

# Post-Harvest Onion Disease Identification and Classification Using Transfer Learning

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**Abstract:** The identification and classification of diseases in onions after harvest is critical for maintaining quality and minimizing economic losses. Traditional methods for disease detection are labor-intensive, subjective, and prone to error. This study investigates the use of transfer learning to develop an automated system for identifying and classifying healthy and diseased onions using image analysis. This is achieved by creating a model using transfer learning technique with pre-trained Convolutional Neural Networks (CNNs) models such as VGG16, ResNet50, and InceptionV3. Fine-tuning and dense layers are added at the end of the pretraining models for accurate classification of onions. Performance is assessed using metrics including accuracy, precision, recall, and F1-score. The ResNet50 model, in particular, achieved the highest accuracy, with a classification rate of 95.6%, outperforming other tested architectures. This approach promises to streamline post-harvest disease management, reduce losses, and ensure higher quality produce reaches consumers.

**Keywords:** Convolutional Neural Networks (CNNs), Transfer Learning, VGG16, ResNet50, Inceptionv3, F1-score.

## 1. Introduction

The global agricultural industry continually grapples with the challenge of crop diseases [1], which can lead to significant economic losses and increased food wastage. Onions, a staple in diets worldwide, are particularly susceptible to various diseases, especially after harvest. Traditional methods of identifying and classifying these diseases rely on manual inspection by experts, which is often labor-intensive, time-consuming, and prone to human error. These limitations underscore the need for more efficient and accurate techniques [2] to ensure the quality and marketability of onions.

Recent advancements in artificial intelligence (AI) and machine learning (ML) offer promising solutions to these challenges. Transfer learning [3], in particular, has emerged as a powerful technique in the realm of image classification. It leverages pre-trained neural networks to address specific tasks with limited data and computational resources. By utilizing pre-trained models such as VGG16, ResNet50, and InceptionV3, transfer learning can significantly enhance the accuracy of disease identification while reducing the need for extensive labeled datasets.

This study aims to develop a robust and efficient system for the identification and classification of onion diseases after harvest using transfer learning. Automating the detection process can enhance the efficiency of post-harvest disease

management, reduce losses, and improve the overall quality of onions reaching the consumer market. The proposed system involves collecting a comprehensive dataset of onion images, preprocessing and augmenting the data, and fine-tuning pre-trained convolutional neural networks [14-15], to accurately classify healthy and diseased onions.

This work details about the dataset collection and preprocessing methods, the implementation of transfer learning, and the evaluation of the model's performance. Through this research, the aim is to contribute to the development of intelligent agricultural systems that support farmers and stakeholders in ensuring the quality and safety of their produce

## 2. Related Work

The advent of deep learning has revolutionized the field of plant disease detection and classification. Deep learning models, particularly Convolutional Neural Networks (CNNs), have been extensively employed due to their superior performance in image processing tasks. This literature review consolidates insights from multiple studies that focus on the application of deep learning techniques for plant disease detection, highlighting the advancements, methodologies, and outcomes of various research efforts.

Li et al. (2021) present a comprehensive review of the application of deep learning in plant disease detection and classification. The study emphasizes the potential of deep learning models to outperform traditional image processing methods. The authors discuss various CNN architectures such as AlexNet, GoogLeNet, and ResNet, highlighting their effectiveness in feature extraction and disease identification. The review also addresses the challenges associated with deep learning, including the need for large

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annotated datasets and the complexity of model training. Li et al. underscore the importance of transfer learning and data augmentation techniques to enhance model performance and generalization capabilities.

Shoaib et al. (2022) focus on the segmentation and classification of tomato plant diseases using deep learning. The study employs a CNN-based approach for the automatic identification of diseases from leaf images. The authors utilize a dataset comprising various tomato leaf diseases and implement a segmentation algorithm to isolate the diseased regions. Following segmentation, a CNN classifier is employed to categorize the diseases. The results demonstrate high accuracy and robustness of the proposed method, suggesting that deep learning can significantly enhance the precision of plant disease diagnostics.

Ahmad et al. (2023) provide a survey of deep learning techniques used in plant disease diagnosis. The paper reviews different CNN architectures and their applications in disease detection. The authors also discuss the integration of deep learning with Internet of Things (IoT) and remote sensing technologies for real-time disease monitoring. The survey highlights the potential of these combined approaches to create smart agricultural tools that can assist farmers in early disease detection and management. Additionally, the authors offer recommendations for future research, emphasizing the need for more diverse datasets and the development of user-friendly diagnostic tools.

Tyagi et al. (2024) explore the implementation of various CNN architectures, including Inception v3, VGG-16, and VGG-19, for the identification and disease detection of medicinal plant leaves. The study compares the performance of these models in terms of accuracy, computational efficiency, and robustness. The authors report that Inception v3 outperforms VGG-16 and VGG-19 in terms of accuracy, while VGG-16 and VGG-19 offer competitive results with lower computational costs. The findings highlight the importance of choosing appropriate CNN architectures based on specific application requirements.

Srivastava et al. (2020) propose a novel deep learning framework for the detection of diseases in sugarcane plants. The framework integrates a CNN with a feature extraction module to enhance the accuracy of disease identification. The study utilizes a large dataset of sugarcane leaf images, including various disease conditions. The authors implement data augmentation techniques to improve the model's robustness and generalization. The results indicate that the proposed framework achieves high accuracy and can effectively differentiate between healthy and diseased leaves, providing a reliable tool for sugarcane disease management.

Shahoveisi et al. (2023) investigate the use of image

processing and transfer learning for the detection of rust disease in plants. The study employs a pre-trained CNN model fine-tuned on a dataset of rust-infected leaf images. The authors utilize transfer learning to leverage the knowledge from the pre-trained model, significantly reducing the need for extensive training data. The approach demonstrates high accuracy in rust disease detection, showcasing the effectiveness of transfer learning in overcoming data scarcity challenges in plant disease diagnostics.

Algani et al. (2023) present an optimized deep learning approach for the identification and classification of leaf diseases. The study employs a CNN model optimized using techniques such as hyperparameter tuning and model pruning to enhance performance and reduce computational overhead. The authors compare the optimized model with standard CNN architectures, reporting superior accuracy and efficiency. The study underscores the importance of model optimization in developing practical and deployable deep learning solutions for plant disease detection.

Historically, farmers relied on visual inspection and traditional knowledge to identify and manage crop diseases. Over time, the integration of plant pathology with agricultural practices allowed for a more scientific approach to disease management. Disease identification and classification in agricultural crops are crucial for ensuring food security, improving crop yields, and maintaining the health of agricultural ecosystems. Identifying and classifying crop diseases accurately enables timely interventions, minimizing crop losses and promoting sustainable agriculture. The following table 1 summarizes about the crop disease and how deep learning techniques are evolved for identification. This table highlights the methodologies in the field, providing a comprehensive overview of the latest research on deep learning, transfer learning, and agricultural disease classification.

### 3. Research Objective

The primary objective of this research is to develop an automated system for the identification and classification of post-harvest onion diseases using transfer learning through data collection, preprocessing, augmentation, pre-training and fine-tuning for the contribution to best agricultural practices to reduce post-harvest loss.

### 4. Proposed Methodology

The proposed methodology is to develop a system to classify healthy and diseased onions using onion image dataset. The system architecture Figure 1 depicts the steps that are used to classify onions with collection of labelled datasets. The resized and normalized images are fed to pre-trained models which composes of Convolution layers [16-17], ReLU activation and MaxPooling. The output from the pretrained layers is passed into dense layer of 1024 units and

512 units which generated an output classification of the onion images.

#### 4.1. Data Collection and Annotation

A dataset of 1500 images of healthy and various diseased onions are collected and categorized as healthy and diseased onions. Annotations are added to these images to create a labelled dataset.

#### 4.2. Data Preprocessing

The dataset images are converted to 224x224 sized images. Normalize these images using histogram techniques to enhance the quality of the images.

#### 4.3. Data Augmentation

The data augmentation is performed to increase the diversity of the training set and reduce overfitting. This may include rotations, translations, scaling, and flipping. Data

augmentation often involves combining multiple techniques to create a richer dataset. For instance, an image may be first rotated, then translated, and finally scaled. The overall transformation can be represented as a sequence of individual transformations applied to the image. For example, combining rotation, translation, and scaling.

$$I''(x, y) = I\left(\frac{(x \cos \theta - y \sin \theta - \Delta x)}{s}, \frac{(x \sin \theta + y \cos \theta - \Delta y)}{s}\right) \quad (1)$$

Where  $x$  represents the horizontal coordinate of a pixel, representing the column index and  $y$  represents the vertical coordinate of a pixel, representing the row index.  $\theta$  is rotation angle in radians,  $s$  is the scaling factor.  $\Delta x$  and  $\Delta y$  defines the top-left corner of the cropping window.

**Table 1:** Summary of related work on plant disease classification using Deep Learning

Reference	Research Problem & Significance	Methodology	Key Findings & Results	Contributions	Strengths	Weaknesses
Lili Li, et al. (2021) [4]	Review of deep learning applications in plant disease detection to highlight advancements and challenges	Comprehensive literature review of various CNN architectures (AlexNet, GoogLeNet, ResNet) and techniques like transfer learning and data augmentation	Deep learning models significantly outperform traditional methods; challenges include large dataset requirements and training complexity	Overview of current state-of-the-art, identification of key challenges, and future research directions	Extensive review with detailed analysis	Limited empirical results; primarily theoretical
Muhammad Shoaib, et al. (2022) [5]	Detection and classification of tomato plant diseases using deep learning	CNN-based segmentation algorithm to isolate diseased regions followed by classification	High accuracy and robustness in disease detection	Demonstrates effective segmentation and classification methodology	High precision and robust model	Focuses only on tomato plant diseases; needs validation on other crops
Aanis Ahmad, et al. (2023) [6]	Survey of deep learning techniques for plant disease diagnosis and development of appropriate tools	Review of various CNN architectures and integration with IoT and remote sensing	Highlights potential of integrated approaches for real-time disease monitoring	Provides recommendations for future research and tool development	Comprehensive survey with practical recommendations	Lacks empirical validation of surveyed techniques

Kunal Tyagi, et al. (2024) [7]	Identification and disease detection of medicinal plant leaves using different CNN architectures	Comparison of Inception v3, VGG-16, and VGG-19 architectures	Inception v3 outperforms VGG-16 and VGG-19 in accuracy; VGG models offer lower computational costs	Highlights strengths of different CNN architectures for specific tasks	Comparative analysis provides insights into model selection	Limited to medicinal plants; computational efficiency not deeply explored
Sakshi Srivastava, et al. (2020) [8]	Development of a deep learning framework for sugarcane disease detection	CNN integrated with feature extraction module, using data augmentation techniques	High accuracy in differentiating healthy and diseased leaves	Effective framework for sugarcane disease management	High accuracy and robust framework	Focused on a single crop; needs validation on other plants
Fereshteh Shahoveisi, et al. (2023) [9]	Detection of rust disease using image processing and transfer learning	Fine-tuning a pre-trained CNN on rust-infected leaf images	High accuracy in rust disease detection	Demonstrates effectiveness of transfer learning in plant disease detection	Utilizes transfer learning to overcome data scarcity	Limited to rust disease; may not generalize to other diseases
Yousef Methkal Abd Algani, et al. (2023) [10]	Identification and classification of leaf diseases using optimized deep learning	CNN model optimized with hyperparameter tuning and model pruning	Superior accuracy and efficiency compared to standard CNNs	Highlights importance of model optimization	High accuracy and computational efficiency	Specific optimization techniques may not be universally applicable
Dwivedi et al. (2021) [11]	Multi-task learning and attention features for grape disease detection. Aims to enhance detection performance.	Multi-task learning and attention mechanisms in a CNN framework.	Improved accuracy and robustness in grape disease detection.	Introduces multi-task learning and attention features in plant disease detection.	Enhanced performance through multi-task learning.	Specific to grape disease detection.
Hridoy et al. (2021) [12]	Recognition of papaya diseases using an ensemble of EfficientNet models. Aims for high accuracy and robustness.	Deep ensemble approach using multiple EfficientNet models.	High accuracy in papaya disease recognition.	Demonstrates the effectiveness of ensemble methods.	High accuracy through ensemble learning.	Limited to papaya diseases.

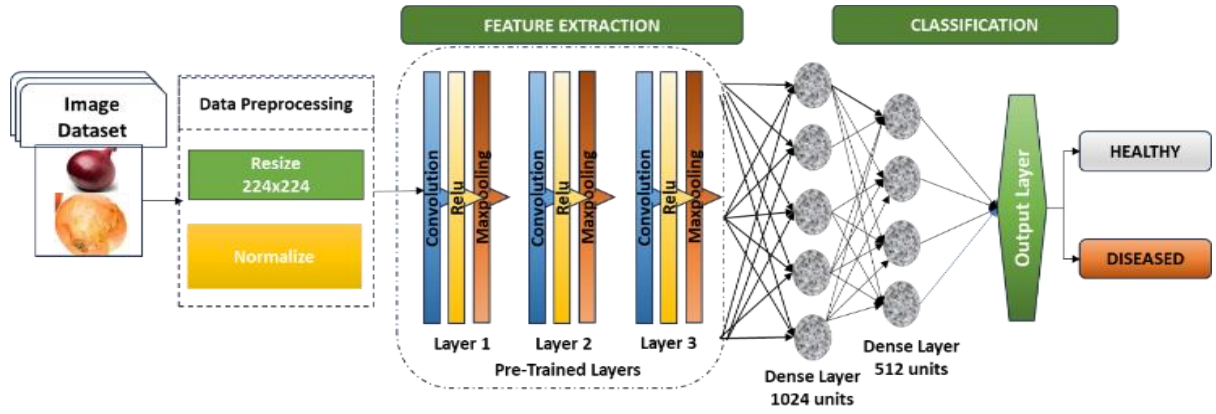


Fig. 1. System architecture to classify healthy and diseased onions

#### 4.4. Transfer Learning with Pre-trained CNNs

To implement transfer learning, pre-trained models such as VGG16, ResNet50, and InceptionV3 are used. The top layers of the pre-trained models are removed and replaced with new fully connected layers tailored to the classification of onion diseases.

##### i) VGG16 training model

The VGG16 model is a convolutional neural network architecture for Large-Scale Image Recognition. The first layer is the input layer which takes input as an image of fixed size  $224 \times 224 \times 3$  (width, height, and RGB channels). It consists of multiple convolutional layers. Each convolutional layer performs the following operation,

$$Output = ReLU(W * X + b) \quad (2)$$

Where  $W$  represents the filter weights,  $X$  is the input feature map,  $b$  is the bias term,  $*$  denotes the convolution operation, ReLU is the Rectified Linear Unit activation function. VGG16 has a total of 13 convolutional layers organized into 5 blocks, where each block has 2 or 3 convolutional layers. After each block of convolutional layers, a max-pooling layer is applied to reduce the spatial dimensions.

$$Output_{i,j} = \max_{m,n}(Input_{2i+m,2j+n}) \quad (3)$$

Where the pooling operation considers a  $2 \times 2$  window with a stride of 2. The output is passed through a softmax function to obtain class probabilities.

$$P(y = c|x) = \frac{\exp(W_c \cdot X + b_c)}{\sum_{j=1}^{1000} \exp(W_j \cdot X + b_j)} \quad \text{Eq. (4)}$$

Where  $P(y=c|x)$  is the probability of class  $c$  given input  $x$ .  $W_c$  and  $b_c$  are the weights and bias for class  $c$ . The denominator sums over all 1000 classes. Each "Conv3-X" denotes a convolutional layer with a  $3 \times 3$  kernel and  $X$  filters. The max-pooling layers have a  $2 \times 2$  window with a stride of 2. The fully connected layers (FC) have 4096 neurons each, except for the final one, which has 1000 neurons for classification.

##### ii) ResNet50 training model

ResNet50, a variant of the ResNet (Residual Network) architecture, is designed to ease the training of very deep networks by introducing residual learning. The input to ResNet50 is an image of fixed size  $224 \times 224 \times 3$  (width, height, and RGB channels). ResNet50 starts with a convolutional layer followed by a max pooling layer.

$$Conv1: X_1 = ReLU(W_1 * X + b_1) \quad (5)$$

$$Max Pooling: X_2 = Max Pooling (X_1) \quad (6)$$

Where  $W_1$  and  $b_1$  are the weights and biases of the first convolutional layer and MaxPool denotes the max pooling operation. ResNet50 consists of multiple residual blocks. Each residual block can be represented by the following equations,

$$Output = ReLU(F(X, \{W_i\}) + X) \quad (7)$$

where  $X$  is the input to the residual block,  $F(X, \{W_i\})$  is the residual function representing the stack of convolutional layers within the block,  $\{W_i\}$  denotes the weights of these convolutional layers. Each residual block in ResNet50 has two types: Identity Block with no change in dimensions and Convolutional Block with downsampling,

$$Output (Identity Block) = ReLU(W_3 * ReLU(W_2 * ReLU(W_1 * X + b_1) + b_2) + b_3 + X) \quad (8)$$

$$Output (Conv Block) = ReLU(W_s * X + b_s + F(X, \{W_i\})) \quad (9)$$

In ResNet50, each residual block uses a bottleneck architecture which consists of three layers  $1 \times 1$  Convolution (reduces dimensions),  $3 \times 3$  Convolution and  $1 \times 1$  Convolution (restores dimensions). After the stack of residual blocks, an average pooling layer is applied, followed by a fully connected layer for classification.

$$Average Pooling: X_{avg} = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W X_{i,j} \quad (10)$$

Where  $H$  and  $W$  are the height and width of the feature map.

$$\text{Fully Connected Layer: } P(y = c | X_{avg}) = \frac{\exp(W_c X_{avg} + b_c)}{\sum_{j=1}^{1000} \exp(W_j X_{avg} + b_j)} \quad (11)$$

Each convolutional block and identity block follows the bottleneck architecture, allowing for the efficient training of deep networks through residual connections.

### iii) InceptionV3

InceptionV3 is a convolutional neural network architecture which includes several improvements over its predecessors to increase efficiency and accuracy. The input to Inception V3 is an image of fixed size 299×299×3 (width, height, and RGB channels). Inception V3 begins with several convolutional and pooling layers.

$$\begin{aligned} \text{Conv2: 1a: } 3 \times 3: X_1 &= \text{ReLU}(W_1 * X + b_1) \\ \text{Conv2: 2a: } 3 \times 3: X_2 &= \text{ReLU}(W_2 * X_1 + b_2) \\ \text{Conv2: 2b: } 3 \times 3: X_3 &= \text{ReLU}(W_3 * X_2 + b_3) \\ \text{Max Pooling: } X_4 &= \text{MaxPool}(X_3) \\ \text{Conv2: 2d: 3b: } 1 \times 1: X_5 &= \text{ReLU}(W_4 * X_4 + b_4) \\ \text{Conv2: 2d: 4a: } 3 \times 3: X_6 &= \text{ReLU}(W_5 * X_5 + b_5) \\ \text{Max Pooling: } X_7 &= \text{MaxPool}(X_6) \end{aligned} \quad (12)$$

Inception modules are the core components of InceptionV3, allowing multiple convolution operations in parallel within the same layer. Each Inception module can be represented by,

$$\begin{aligned} \text{Output} &= \\ &\text{Concat}(\text{Branch1}, \text{Branch2}, \text{Branch3}, \text{Branch4}) \end{aligned} \quad (13)$$

Where Concat denotes the concatenation of outputs from different branches. Each branch applies different operations such as 1×1, 3×3 and 5×5 convolutions, or pooling operations. Reduction modules reduce the spatial dimensions of feature maps, usually with stride-2 convolutions or pooling. Inception V3 includes auxiliary classifiers to help with gradient flow during training,

$$\text{Auxiliary Output} = \text{Softmax}(W_a \cdot (\text{AvgPool}(X) + b_a)) \quad (14)$$

Where AvgPool is average pooling,  $W_a$  and  $b_a$  are weights and biases for the auxiliary classifier. Inception V3 uses these sophisticated modules to efficiently capture both local and global features, and the auxiliary classifiers help improve the training process.

### 4.5. Fine-tuning

Fine-tune the pre-trained models on the onion dataset by adjusting the weights of the new layers while keeping the pre-trained weights fixed or with minimal adjustments. A fully connected layer with 1024 units and ReLU activation

is added. A dropout layer with a dropout rate of 0.5 is used to prevent overfitting.

### 4.6. Dense Layer

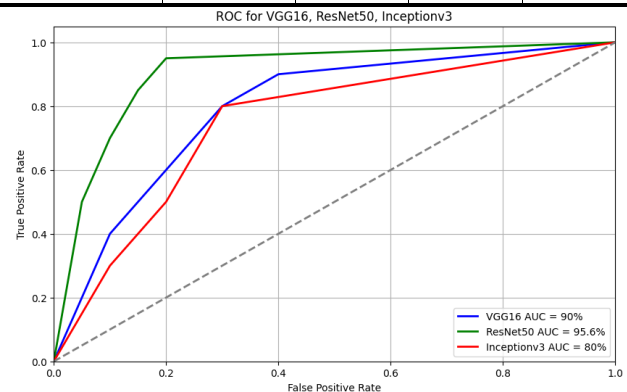
A fully connected layer with 512 units and ReLU activation is added and a dropout layer with a dropout rate of 0.5 is used for regularization. The final dense layer has 2 units (assuming binary classification) and uses softmax activation to output class probabilities. The model is compiled with the Adam optimizer, categorical cross-entropy loss (suitable for multi-class classification), and accuracy as the evaluation metric. This designed system is to leverage the feature extraction capabilities of the pre-trained model while fine-tuning the dense layers for the specific task of onion disease classification.

## 5. Results and Discussions

The models are evaluated using the metrics such as accuracy, precision, recall, and F1-score. The accuracy metric for each model is depicted in the below table 2 and ROC graphical representation is given in figure 2. The table and figure shows that ResNet50 produces accurate classification of onion images compared to VGG16 and Inceptionv3.

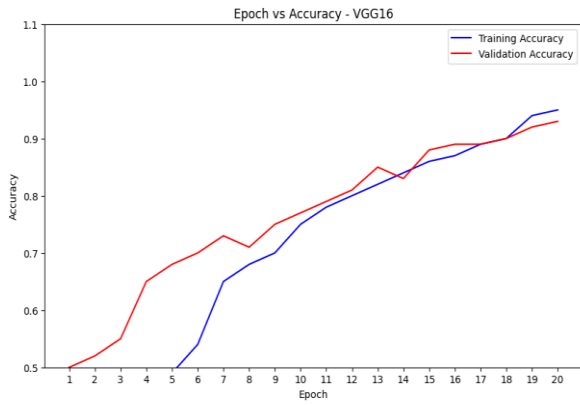
**Table 2:** Metrics of Performance

Model	Accuracy	Precision	Recall	F1-Score
<b>VGG16</b>	0.90	0.94	0.96	0.95
<b>ResNet50</b>	0.956	0.96	0.98	0.95
<b>Inceptionv3</b>	0.80	0.95	0.97	0.96

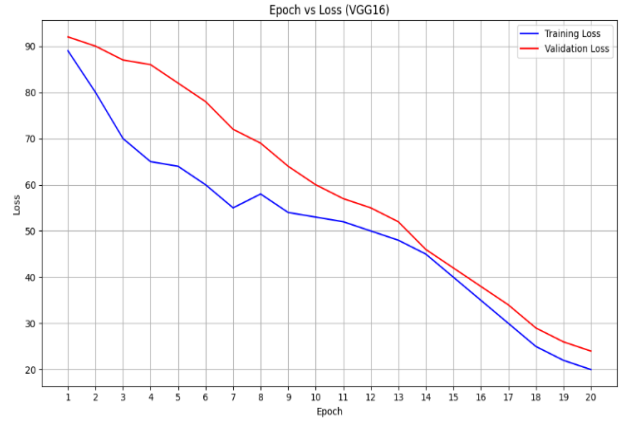


**Fig. 2.** ROC for performance of models

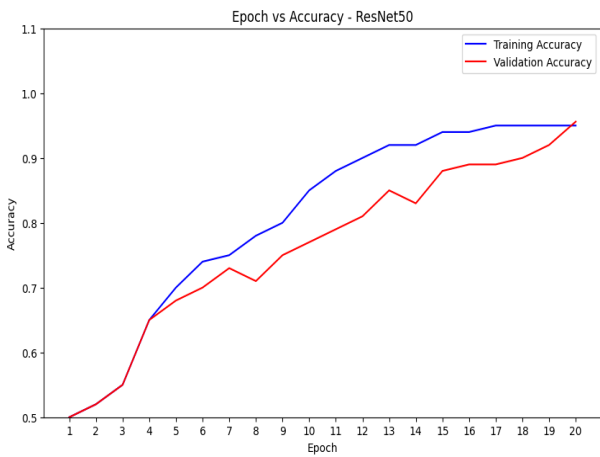
The following graph figure 3 to figure 5 depicts the training and validation accuracy with accuracy vs epoch starting from 1 for each model.



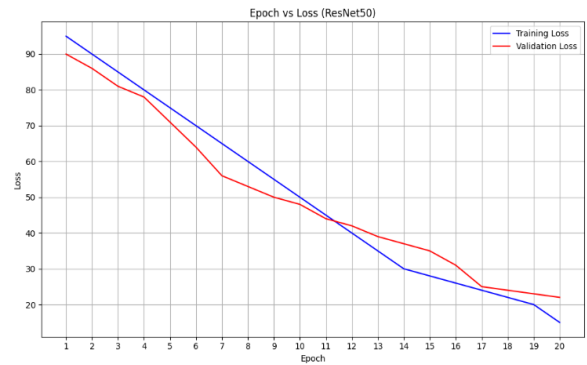
**Fig. 3.** Accuracy graph of VGG16



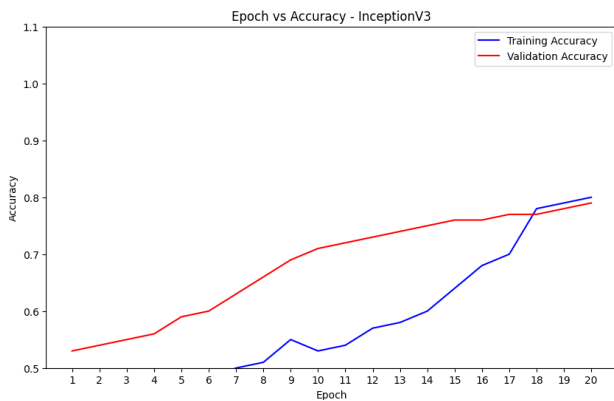
**Fig. 6.** Loss graph of VGG16



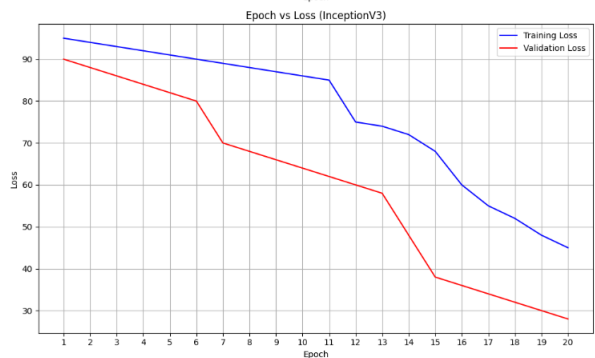
**Fig. 4.** Accuracy graph of ResNet50



**Fig. 7.** Accuracy graph of ResNet50



**Fig. 5.** Accuracy graph of Inception V3



**Fig. 8.** Loss graph of Inception V3

The VGG16, ResNet50, Inception V3 model accuracy as epochs progress is measured, starting at 1 epochs with ResNet50 giving more accuracy and other models accelerate more trainings. The loss represented in figure 6 to figure 8 is measured across epoch measures consistent reduction and effective optimized learning with ResNet50 model having minimum loss and other models initiate learning phase. Table 3 represents the maximum values obtained for Accuracy and loss in each model.

**Table 3.** Accuracy and Loss Values

Model	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
VGG16	0.95	0.93	20	25
ResNet50	0.95	0.93	20	25
Inception V3	0.80	0.80	52	52

VGG16	93.2	91.2	20.2	24.6
ResNet50	94.5	95.6	15.9	22.3
Inception V3	82.7	81.2	43.3	20.6

## 6. Conclusion

This work inculcates transfer learning for the identification and classification of post-harvest onion diseases. The deep architecture of ResNet50, with its residual connections, enabled the model to extract and learn complex features from the onion images. This robust feature extraction was crucial for achieving high classification performance. By leveraging the power of pre-trained convolutional neural networks, specifically ResNet50, we achieved significant results in accurately detecting and categorizing onion diseases. The transfer learning approach using ResNet50 achieved a commendable accuracy of 95.6%. This efficiency makes transfer learning a practical and scalable solution for agricultural applications where large datasets may not be readily available. The successful implementation of transfer learning for onion disease identification automates the disease identification process by reducing the need for manual inspections, saving time and reducing labor costs. The future work can include real-time implementation of tools like mobile applications or IoT systems to make it more user friendly. It can also be combined using other techniques for enhancing disease identification accuracy and reliability.

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## Author contributions

**Ms. Mythili. M:** was identified Initial problem identification, algorithm write-up, analysis, drafting of the manuscript, and simulation, drawing of the figures, final formatting and applied for the journal.

**Dr. Vasanthi Kumari P:** was responsible for the Literature survey and helped in the initial review process and was also responsible for the Complexity analysis of the research, evaluation of the research work.

All authors worked together to implement and evaluate the integrated system, and approved the final version of the paper.

## Conflicts of interest

The authors declare no conflicts of interest.

## References

- [1] Debasish Swapnesh Kumar Nayak, Saumendra Pattnaik, "Challenges and Solution for Identification of Plant Disease Using Machine Learning & IoT", *International Journal of Computer and Communication Technology*, July 2023.
- [2] R. Manavalan, "Automatic identification of diseases in grains crops through computational approaches: A review", *Computers-and-Electronics-in-Agriculture*, Volume 128, November 2020.
- [3] S. Divya Meena, Katakam Ananth Yasodharan Kumar, Devendra Mandava, "Plant Diseases Detection Using Transfer Learning", *Proceedings of Fourth International Conference on Computer and Communication Technologies*, March 2023.
- [4] Lili Li, Shujuan Zhang, And Bin Wang, "Plant Disease Detection and Classification by Deep Learning—A Review", *IEEE Access PP(99)*, April 2021.
- [5] Muhammad Shoaib, Tariq Hussain, Babar Shah, Ihsan Ullah, Sayyed Mudassar, Farman Ali, Sang Hyun Park" Deep learning based segmentation and classification of leaf images for detection of tomato plant disease", *Front. Plant Sci., Sec. Plant Bioinformatics*, 07 October 2022
- [6] Aanis Ahmad, Dharmendra Saraswat, Aly El Gamal, "A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools", *Smart Agricultural Technology*, Volume 3, February 2023.
- [7] Kunal Tyagi, Saksham Vats, Vasudha Vashisht, "Implementing Inception v3, VGG-16 and VGG-19 Architectures of CNN for Medicinal Plant leaves Identification and Disease Detection", *Journal of Electrical Engineering*, Vol 20, May 2024.
- [8] Sakshi Srivastava, Prince Kumar, Noor Mohd, Anuj Singh, Fateh Singh Gill, "A Novel Deep Learning Framework Approach for Sugarcane Disease Detection", *SN Computer Science*, Springer Nature Journal, March 2020.
- [9] Fereshteh Shahoveisi, Hamed Taheri Gorji, Seyedmojtaba Shahabi, Seyedali Hosseinirad, Samuel Markell & Fartash Vasefi, "Application of image processing and transfer learning for the detection of rust disease", *Scientific Reports*, 2023.
- [10] Yousef Methkal Abd Algani, Orlando Juan Marquez Caro, Liz Maribel Robladillo Bravo, "Leaf disease identification and classification using optimized deep learning", *Measurement: Sensors*, Volume 25, February 2023.
- [11] Rudresh Dwivedi; Somnath Dey; Chinmay

Chakraborty; Sanju Tiwari "Grape Disease Detection Network Based on Multi-Task Learning and Attention Features", IEEE Sensors Journal, Vol. 21, No. 16, August 15, 2021.

- [12] Rashidul Hasan Hridoy; Mosammat Rokeya Anwar Tuli, "A Deep Ensemble Approach for Recognition of Papaya Diseases using EfficientNet Models", International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), 2021.
- [13] Andrew J, Jennifer Eunice, Daniela Elena Popescu, M. Kalpana Chowdar, Jude Hemanth "Deep Learning-Based Leaf Disease Detection in Crops Using Images for Agricultural Applications", Agronomy 2022, 12(10), 2395; <https://doi.org/10.3390/agronomy12102395>.
- [14] S. B. et al., "Machine learning model for emotion detection and recognition using an enhanced Convolutional Neural Network," Journal of Integrated Science and Technology, vol. 12, no. 4. The ScienceIn Publishing, Feb. 08, 2024. doi: 10.62110/sciencein.jist.2024.v12.786.
- [15] H. V. Ramachandra et al., "Secured Wireless Network Based on a Novel Dual Integrated Neural Network Architecture," Journal of Electrical and Computer Engineering, vol. 2023. Hindawi Limited, pp. 1–11, Sep. 28, 2023. doi: 10.1155/2023/9390660.
- [16] D. R. Ganesh and M. Chithambarathanu, "Analyzing and securing information, images of women in online portal using CNN algorithm," AIP Conference Proceedings. AIP Publishing, 2023. doi: 10.1063/5.0175977.
- [17] M. Chithambarathanu and D. Ganesh, "Character Recognition Tamil Language in Printed Images using Convolutional Neural Network (CNN) analysis," 2021 4th International Conference on Computing and Communications Technologies (ICCCT). IEEE, Dec. 16, 2021. doi: 10.1109/iccct53315.2021.9711893.