KEC Conference 2025

ISSN: 3021-940X (Print) DOI: https://doi.org/10.3126/injet.v2i2.78606

Detection and Classification of Corn Leaf Diseases Using Resnet-18

Dilli Raman Oli[1, *], Manisha Dahal[2], Suraksha Pokhrel[3], Binod Dhakal[4]

[1]*Department of Computer and Electronics Engineering, Kantipur Engineering College, Dhapakhel, olidilliraman361@gmail.com*
[2]*Department of Computer and Electronics Engineering, Kantipur Engineering College, Dhapakhel, maneeshadahal85@gmail.com*
[3]*Department of Computer and Electronics Engineering, Kantipur Engineering College, Dhapakhel, suraksha2060@gmail.com*
[4]*Department of Computer and Electronics Engineering, Kantipur Engineering College, Dhapakhel, dhakalbinod19@gmail.com*

Abstract

Crop disease is a major problem for farmers, especially in Nepal, where many people depend on agriculture for their livelihood. Traditional methods of disease detection are often time-consuming, labor-intensive, and prone to human error. This study proposes an automated system for detecting and classifying corn leaf diseases using deep learning techniques. The ResNet-18 model is employed to detect and validate corn leaves and to classify diseases such as Common Rust, Blight, and grey Leaf Spot. The system achieved an accuracy of 91%, with a precision of 91.91% and a recall of 91.44%. By leveraging image processing and deep learning, this research provides a scalable and cost-effective solution for early disease detection in corn leaves, aiding farmers in timely intervention and crop management.

Keywords: Corn Leaf Diseases, Deep Learning, ResNet-18, Convolutional Neural Networks, Image Processing

1. Introduction

Agriculture is the backbone of Nepal's economy, and most individuals make a living through agriculture. The agriculture sector, too, faces many problems, one of which is the adverse effect of plant diseases on crop quality and quantity. Conventional methods of plant disease diagnosis, like manual inspection by experts, are typically time-consuming, expensive, and prone to human mistakes. In response to these difficulties, this research proposes an improved detection system based on image processing and deep learning models to detect and classify corn leaf diseases (Barman, 2019).

ResNet-18 architecture is employed for classification problems. ResNet-18 employs residual connections to address the vanishing gradient problem, enabling deeper networks to be trained. The model learns from a dataset containing over 10,000 images of corn leaves, recording the distinctive patterns for each disease. Through an accurate and automated process of disease detection, this study seeks to aid farmers in making well-informed decisions regarding plant health.

2. Related Works

(Dawood Idressa, 2024) aims to develop a machine-learning-based system for detecting diseases in maize plants using image-processing techniques. It focuses on identifying healthy maize leaves and two common diseases: grey leaf spots and common rust. The paper uses 600 images as a dataset. The Machine Learning Algorithms used here are Decision Tree (DT-90%), Support Vector Machine (SVM-90%), K-Nearest Neighbors (KNN-91.3%), and Artificial Neural Network (ANN-92.7%).

(Abhishek, 2022) explores the integration of a sequential layer into the ResNet18 architecture to improve accuracy in image classification tasks. The research aims to evaluate how this enhancement impacts the performance of ResNet18 on datasets like CIFAR10 and Intel Scene. The paper suggests that the authors have added sequential layers after the final layer of ResNet18. This layer includes the Linear (512, 512) layer, ReLU activation function, Dropout (0.2) layer, Linear (512, 2) layer, and LogSoftmax for computing class probabilities.

(Thongpance, 2023) studied the advantages of using multiple ResNet-18 models for object recognition tasks, with a specific focus on fruit image classification. It provides insights into improving the robustness and

**Corresponding Author*

accuracy of classification systems, paving the way for broader applications in real-world automated systems.The efficiency of single versus multiple ResNet-18 models is compared. A unique aspect of this study is the establishment of a 90% decision threshold, introduced to mitigate the risk of incorrect classification.

In the study by (Gnawali, 2024), there arises the problem of gradient vanishing or explosion due to extended training time. Transfer learning models, specifically ResNet18, effectively address this issue. That is why they have used ResNet18 for segmented feature extraction. And they can achieve 92.33% accuracy,92.52% precision, 92.33% recall, and 92.31% f1 score for 50 epochs.

In the study by (Pandey, 2023) the authors used three different CNN algorithms to train the model. The main motto of their system is plant disease detection, weather casting API, and information related to crops and plants and their cultivation methods, along with a communication system with field experts. The attractive part of this paper is the use of three different CNN algorithms: VGG16, ResNet50, and Inception V3. Among these three, ResNet stands out the most with 98.05% accuracy for 5 epochs and 87.47% and 94.12% accuracy by VGG 16 and Inception V3, respectively.

3. Methodology

The system uses a Raspberry Pi with a camera to capture images. A ResNet-18 CNN model validates the corn leaf and then classifies diseases. The results are displayed on a user interface for user interaction.

3.1. Dataset Description

The dataset used for the corn leaf disease detection includes two sources:

- ***Corn leaves and not corn leaves:*** This collection consists of 8,028 images of corn leaves and non-corn leaves, created by gathering images from diverse sources such as Kaggle, Flickr, and other publicly available repositories. The non-corn leaves class was augmented to balance the dataset by applying transformations such as rotation, flipping, and noise addition. The dataset distribution of this dataset is given in the figure below:

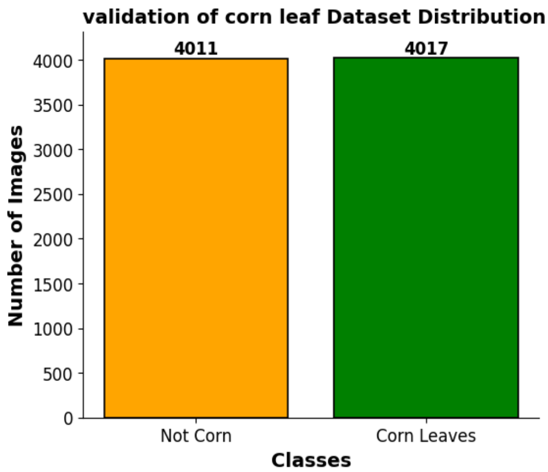

Figure 1. Validation of corn leaves dataset

- ***Corn or Maize Leaf Dataset in Kaggle by Smaranjit Ghose:*** The "Corn or Maize Leaf Disease Dataset" by Smaranjit Ghose is designed for classifying diseases in corn or maize plant leaves. It comprises images categorized into four classes: Common Rust, Grey Leaf Spot, Blight, and Healthy Leaves total of 4188 images. The dataset is derived from the PlantVillage project and is available on Kaggle. The dataset distribution of this dataset is shown in the figure below:

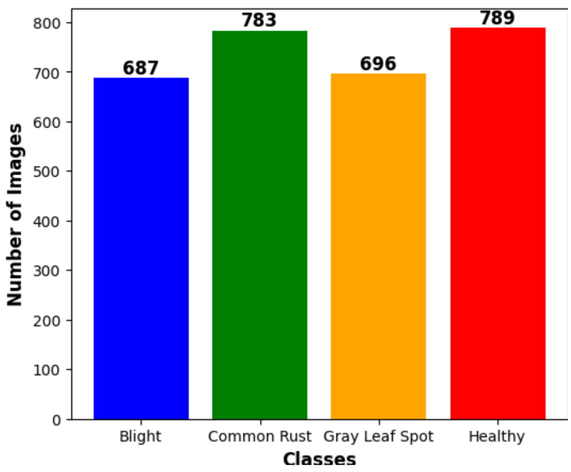

Figure 2. Corn leaf disease dataset

3.2. Data Transformation

Augmentation was performed on the minority class to balance the dataset.

- **Augmentation:** The Following transformations were applied:
- **Random Horizontal Flip (Image):** This transformation randomly flips the images horizontally with a 50% probability. It helps the model become invariant to left-right orientation. image = Flip(image, direction='horizontal')
- **Random Rotation (Image):** This transformation randomly rotates the images by an angle within a limit of 30 degrees with a 50% probability. This helps the model handle variations in image orientation. image = Rotate(image, angle)
- **Random Brightness and Contrast Adjustment (Image):** This transformation adjusts the brightness and contrast of the images with a 50% probability. This helps the model handle lighting variations. image = AdjustBrightnessContrast(image, brightness_factor, contrast_factor)
- **Gaussian Blur (Image):** This transformation applies a Gaussian blur with a 30% probability. This makes the model robust to blurry inputs. image = GaussianBlur(image, kernel_size)
- **Random Shift, Scale, and Rotation (Image):** This transformation applies random shifts, scaling, and rotation to the images. The shift limit is 5%, the scale limit is 5%, and the rotation limit is 15 degrees, all with a 50% probability. This enhances the model's robustness to small translations, scaling, and rotation. image = ShiftScaleRotate(image, shift_limit=0.05, scale_limit=0.05, rotate_limit=15)
- **Resizing:** This transformation resizes the images to 224x224 pixels, ensuring a uniform size for model input. It helps prepare the data for the model, making it compatible with networks like ResNet, which expect a fixed input size. image = Resize(image, (224, 224))

3.3. Model selection

Convolutional Neural Networks (CNNs) were initially considered for corn leaf validation and disease classification. However, after some study, CNN-based layers were discarded. Given the complex patterns in images and the potential vanishing gradient problem in deep CNNs, it was concluded that CNNs might not be the most effective approach for capturing the necessary features and achieving robust classification performance in this specific task.

In the initial experiments, a single-class Support Vector Machine (SVM) classifier was first employed to validate corn leaves. However, this approach did not work well because the model had difficulty distinguishing between corn leaves and non-corn leaves. Subsequently, a multi-class SVM classifier was used, expecting it to better handle the complexity of distinguishing between various categories. However, the multi-class SVM also failed to produce satisfactory results, indicating that this method was not well-suited for our dataset and problem.

After the limitations of SVMs, ResNet-18 was selected for its ability to handle complex image classification tasks. ResNet-18 was selected for its effectiveness in capturing intricate patterns due to its residual connections that mitigate issues like the vanishing gradient problem. The availability of pre-trained weights on ImageNet also provided a strong foundation for fine-tuning our corn leaf validation and disease classification task. This architecture offered the best potential to overcome the drawbacks of CNNs and SVMs, providing robust and accurate predictions.

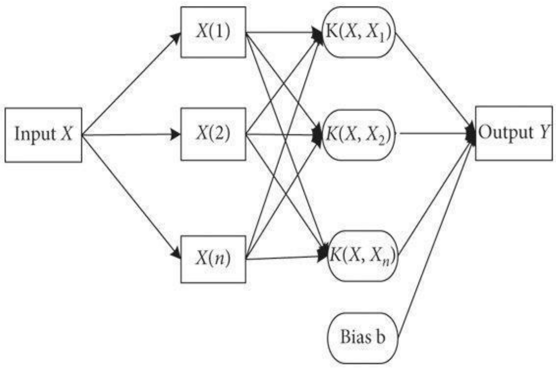

Figure 3. Support Vector Machine (SVM) with a kernel function

3.3.1. Resnet-18

ResNet18 is a deep learning model designed to overcome the gradient vanishing problem using residual connections, which allow stable gradient flow during training. It is widely used for image classification and segmentation, leveraging convolutional layers, batch normalization, and the ReLU activation function for effective feature extraction. ResNet18 also includes skip connections that improve learning efficiency and reduce computational complexity. Pretrained on ImageNet, it can quickly adapt to various tasks through transfer learning.

Layer Name	Output Size	ResNet-18
conv1	112 × 112 × 64	7 × 7, 64, stride 2
conv2_x	56 × 56 × 64	3 × 3 max pool, stride 2 [3 × 3, 64] [3 × 3, 64] × 2
conv3_x	28 × 28 × 128	[3 × 3, 128] [3 × 3, 128] × 2
conv4_x	14 × 14 × 256	[3 × 3, 256] [3 × 3, 256] × 2
conv5_x	7 × 7 × 512	[3 × 3, 512] [3 × 3, 512] × 2
average pool	1 × 1 × 512	7 × 7 average pool
fully connected	1000	The original ResNet-18 FC layer with 1000 outputs was replaced with a new one having 4 outputs for custom classification
softmax	4 outputs(custom)	

Figure 4. Resnet-18 architecture for disease

Layer Name	Output Size	ResNet-18
conv1	112 × 112 × 64	7 × 7, 64, stride 2
conv2_x	56 × 56 × 64	3 × 3 max pool, stride 2 [3 × 3, 64] [3 × 3, 64] × 2
conv3_x	28 × 28 × 128	[3 × 3, 128] [3 × 3, 128] × 2
conv4_x	14 × 14 × 256	[3 × 3, 256] [3 × 3, 256] × 2
conv5_x	7 × 7 × 512	[3 × 3, 512] [3 × 3, 512] × 2
average pool	1 × 1 × 512	7 × 7 average pool
fully connected	1000	The original ResNet-18 FC layer with 1000 outputs was replaced with a new one having 2 outputs for custom leaf classification
softmax	2 outputs(custom)	

Figure 5. Resnet-18 architecture for validation

3.4. Evaluation Metrics

After building the system, it is trained using a standard dataset. Once trained, it is tested with another dataset to check how well it performs. The model's effectiveness is measured using **Accuracy, Precision, F1 Score, and Recall**. These metrics help determine how reliable the predictions are.

3.4.1. Accuracy

The accuracy of a model is defined as the ratio of true positives and true negatives to all positive and negative observations.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

where, TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative

3.4.2. Precision

The precision of a model is defined as the percentage of labels correctly predicted positively.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

3.4.3. Recall

The recall or sensitivity of a model is defined as the ratio of true positives to all the positive instances.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

3.4.4. F1-score

The F1-score is a metric that calculates the harmonic mean of precision and recall.

$$\text{F1-score} = \frac{2*precision*recall}{precision + recall} \tag{4}$$

3.5. Experimental Results

Table 1. Hyperparameter used

Parameter	**Values**
Epoch	30
Batch Size	32
Optimizer	Adam
Learning rate	0.001

3.5.1 Confusion matrix

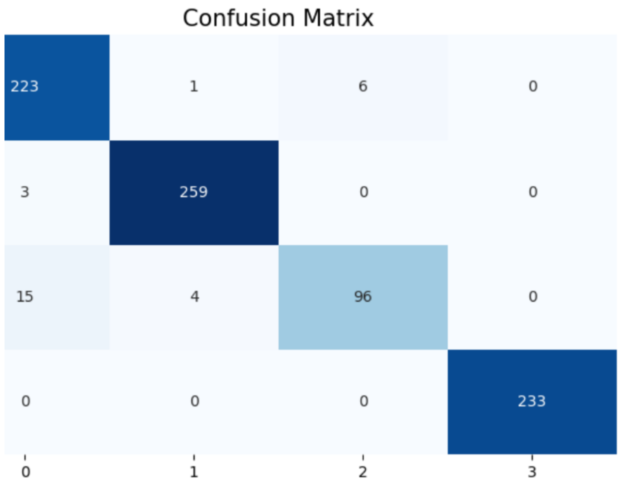

Figure 6. Confusion Matrix

3.5.2. Loss and Accuracy graph (Resnet-18)

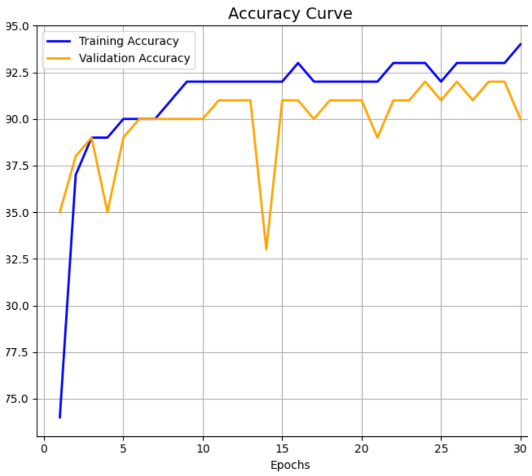

Figure 7. Accuracy Curve

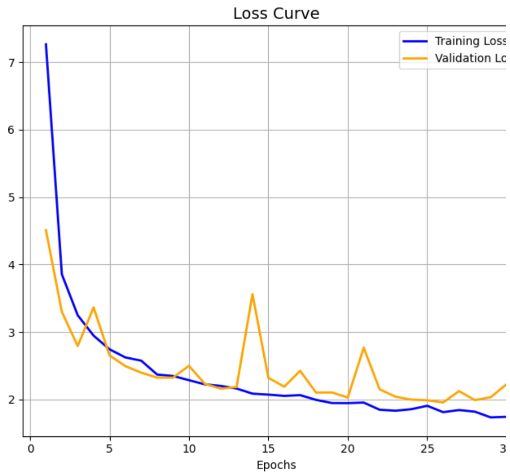

Figure 8. Loss Curve

Table 2. Classification Report

Class	Precision	Recall	F1-score	Support
Blight	0.92	0.83	0.88	102
Common Rust	0.92	0.99	0.95	69
grey Leaf Spot	0.62	0.72	0.67	32
Healthy	0.99	0.99	0.99	124
Accuracy			0.91	327
Weighted Avg	0.86	0.88	0.87	327
Macro Avg	0.92	0.91	0.92	327

4. Real-time implementation

The system captures images using a Raspberry Pi camera or allows users to upload an image. First step is corn leaf detection using a trained model, if the image is not a corn leaf, it says not corn leaf. If the input image is identified as a corn leaf, the system proceeds with disease detection and classification. A deep learning model determines whether the leaf is healthy or diseased. If healthy, the system displays "Healthy"; otherwise, it predicts the disease name and suggests an appropriate remedy.

5. Conclusion and Future Enhancements

This study aimed to develop a robust model using Raspberry Pi for the detection and classification of diseases in corn leaves using image-based analysis. The application successfully identifies whether an uploaded or captured image contains a corn leaf, and if it is a corn leaf, it classifies it as healthy or diseased with high accuracy. If it is not a corn leaf, it will indicate that it is not a corn leaf. For diseased leaves, the model distinguishes specific types of diseases and suggests possible remedies, presenting the results clearly and effectively. The experimental evaluation demonstrated significant improvements in classification performance, with ResNet18 outperforming traditional SVM approaches. While SVM achieved only 69% accuracy due to its reliance on handcrafted features, ResNet18 leveraged deep residual learning and pre-trained ImageNet knowledge to enhance accuracy and robustness significantly. The confusion matrix highlighted the model's strengths in correctly identifying Common Rust and Healthy leaves, with minor misclassifications primarily occurring between Blight and Grey Leaf Spot.

In future advancements, the focus will be on the implementation of lightweight versions of the model for mobile applications and IoT deployment, ensuring accessibility and usability in real-time applications. Collecting a diverse and balanced dataset for training the model will be essential to improve its robustness and classification accuracy, addressing potential biases and expanding its capability to handle various conditions in plant health monitoring.

Acknowledgments

The authors would like to extend their heartfelt gratitude to the Department of Computer and Electronics Engineering at Kantipur Engineering College for their unwavering support and resources, which have been invaluable throughout the duration of this research endeavor. The authors are deeply grateful for their contributions, without which this research would not have been possible.

References

Abhishek, D. a. G. V., 2022. ResNet-18 model with a sequential layer for computing accuracy on image classification dataset. *International Journal of Creative Research Thoughts.*

Barman, U. C. R. a. U. I., 2019. *Predication of Soil pH using K-means segmenatation and HSV color image processing.* India, IEEE.

Dawood Idressa, K. A. G. O. a. B. G., 2024. Machine Learning-based automatic detection of corn-plant diseases using image processing. *Journal of Agircultural Sciences.*

Gnawali, A. D. B. S. B. a. R. D., 2024. *CropCare AI.* s.l., Kantipur Engineering College.

Pandey, P. P. K. P. M. M. R. M. P. a. A. D., 2023. *Plant disease detection using deep learning model - Application FarmEasy.* s.l., IEEE.

Thongpance, N. W. K. W. A. e. a., 2023. Exploring ResNet-18 estimation design through multiple implementation iterations and techniques in legacy databases. *Journal of Robotics and Control (JRC).*