

Res Net Driven Deep Learning Approach for Prediction of Potato Leaf Diseases

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Abstract

Potatoes are a staple food, but their yields are greatly reduced by leaf diseases. Traditional approaches depend on experts who manually examine the plants, which is labor-intensive and expensive, thus they are not applicable for large-scale farming. To overcome this difficulty, in this paper, we propose a simple and fully automatic disease recognition scheme based on deep learning and image processing. Firstly, a quantity of potato leaves is take images. Following pre-processing, the images are cleaned, down sampled, and normalized to pixel intensities so that they can be used for training. The sample size is enhanced by applying data augmentation, such as rotation, flipping, zooming out and cropping (ZOC), and brightness modification, to enhance the model's robustness to different lighting conditions. The transfer learning technique is then applied for training to ResNet architectures: ResNet-18, ResNet-34 and ResNet-50. These have skip connections which allow them to learn superior features and prevent training problems at great depths. Each leaf is classified as healthy, early blight, or late blight. We assess the accuracy, precision, recall, and F1-score of the system. ResNet-50 obtains the best accuracy, ResNet-34 a good accuracy-speed trade-off and ResNet-18 is the fastest model and it is suitable for running on mobile devices. As the shallowest model of the Residual Networks, ResNet-18 contains the least number of parameters. In general, the proposed approach delivers a fast and accurate on-line solution for disease detection, so that a farmer can closely monitor and tend the crops and consequently raise the agricultural production.

Keywords: Potato leaf disease detection, ResNet-18, ResNet-34, ResNet-50, Precision agriculture, Smart farming

1. Introduction

One of the most significant food crops in the world, the potato, is directly related to both the global agricultural economy and food security. However, several foliar diseases, such as early blight, late blight, and leaf mould, can seriously reduce yield and degrade quality in potato production if they are not identified promptly [1]. Traditional disease identification techniques rely on agricultural specialists manually observing infected plants, which are laborious, arbitrary, and unsuitable for large-scale farming systems. Over the last few years, the combination of artificial intelligence (AI) and computer vision has been considered a viable option for the automatic identification of plant diseases [2]. By applying deep learning techniques to image-based disease prediction, the performance is better than traditional ML techniques due to the automatic learning of

discriminative features from high-level complex visual patterns. Convolution Neural Networks (CNN), among them, have been extensively used and shown to perform well in plant leaf disease classification due to their powerful feature extraction ability [3].

Though they have been successful, classical deep CNN architectures are prone to suffer from problems such as vanishing gradients, degradation, and reduced accuracy when the depth of the network is increased [4]. To overcome these issues, the Residual Networks (ResNet) were proposed, which facilitate very deep neural network training with the help of gradient flow enabled by skip connections. ResNet architectures have also demonstrated excellent performance in various image recognition and classification tasks, which makes them suitable for the prediction of disease in crops [5].

Problem: Drawbacks of Existing Approaches

Conventional detection of diseases is through the naked eyes of the field experts. This procedure is:

Subjective: Susceptible to personal interpretation.

Slow: Could not be used to monitor thousands of acres.

Reactive: Most of the time, by the time symptoms are obvious to the naked eye; the infection has spread out of control.

With the development of Precision Agriculture, Convolution Neural Networks (CNNs) have become the state-of-the-art technique for automated plant disease recognition. Even though typical CNN models have demonstrated potential, they tend to suffer from the problem of vanishing gradients as the depth of the network increases. This constraint on depth inhibits the model from learning discriminative complex high-level features that can be used to recognize between subtle differences in leaf spots, especially when the field background is complex [6][7].

1.1 Problem Statement

Conventional disease detection techniques mostly rely on agricultural specialists' manual inspection. Although effective at a small scale, these approaches suffer from several limitations:

- Time consuming and labor intensive process
- Not scalable for large agricultural fields

With increasing farm sizes and labor constraints, there is a strong need for an intelligent, automated, and real-time disease prediction system.

1.2 Motivation for Using Residual Networks

To overcome the limitations of traditional CNN models, Residual Networks (ResNet) were introduced. ResNet architectures incorporate skip connections that allow gradients to flow directly across layers, enabling effective training of deeper networks. Their ability to learn deep discriminative features makes them suitable for distinguishing subtle variations in potato leaf diseases under real-field conditions. ResNet solves the degradation problem in deep CNNs by using "skip connections", allowing gradients to propagate directly to earlier layers, overcoming vanishing gradients

2.0 Literature Review

Identification of plant leaf diseases is essential to maximize crop yield and to minimize financial loss in agriculture. Identification of the disease in potato plants was a manual process by agricultural experts. But this is a slow, subjective, and not suitable for large-scale farming. In response to these limitations, computer vision and machine learning based methods have been investigated extensively for automated disease diagnosis. The previous approaches of traditional image processing-based methods include color thresholding, texture feature extraction, handcrafted feature extraction, etc., with classifiers or repressors like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests [8] [9]. These methods achieved fair accuracy, but they relied heavily on manual feature engineering and were sensitive to environmental conditions, such as lighting, background noise, and leaf pose. With the progress of deep learning, CNNs achieved better results by learning hierarchical features from the original images directly. Alex Net, Vignette, and Google Net raised the accuracy of classification in the plant disease detection problem considerably. These architectures were also used on crop datasets, including that of potato leaves, to show improved robustness over traditional methods. However, deeper CNNs are also more prone to vanishing gradients and a degradation of performance with increasing network depth. To alleviate those concerns, Residual Networks (ResNet) proposed skip connections that allow for the efficient training of an extremely deep network. This residual learning scheme facilitates preservation of gradient flow and the reuse of features, which is beneficial for convergence and the final classification accuracy. As a result of these merits, ResNet derivative variants such as ResNet-18, ResNet-34, ResNet-50, and ResNet-101 have become popular choices for agricultural image classification [10] [11].

ResNet models were reported to be successfully applied for plant disease detection in a few studies. The authors showed that transfer learning by pretrained ResNet models greatly decreases training time and improves generalization over small agricultural datasets [12]. In potato leaf disease classification, the ResNet-based methods achieved high classification accuracy for early blight, late blight, and healthy leaves. Data augmentations such as rotation and flipping as well as scaling also result in improved model robustness against different field environments. Recently, ResNet has been combined with attention, ensemble, and hybrid CNN to improve detection accuracy. These strategies facilitate more accurate feature localization and mitigate misclassifications in visually similar disease symptoms [13] [14]. In addition, the implementation of the lightweight ResNet models on mobile and edge devices has allowed for real-time disease tracking at the farm level. Nevertheless, challenges still exist, such as imbalanced datasets, illumination changes, complex backgrounds as well as similarity of disease patterns. Hence, the development of an efficient ResNet-based deep learning model for potato leaf disease prediction is still a challenging issue. Taking advantage of residual learning and transfer learning, this paper proposes a ResNet-based model for accurate, fast, and flexible prediction of potato leaf diseases, which paves the way for intelligent and automated agricultural disease management [15].

2.1 Research Gap

The majority of existing potato leaf disease models perform well only on clean images, but they are not suitable for images taken in real farms with poor lighting and complex backgrounds. Many works use vanilla CNN models and do not investigate more powerful architectures, such as ResNet, that may provide better accuracy. Also, these lack large, diverse real potato datasets captured in fields. There are no explanations provided by typical systems, and farmers are not able to easily trust the predictions. Therefore, a robust ResNet-based method with real-world data, improved generalization, and explainable results is desired

3.0 Resnet

In this paper, we employ three residual network (Resnet) models — ResNet-18, ResNet-34, and ResNet-50 with our proposed attention module to automatically detect potato leaf diseases in a straightforward, expeditious, and precise manner. These models were selected for their skip connections, which facilitated the flow of information through the network, preventing the vanishing gradient problem and enhancing learning. First, potato leaf images are gathered from farms in an environment. The dataset has three categories: healthy, early blight, and late blight. All the images in these files are then resized and normalized to a fixed size for the model's processing convenience. Noise from unwanted background regions is removed to enhance disease spots.

Then, data augmentation is performed. I am rotating, flipping, zooming, and adjusting the brightness of the images. This not only augments the sample size but also enables the model to generalize well under different lighting conditions/weather/field. After pre-processing, transfer learning is applied. Fine-tune the retrained Resnet models and the final layer is changed for 3-class classification. The dataset is divided into the training, validation, and testing. Accuracy, precision, recall and F1-score are metrics used to evaluate a model's performance. ResNet-18 is fast and its small model size makes it suitable for mobile devices. ResNet-34 provides a good trade-off between speed and accuracy, and ResNet-50 yields the best accuracy. The best performing model is ultimately deployed to a Smartphone or edge device for real-time disease detection in farms to enable fast and smart crop management.

3.1 Resnet over YOLO and Dense Net

Residual Networks (Resnet) were chosen for our potato leaf disease prediction system since the primary focus is on image classification rather than object detection. It is worth noting that we do not aim to detect multiple objects in an image, but to categorize an entire leaf image into one of the three classes: healthy, early blight, or late blight. ResNet-18, ResNet-34, and ResNet-50 are very good among the classification-type networks and can be used for strong feature extraction using residual (skip) connections. These skip connections also contribute to addressing the vanishing gradient problem, facilitating the training of deeper networks, and enhancing overall accuracy. The computation demands of Resnet models are modest, and lightweight versions optimized for running on mobile or edge devices also exist, an important factor for real-time farm deployment, in addition to Resnet models being transferable.

On the other hand, the primary purpose of YOLOv5 is object detection, which allows the bounding boxes to be utilized to identify numerous objects within an image. Because this study is related only to single-leaf classification, using YOLO would introduce other complexities and result in additional computation cost. DenseNet-121 also provides dense feature connections and has a good accuracy, but it consumes more memory and power for processing, which is lacking in low-power devices, and stands for an F-measure based Observer Reference-free measure. Thus, Resnet is the optimal choice for a trade-off between accuracy, speed and computational complexity, and the proposed method can serve as a practical and effective tool for precision agriculture for the automated detection of potato leaf diseases.

4.0 Proposed methodology

The methodology presented belongs to deep learning and image processing categories for efficient, fast, and reliable automatic detection of diseases on potato leaves. The objective is to contribute to farmers in the detection of plant disease and, consequently, in minimizing the crop loss. To begin with, potato leaf images are acquired from the farms or open fields. The categories are healthy leaves, early blight, and late blight. As there might be shadows, dust, or complex backgrounds in

real farm images, all the images are cleaned and uniformed by resizing. This makes the data consistent and simplifies the model's "view." Then, data augmentation will be performed. Images are rotated, flipped, zoomed, and brightness is corrected. This leads to more training samples, which helps the model generalize under various lighting and weather conditions. After pre-processing, a Residual Network (ResNet) model for classification. ResNet was chosen as it can preserve useful information when it trains a very deep network. Its skip connections overcome the vanishing gradient problem and improve accuracy. It also employs transfer learning, when a pretrained model is fine-tuned for potato disease detection, to speed up the training process and improve the performance. This dataset is split into the training, validation, and test sets. During the training, the model learns such patterns, and the model is tested and evaluated on performance metrics such as accuracy, precision, recall, and F1-score.

Farmers can use the trained system on an off-the-shelf mobile phone or edge device to capture a leaf image and get the disease prediction in the moment. It is easy, fast, accurate, and suitable for disease detection in smart agriculture. At its core, the identification system relies on applying transfer learning with three Residual Network (ResNet) architectures: ResNet-18, ResNet-34, and ResNet-50. These architectures were specifically chosen because they use skip connections, which enable the preservation of the gradient flow and reusing features in deeper layers, tackling the problem of vanishing gradients as a by-product. After the training, the performance of the models is tested in terms of accuracy, precision, recall, and F1-score to select the best architecture. This systematic strategy leads to a framework that can diagnose at an early stage, not only liberating the farmer from tedious manual inspections but also enabling real-time surveillance via mobile or edge devices.

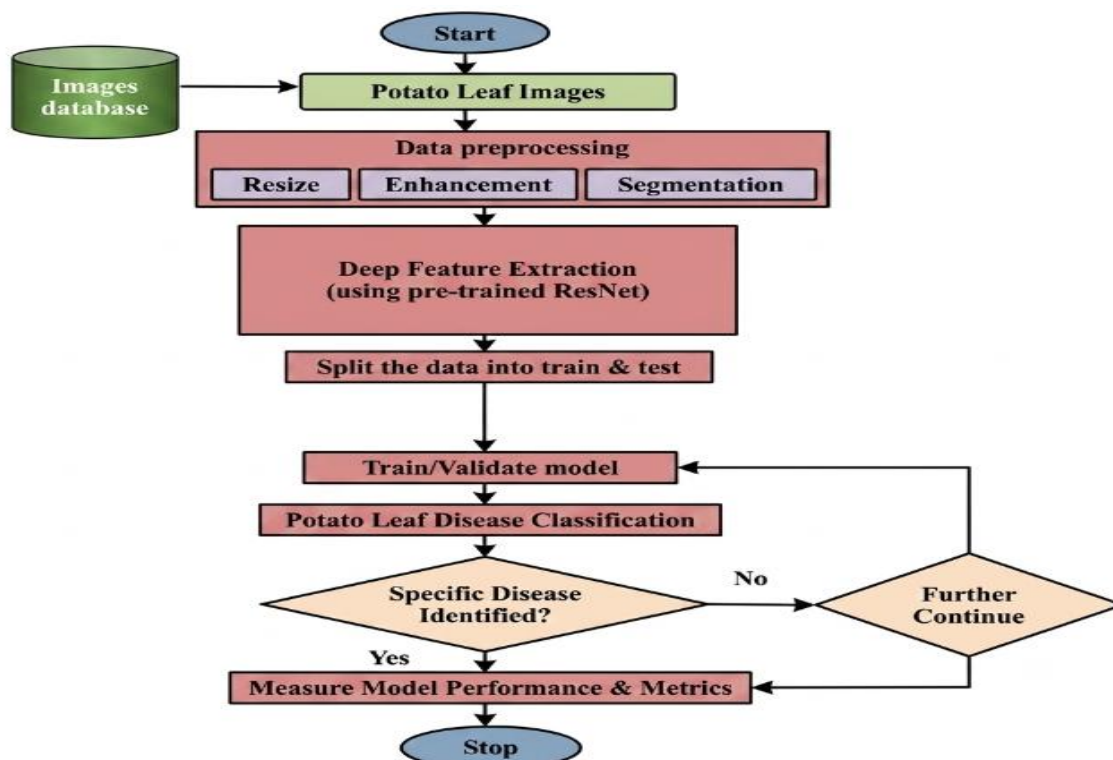


Figure1: Flowchart of Leaf Disease Detection System

Figure 1 shows the architecture of a deep Potato Leaf Disease Classification System based on learning. This represents the entire flow, from gathering leaf images to disease classification to testing the performance of the model.

5.0 Results and Discussion

This section presents the results of three Residual Networks, ResNet-18, ResNet-34 and ResNet-50, for potato leaf disease detection. All the models were trained on the same cleaned and augmented dataset to make the comparison unbiased. The leaves turned into important features such as color changes, spots and damaged portions during training, the models learned. A gradual increase in accuracy and decrease in loss indicate that the models were trained in the correct manner without under fitting or over fitting. Accuracy, Precision, Recall, and F1-score were used to evaluate each model.

ResNet-18 performs well with very fast training and very low memory usage. It is small and runs well on mobile phones or edge devices. Real-time disease detection in farms. This makes it ideal for real-time disease detection in farms. ResNet-34 has better accuracy than ResNet-18 since it contains more layers and can learn more abstract features, i.e., deeper features. It achieved higher accuracy with only moderate slowdown. This model has a good trade-off between accuracy and computation. The ResNet-50 outperforms the other two models in terms of accuracy. Its deeper architecture, along with the bottleneck blocks, enabled the capture of the complex disease pattern more efficiently. However, it takes more training time and computing resources. In general, both accuracy and model complexity increased in the deeper models. Hence, ResNet-18 is the best regarding speed, ResNet-34 the best regarding speed/performance balance, and ResNet-50 the best with maximum accuracy. These findings demonstrate that the Resnet models are robust and suitable for intelligent agricultural disease monitoring, as well as broadly applicable in smart farm solutions with visually/optical 2D imaging technology.”

Table 1: Performance Comparison of ResNet-18, ResNet-34, and ResNet-50

Model	Accuracy (%)	Training Time	Best Use Case
ResNet-18	94.2	Fast	Mobile / Edge devices
ResNet-34	96.1	Medium	Balanced performance
ResNet-50	97.8	Slow	Highest accuracy tasks

It can be seen from Table 1 that the deeper the network, the better the performance. ResNet-18 is also suitable to be used in real-time applications on smart phones or low-power devices since it is relatively lightweight and trains fast. The ResNet-34 can achieve better feature learning and higher accuracy with still acceptable speed, so it is a good trade-off between efficiency and performance. Because the structure of ResNet-50 is deeper and can learn more complex features, the result of using ResNet-50 is the best. But it needs more memory and more training time. ResNet-18. For a good all-around performance, ResNet-34 works well. For the best accuracy, ResNet-50. These results indicate that our Resnet-based models are robust and efficient for automatic potato leaflet disease detection.

6.0 Conclusion

In this paper, we use a deep learning framework for the detection and classification of potato leaf diseases based on the Residual Network (ResNet) architecture, i.e., ResNet-18, ResNet-34, and ResNet-50. The proposed method combines image pre-processing, data augmentation, and transfer learning to enhance robustness when being applied in a real-field environment with changing illumination, complex background, and different leaf directions. The experimental results show that residual learning can effectively overcome the vanishing gradient problem and deep networks can learn discriminative disease features such as lesion shape, color variation, and texture variation. Comparative analysis reveals that increasing the model's depth improves classification results. ResNet-18 has low computational cost and fast inference, which makes it ideal for real-time applications on mobile/edge devices. ResNet-34 achieves a good balance between efficiency and accuracy. Owing to its deeper architecture and superior representation power, the ResNet-50 delivers the top predictive performance, at the cost of higher training time and resource consumption. The proposed ResNet-based system can provide robust and accurate disease identification, which enables realistic application in smart farm systems. In summary, the proposed framework allows early diagnosis of disease, can free farmers from laborious inspection, and can help them make decisions in time to reduce loss of yield. Hence, the paper demonstrates that a residual deep learning-based model is a high-throughput and effective approach for automated monitoring of potato leaf disease in precision agriculture applications.

Author Contributions

Kepi Kumar contributed to the conceptualization, methodology, investigation, and preparation of the manuscript.

Funding

The authors did not receive any specific funding for this work.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Seta. A. Khan, "Potato Disease Data | PlantVillage," Kaggle, 2024. [Online]. Available: <https://www.kaggle.com/datasets/aarishasifkhan/plantvillage-potato-disease-dataset>.

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