Inception V3 Model for Detecting and Classifying Potato Leaf Disease Using High Performance Convolutional Neural Network

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Abstract

Agriculture has been a vital industry for centuries, with approximately 60–70% of India's population relying on it for their livelihoods. Unfortunately, crop losses due to various factors such as weeds, diseases, and arthropods have increased over time, from 34.9% in 1965 to 42.1% in the late 1990s worldwide. One of the crops that face significant infections from bacteria and fungi is potato plants. Common fungal diseases that infect tater includes Alternaria solani (Early blight) and Phytophthora infestans (late blight). To address this issue, a CNN model is proposed an algorithm capable of detecting these diseases from the plant's leaves. The developed model was trained to analyze and understand diseased leaves with the accuracy level of 91.41% before identifying the specific disease. This approach leverages the InceptionV3 algorithm

Keywords: *Alternaria solani, Convolutional Neural Network, InceptionV3, Phytophthora infestans, Plant Village, Softmax.*

1. Introduction

Agriculture is a fundamental component of any civilization, and India has been a major player in this sector for many years [2]. With a rich agricultural history, this industry plays a crucial role in the country's economy. Among the many crops grown in India, potato is the most popular and successful, particularly in the country's subtropical climate.

Diseased plants are those that have been negatively impacted in terms of their normal growth and vitality. These diseases vary depending on environmental conditions and the specific crop variety, making them a major concern for potato farmers in India. Common potato diseases include Late Blight and Early Blight [2], which can have severe consequences for agricultural productivity. Detecting these diseases manually is a time-consuming process, highlighting the need for more efficient solutions.

There are various ways to identify objects and their features within images using computer vision and image processing techniques. One of the most effective approaches is a deep learning CNN model [3], which we have employed in our study to detect disease from images of potato leaves.

2. Related Work

Detecting plant diseases in their early stages is a major concern in agriculture. Numerous researchers are working on this issue, and their findings are helping to diagnose and detect plant diseases. As an example, Tiwari et al. [2] employed transfer learning techniques and multiple pre-trained models to analyze a dataset of potato leaf images. Their results showed that VGG 19 achieved the highest accuracy of 97.8%, while backpropagation neural networks and support vector machines attained accuracies of 92% and 95%, respectively.

Sardogan et al. [4] employed a Convolutional Neural Network in combination with the Learning Vector Quantization (LVQ) algorithm to identify and classify diseases in tomato leaves. Their approach involved utilizing 500 images of tomato leaves to generate three input matrices corresponding to the R, G, and B channels of each image in the dataset. The LVQ algorithm was then applied for image classification and the detection of leaf diseases. They concluded that the LVQ algorithm, combined with CNN, effectively classified the types of tomato leaf diseases.

Durmus et al. [5] investigated disease detection using two architectures, AlexNet and Squeeze Net, on the Nvidia Jetson Tx1 hardware. They found that AlexNet was not suitable for diseases detection on mobile devices because the model was bulky (227.6 Mbyte), whereas the model developed on the Squeeze Net architecture was small (2.9 Mbyte) and showed significant improvement in inference time. Therefore, Squeeze Net is the best architecture for mobile devices like the Nvidia Jetson Tx1.

Atila et al. [6] compared leading-edge deep neural net architectures with the Efficient Net deep learning architecture to notice plant leaf ailments in the Google Cloud Environment. They found that the accuracy of the Efficient Net architecture was better than added CNN designs, with an accurateness of 99.97%. The precision of the Efficient Net architecture was also better than other CNN Architectures.

The Plant Village Dataset [1], obtained from Kaggle, serves as the foundational dataset for this deep learning-driven paper. Kaggle is an online platform where data scientists and ML engineers can participate in ML competitions, work with various datasets, and access notebooks [2]. The Plant Village Dataset contains approximately 20,000 images of leaves from tomato, bell pepper, potato, and other plants in jpg/png format. The dataset includes both vigorous and contaminated leaves, with the diseased leaves divided into two categories: early blight and late blight.

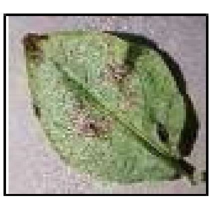

Fig. 1 Early Blight

Fig. 2 Late Blight

For the purpose of this paper, the subset of the dataset used focuses on potato plants. Specifically, it includes 1,000 images of Alternaria solani and 1,000 pictures of Phytophthora infestans, and 152 images of healthy leaves. The training and testing datasets are divided such that 80% of the healthy leaves are allocated to training, and the remaining 20% to testing. The same division applies to the diseased leaves. The dataset is organized such that there is a separate directory for each plant, and each disease type within that plant has its own folder. Some model pictures from the dataset are displayed above in figures 1 and 2.

3. Proposed Approach

The study working on a CNN archetypal to train on a pre-processed dataset, and subsequently tested its accuracy to draw conclusions. In this research inception v3 model has applied to analyze the disease. The Inception v3 architecture is an evolution of the original Inception model, designed to optimize both performance and computational efficiency for image classification tasks. Its design is focused on making deep learning networks wider and deeper while avoiding the computational bottlenecks associated with large layers.

To scale the pixel values from a range of [0, 255] to [0, 1] (for RGB images), the normalization formula is given below in Eq. (1), where I (Original) represents the pixel intensity of the image and I (Normalized) is the scaled value used for training the model:

$$I_{normalized} = I_{\frac{original}{255}} \qquad (1)$$

One of the significant advancements in Inception v3 is the use of factorized convolutions to reduce computational complexity. For example:

- Instead of using a single 5x5 convolution, which is computationally expensive, two 3x3 convolutions are applied sequentially. This has the same receptive field as a 5x5 convolution but with fewer parameters.
- The use of asymmetric convolutions (e.g., breaking down a 3x3 convolution into a 1x3 convolution followed by a 3x1 convolution) further reduces the number of operations while maintaining the link's capability to excerpt eloquent features. In CNNs, convolutions help in feature mining from the pictures. The convolution operation is given by below Eq. (2):

$$(I * K)\ (i, j) = \sum m \sum n\ I\ (i - m, j - n).K(m, n) \qquad (2)$$

Where,

- I is the participation image,
- K is the kernel filter,
- i, j represent the altitudinal coordinates of the yield feature plan, and
- m, n are indices for summation over the filter size.

The following figure 3, shows that architecture for CNN based inception v3 model.

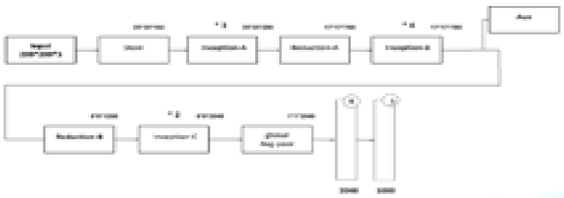

Fig. 3 CNN Based Inception V3 Architecture

Subsequently the CNN layer, an stimulation function is used to familiarize non-linearity into the archetypal, which agrees the network to acquire multifaceted forms. Common activation functions are as follows, denoted by Eqs. (3–5):

$$ReLU = f(x) = \max(0, x) \qquad (3)$$

ReLU swaps undesirable values with zero and leaves constructive values untouched.

Sigmoid for binary classification,

$$\sigma(x) = \frac{1}{1+e^{-1}} \qquad (4)$$

Softmax for multi-class classification,

$$Softmax(z) = \frac{e^{z_i}}{\sum_{j=1}} \qquad (5)$$

Reducing the spatial dimensions of feature maps is critical for maintaining efficiency in deep networks. Instead of using conventional max pooling for down sampling, Inception v3 applies convolutions with strides greater than 1 (e.g., 3x3 stride-2 convolutions).

This approach helps preserve more information while reducing the resolution of feature maps in a computationally efficient manner.

3.1 Feature Extraction

To extract features in this study, the Inception v3 architecture [7], which was collaboratively developed by Google and other researchers, was utilized. Inception v3 consists of building blocks such as convolutions, max pooling, concatenates, dropouts, fully associated layers, and average pooling. Moreover, batch normalization was implemented through the prototypical and applied to stimulation contributions [7, 12]. Feature extraction aided in enabling the design to effectively distinguish among all of the image's attributes and comprehend them for subsequent scrutiny [3].

3.2 Classification

In this research paper, convolutional neural network has exploited to classify images and identify the occurrence of Alternaria solani and Phytophthora infestans. Inception v3 is used to extract features, and then trained deep neural networks for classification. To optimize the training process and minimize loss, Adam optimizer is used here.

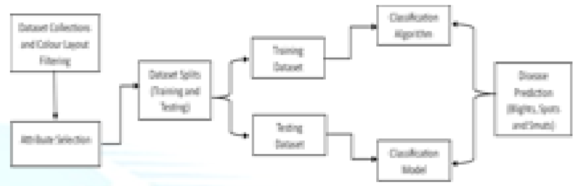

Fig. 4 Overall System Design for the Proposed Model

This optimizer is a popular extension of SGD in computer vision. For classifying different labels, Softmax activation function has been employed, which renovates a trajectory of n actual morals into a trajectory of n real values that sum up to 1. This function transforms input values into probabilities by scaling them between 0 and 1. Deep networks often suffer from vanishing gradients, which makes it difficult to train earlier layers effectively. Inception v3 mitigates this by incorporating auxiliary classifiers at intermediate layers [13]. The above figure 4 demonstrates that the complete system design for the planned model. These classifiers, which are additional softmax layers, serve two purposes:

- They help ensure gradient signals reach earlier layers more effectively, which assists with training deeper models.
- They act as a form of regularization, improving overall generalization.

To train the model, a loss function trials the variance between the design's prophecies and the factual labels (disease types).

Common loss functions include as follows in the Eq. (6):

$$Loss = -\frac{1}{N}\sum_{i=1}^{n}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)] \qquad (6)$$

Where y (i) is the fact tags (0 or 1), p(i) is the forecasted possibility, and N is the trial volumes.

4. Result

In this paper, Plant Village dataset [1] has been utilized, which consists of approximately 1000 leaf images affected by Alternaria solani and 152 pictures of hale and hearty plants; to propose this model Deep learning techniques have proven highly effective in detecting plant leaf diseases, helping to enhance crop efficiency and superiority by managing biotic factors that lead to significant productivity losses. In this project, we propose a profligate and effectual multi-level machine learning design for recognizing potato leaf diseases. The model first extracts potato leaf images and then uses a specialized convolutional neural network to classify Alternaria solani and Phytophthora infestans diseases. Additionally, it accounts for the impression of conservational features on these diseases.

The recital of the planned potato disease detection was appraised using another dataset, where it surpassed other existing methods. The model was accomplished on the Potato Leaf Disease (PLD) dataset, both data expansion, attaining an accurateness of 91.41% along with high precision, recall, F1-score, and ROC curve performance. With fewer parameters and a simpler design related to top notch modelling approaches, the proposed method offers substantial computational savings and faster processing times.

5. Conclusions

A Convolutional Neural Network (CNN) was designed to identify and classify diseases in potato plants, such as early and late blight. Leveraging the Inception V3 architecture and the Adam optimizer, the model demonstrated a classification accuracy of 91.41% on the test data. This approach offers farmers an efficient way to monitor crop health, enabling early disease detection and diagnosis, which can contribute to increased agricultural productivity. This research suggests that a computer-based system utilizing our model could be an efficient tool for farmers to enhance their crop yield and improve plant health.

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