plant disease detection. It not only outperforms traditional CNNs and standard architectures like ResNet50, but also demonstrates the value of incorporating advanced pre-processing techniques in agricultural image analysis tasks. This integrated approach has the potential to be deployed in real-world agricultural settings for early and accurate disease diagnosis, ultimately contributing to improved crop management and yield.

Conclusion

The main objective of this study is to identify plant diseases by the plant leaves' analysis. In the past, plant disease detection was conducted manually via the use of a microscope, which was an inefficient way for the identification of large-scale diseases due to its impracticality. However, with the advent of digital image processing and machine learning algorithms, plant pathologists can now detect diseases from digital images of plant leaves. The presented scheme exploits a voting-based architecture in conjunction with digital image processing methods for disease detection. Digital cameras have the capability to capture images, and image processing helps extract relevant features. Also, a transfer learning model is employed in this work for the plant disease detection. In the model, the accuracy of the diagnosis is up to 98%, which is approximately 8% higher than existent models.

References

1. A. Kaur and R. Chadha, "An Optimized Ant Gardient Convolutional Neural Network for Disease Detection in Apple Leaves," 2023 2nd International Conference for Innovation in Technology (INOCON), Bangalore, India, 2023, pp. 1-8
2. D. Jawale and M. Deshmukh, "Real time automatic bruise detection in (Apple) fruits using thermal camera," 2017 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 2017, pp. 1080-1085
3. Y. Tian, E. Li, L. Yang and Z. Liang, "An image processing method for green apple lesion detection in natural environment based on GA-BPNN and SVM," 2018 IEEE International Conference on Mechatronics and Automation (ICMA), Changchun, China, 2018, pp. 1210-121
4. Y. Gao, Z. Cao, W. Cai, G. Gong, G. Zhou and L. Li, “Apple Leaf Disease Identification in Complex Background Based on BAM-Net”, Agronomy, vol. 13, pp. 12-20, 2023
5. V. Kukreja, R. Sharma, T. P. S. Brar and A. Bhattacharjee, "Classification of the Severity Levels of Apple Rot Disease: A Hybrid Dual CNN and LSTM Deep Learning Approach," 2023 IEEE International Conference on Contemporary Computing and Communications (InC4), Bangalore, India, 2023, pp. 1-5
6. W. Zhang, G. Zhou and Y. Hu, “Deep multi-scale dual-channel convolutional neural network for Internet of Things apple disease detection”, Computers and Electronics in Agriculture, vol. 192, pp. 145-152, 12 February 2022
7. P. K. S and N. K. K, “Drone-based apple detection: Finding the depth of apples using YOLOv7 architecture with multi-head attention mechanism”, Smart Agricultural Technology, vol. 5, pp. 963-970, 24 August 2023
8. R. Sharma, V. Kukreja, P. Sood and A. Bhattacharjee, "Classifying the Severity of Apple Black Rot Disease with Deep Learning: A Dual CNN and LSTM Approach," 2023 3rd International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS), Kalady, Ernakulam, India, 2023, pp. 173-177
9. H. Sun, H. Xu and N. Geng, “MEAN-SSD: A novel real-time detector for apple leaf diseases using improved light-weight convolutional neural networks”, Computers and Electronics in Agriculture, vol. 13, pp. 12-20, 20 August 2021
10. M. N. Isty et al., "Deep Learning for Real-Time Leaf Disease Detection: Revolutionizing Apple Orchard Health," 2023 4th International Conference on Big Data Analytics and Practices (IBDAP), Bangkok, Thailand, 2023, pp. 1-6
11. L. Tian et al., "VMF-SSD: A Novel V-Space Based Multi-Scale Feature Fusion SSD for Apple Leaf Disease Detection," in IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 20, no. 3, pp. 2016-2028, 1 May-June 2023

12. J. Li, X. Zhu, R. Jia, B. Liu and C. Yu, "Apple-YOLO: A Novel Mobile Terminal Detector Based on YOLOv5 for Early Apple Leaf Diseases," 2022 IEEE 46th Annual Computers, Software, and Applications Conference (COMPSAC), Los Alamitos, CA, USA, 2022, pp. 352-361
13. M. Zhang, H. Liang and X. Luo, “Damaged apple detection with a hybrid YOLOv3 algorithm”, Information Processing in Agriculture, vol. 34, no. 6, pp. 3259-3272, 11 December 2022
14. V. K. Vishnoi, K. Kumar, B. Kumar, S. Mohan and A. A. Khan, "Detection of Apple Plant Diseases Using Leaf Images Through Convolutional Neural Network," in IEEE Access, vol. 11, pp. 6594-6609, 2023
15. K. Zhao, H. Li and J. Wu, “Detection of sub-healthy apples with moldy core using deep-shallow learning for vibro-acoustic multi-domain features”, Measurement: Food, vol. 10, no. 2, pp. 65426-65438, November 2022
16. P. Karpyshev, V. Ilin, I. Kalinov, A. Petrovsky and D. Tsetserukou, "Autonomous Mobile Robot for Apple Plant Disease Detection based on CNN and Multi-Spectral Vision System," 2021 IEEE/SICE International Symposium on System Integration (SII), Iwaki, Fukushima, Japan, 2021, pp. 157-162
17. Z. Yin et al., “Nondestructive detection of apple watercore disease content based on 3D watercore model,” Industrial Crops and Products, vol. 228, pp. 120888–120888, Mar. 2025, doi: https://doi.org/10.1016/j.indcrop.2025.120888.
18. H. Li, J. Zan, L. Cai, Z. Fan, T. Sun, and D. Hu, “Effect of light source spot diameter on near-infrared detection of mildly moldy core in apples,” Food Control, pp. 111139–111139, Jan. 2025, doi: https://doi.org/10.1016/j.foodcont.2025.111139.
19. B. Liu, X. Huang, L. Sun, X. Wei, Z. Ji, and H. Zhang, “MCDCNet: Multi-scale constrained deformable convolution network for apple leaf disease detection,” Computers and Electronics in Agriculture, vol. 222, pp. 109028–109028, May 2024, doi: https://doi.org/10.1016/j.compag.2024.109028.
20. Z. Liu et al., “Detection of apple moldy core disease by fusing vibration and Vis/NIR spectroscopy data with dual-input MLP-Transformer,” Journal of Food Engineering, vol. 382, pp. 112219–112219, Jul. 2024, doi: https://doi.org/10.1016/j.jfoodeng.2024.112219.
21. V. K. Vishnoi, K. Kumar, B. Kumar, S. Mohan and A. A. Khan, "Detection of Apple Plant Diseases Using Leaf Images Through Convolutional Neural Network," in IEEE Access, vol. 11, pp. 6594-6609, 2023
22. X. Song and V. Y. Mariano, "Image-based Apple Disease Detection Based on Residual Neural Network and Transfer Learning," 2023 IEEE 3rd International Conference on Power, Electronics and Computer Applications (ICPECA), Shenyang, China, 2023, pp. 365-369
23. K. Zhao, H. Li and J. Wu, “Detection of sub-healthy apples with moldy core using deep-shallow learning for vibro-acoustic multi-domain features”, Measurement: Food, vol. 10, no. 2, pp. 65426-65438, November 2022
24. R. Ding, Y. Qiao and H. Liu, “Improved ResNet Based Apple Leaf Diseases Identification”, IFAC, vol. 55, no. 32, pp. 78-82, 22 November 2022
25. P. Karpyshev, V. Ilin, I. Kalinov, A. Petrovsky and D. Tsetserukou, "Autonomous Mobile Robot for Apple Plant Disease Detection based on CNN and Multi-Spectral Vision System," 2021 IEEE/SICE International Symposium on System Integration (SII), Iwaki, Fukushima, Japan, 2021, pp. 157-162