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Implementation of Deep Learning for Image-Based Potato Leaf Disease Detection

K Sharath Chandra¹, K Varun², L Rakesh³, L Ashrith⁴
^{1, 2, 3, 4}Artificial Intelligence & Machine Learning, Malla Reddy University

Abstract: *Crop Potato is one of the most important food crops worldwide, and potato tuber diseases can cause significant economic losses to farmers and affect food security. Early detection and timely management of potato tuber diseases are critical for reducing losses and increasing crop yields. However, traditional methods of disease detection rely heavily on visual inspection by trained experts, which can be time-consuming, subjective, and prone to errors. The use of deep learning for image-based potato tuber disease detection offers several advantages over traditional methods. First, it is a non-invasive and non-destructive approach, which means that the potatoes can be inspected without damaging them. Second, it can provide objective and consistent results, which can reduce the variability of disease diagnosis among different experts. Third, deep learning models can process large amounts of data quickly and accurately, making it possible to analyze images from different regions and different seasons. The proposed deep learning approach in this study uses a CNN, which is a type of neural network that is particularly effective for image analysis tasks. The CNN is trained on a dataset of potato tuber images labeled with their corresponding disease classes. The dataset used in this study comprises high-quality images of healthy and diseased potato tubers collected from various sources. The network learns to identify features in the images that are relevant for disease detection. In conclusion, the use of deep learning for image-based potato tuber disease detection offers a promising solution for improving the accuracy and efficiency of disease diagnosis in agriculture.*

I. INTRODUCTION

People all throughout the world are familiar with potatoes, which are also a staple cuisine in many other nations. In India, potatoes are grown in practically every state and in a variety of agroclimatic conditions. However, a number of potato leaf diseases are impeding its output. But the reality is that during the past few years, significant potato leaf diseases including early blight, late blight, brown spot, bacterial wilt, Septoria blight, etc. have caused a decline in both exports and production levels. Our goal is to create an automated system that can forecast potato illness and assist farmers in taking the appropriate action. For the purpose of predicting and classifying unknown leaves, we constructed a model based on convolutional neural networks (CNN) in this study. Agriculture-related crop diseases pose a serious risk to both productivity and the economy. In India, 17% of the GDP comes from agriculture, which supports 70% of the people. A farmer's transition from one disease control strategy to another is quite challenging. The traditional way is expert observation with the naked eye, however this approach can be time-consuming, expensive, and inaccurate. If infections are appropriately diagnosed and detected early, crop losses can be minimized by using pesticides or their equivalent to combat the influence of particular pathogens.

II. PROBLEM STATEMENT

Each year, a number of illnesses that damage potato plants create substantial financial losses for farmers that grow potatoes. The two most common illnesses are Early Blight and Late Blight. Both early and late blight are brought on by distinct microorganisms, but if farmers can identify the illness early and treat it well, they can avoid a lot of waste and financial loss. It's critical to correctly identify the type of disease present in that potato plant because there are certain differences between the treatments for early and late blight. Convolutional Neural Network - Deep Learning will be used in the background to detect plant illnesses.

III. PROPOSED SYSTEM

Deep learning technique alongside with Convolutional neural networks is deployed for predicting the potato leaf diseases. CNN is a multi-layer and a feed-forward neural network with one or more convolutional layer followed with fully connected layers. One of the attractive features of CNNs is that it can automatically extracts features from images for classification purposes through the learning process. CNN use relatively little pre-processing compared to another image classification algorithm. This means that the networks learn to optimize the filter or convolutional kernels that in traditional algorithms are hand engineered.

A. Convolutional Neural Network

A type of neural network known as a convolutional neural network specializes in processing data with a grid-like architecture. A binary representation of visual data is a digital image. It consists of a series of pixels arranged in a grid-like pattern, along with pixel values that specify the brightness and color of each pixel. A Deep Learning classification system called a convolutional neural network takes an image as input, extracts the features, and ranks the significance of the various objects in the image.

B. Potato Leaf Disease Dataset

1210 photos of potato leaf diseases make up this dataset. Based on the type of sickness, the photos are divided into three classes: Early Blight, Late Blight, and Healthy.

Ref. Figure -1.

C. Image Segmentation

A collection of various pixels make up a photograph. We use picture segmentation to group several pixels with similar characteristics. The process of filtering or classifying a database of images into instructions, subsets, or regions based on specific functions or attributes is known as image segmentation. Each object in the image receives a pixel-detailed mask thanks to image segmentation. This approach provides us with a far more detailed understanding of the object(s) in the picture.

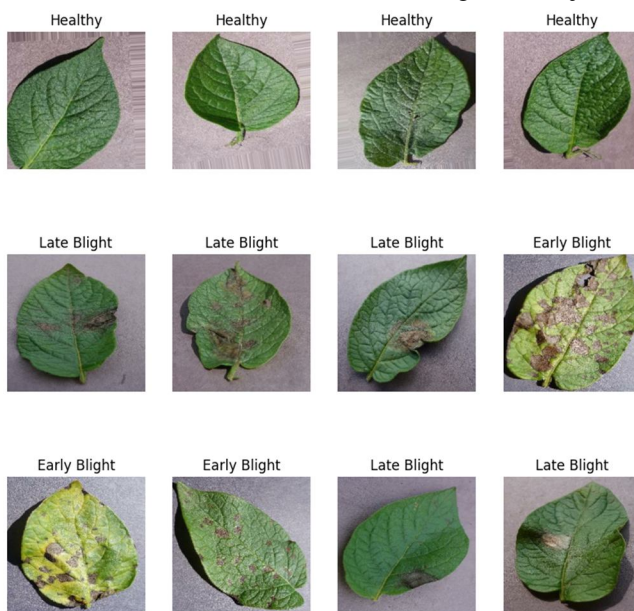
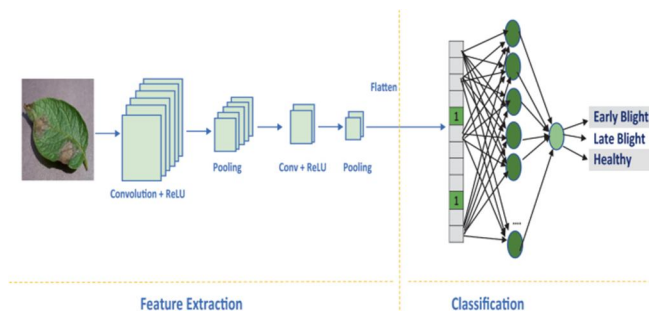


Figure -1: Sample Dataset

D. Feature Extraction

The process of transforming raw data into numerical functions that can be handled while preserving the information in the original data set is known as feature extraction. It produces better results than using equipment to learn the raw data right away.

E. Architecture



IV. RESULTS

A. Training and Validation Datasets

We examined 1210 RGB photos representing Early Blight, Healthy, and Late Blight, three prevalent disorders. It is advised to utilize validation data while choosing the best hyper-parameters to avoid overfitting the model.

B. Model Summary

Constructing a CNN model using the Flatten layer, Dense layer, and Convolution layers, Pooling layer, Dropout layer, Data augmentation, image resizing, and scaling the pixels of an image, Ref. Figure -2.

```
Model: "sequential_2"
```

| Layer (type) | Output Shape | Param # |
|--------------------------------|--------------------|---------|
| sequential (Sequential) | (32, 256, 256, 3) | 0 |
| conv2d (Conv2D) | (32, 254, 254, 32) | 896 |
| max_pooling2d (MaxPooling2D) | (32, 127, 127, 32) | 0 |
| conv2d_1 (Conv2D) | (32, 125, 125, 64) | 18496 |
| max_pooling2d_1 (MaxPooling2D) | (32, 62, 62, 64) | 0 |
| conv2d_2 (Conv2D) | (32, 60, 60, 64) | 36928 |
| max_pooling2d_2 (MaxPooling2D) | (32, 30, 30, 64) | 0 |
| conv2d_3 (Conv2D) | (32, 28, 28, 64) | 36928 |
| max_pooling2d_3 (MaxPooling2D) | (32, 14, 14, 64) | 0 |
| conv2d_4 (Conv2D) | (32, 12, 12, 64) | 36928 |
| max_pooling2d_4 (MaxPooling2D) | (32, 6, 6, 64) | 0 |
| conv2d_5 (Conv2D) | (32, 4, 4, 64) | 36928 |
| max_pooling2d_5 (MaxPooling2D) | (32, 2, 2, 64) | 0 |
| flatten (Flatten) | (32, 256) | 0 |
| dense (Dense) | (32, 64) | 16448 |
| dense_1 (Dense) | (32, 3) | 195 |

Total params: 183,747
 Trainable params: 183,747
 Non-trainable params: 0

Figure -2: Model Summary

C. Validation

The CNN model is trained using the first 50 epochs. Since there have been no more gains in training and validation accuracy, epoch 50 is the best optimized one. Figure 3 shows the forecasts produced by our model. Figure 4 shows the Training and Validation Accuracies and Losses, which together yield a 98.12% accuracy.

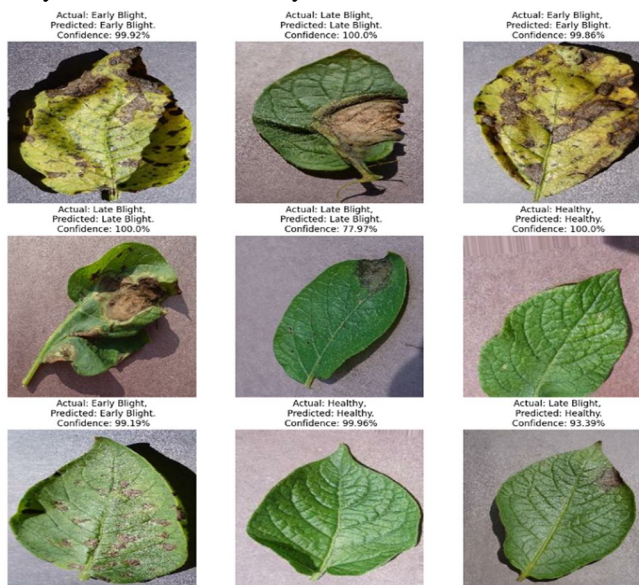


Figure -3: Sample Outcomes

Figure -3 refers to some of the predictions made using our CNN model.

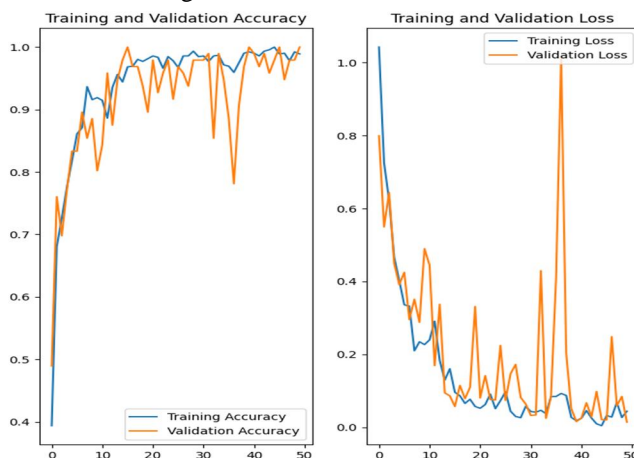


Figure -4: Graphs

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 1.00 | 0.98 | 0.99 | 53 |
| 1 | 0.91 | 1.00 | 0.95 | 52 |
| 2 | 0.98 | 0.91 | 0.94 | 55 |
| accuracy | | | 0.96 | 160 |
| macro avg | 0.96 | 0.96 | 0.96 | 160 |
| weighted avg | 0.96 | 0.96 | 0.96 | 160 |

Figure -5: Classification report

V. CONCLUSION

In conclusion, applying deep learning to image-based disease identification of potato leaves offers a potential approach to raising the precision and effectiveness of disease diagnosis in agriculture. It assists in early disease prediction and enables farmers to apply the proper fertilizers and minimize loss. CNNs are excellent at examining spatial patterns in images, enabling them to detect complex disease-related features automatically. Researchers have distinguished and classified several potato leaf diseases with outstanding accuracy by utilizing large-scale datasets and sophisticated CNN architectures. Although there are still issues with dataset accessibility and computing capacity, continuous research and collaboration in this field have the potential to dramatically improve crop management and increase the productivity and sustainability of the potato crop.

VI. ACKNOWLEDGEMENT

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