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POTATO LEAF DISEASE PREDICTION MOBILE APPLICATION

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ABSTRACT
Optical and imaging technology is a valuable tool for identifying flaws in agricultural products, particularly potatoes. In agriculture, the application of artificial intelligence and image processing to identify and categorize plant and fruit pests and illnesses is growing, and the topic is always being researched. In this research, we also assess five categories of potato illnesses (grouper, black spot, scab, black leg, and red rot) using convolutional neural networks (CNN). A database containing five thousand photos of potatoes is used. We evaluate our approach against other impractical approaches including transfer learning, R-CNN, VGG, Alexnet, and Googlenet. The outcomes demonstrate that the suggested deep learning approach has a greater accuracy than other ongoing initiatives. In certain categories, we attain accuracy rates of 100% and 99%.
Keywords: Convolutional neural network. Deep learning. Misdiagnosis. Potato disease. Potato Classification.

I. Introduction

Food shortages have been getting worse in developing nations in recent years. Potatoes are one of the main basic foods eaten all year round in the majority of these nations. Due to the effects of several diseases, including early and late blight, potato yields have been declining recently, despite big crops. This situation caused great damage to the country's economy. The most dangerous illnesses in the world for farmers and agriculture are those that impact potato quality and productivity. Opportunities to enhance and broaden plant protection are presented by technological advancements in the early categorization and detection of crop blight diseases. Research into the creation of permaculture has become more significant due to the development of agricultural technology and the application of artificial intelligence in the treatment of plant diseases. Numerous illnesses, such early and late blight, have an impact on the number and quality of potatoes, and compiling a dictionary of these illnesses takes a lot of effort and time. The efficient utilization of these illnesses and their identification during germination might assist boost potato yields, despite the high amount of information required. Reports on foliar and plant diseases have been reported [55, 56]. Fruit and plant-related issues have resulted in a decline in both the quantity and quality of agricultural goods. Numerous plant and fruit diseases plague farmers. Herbalists occasionally be unable to identify the exact ailment that would lead to crop loss if care and treatment are not provided on time. Plant pathologists now categorize illnesses using laborious techniques and eye estimations. Manual techniques take a lot of time and produce erroneous findings. Early disease detection and preventive action are necessary to lower crop losses.

II . PROPOSED METHODOLOGY

Data Collection

To develop algorithms for leaf and disease identification, samples are trained and tested using particular data. Three organizations and two distinct formats—PlantVillage and Mendeley—are covered in this article. There are two different varieties of potato diseases: early and late blight. But one of our groups also includes healthy leaves. The data is split in an 80:20 ratio for training and testing so that our network's performance can be predicted. The exact data for each category are displayed in Table 2 and Figure 2, respectively. As data, use two samples.

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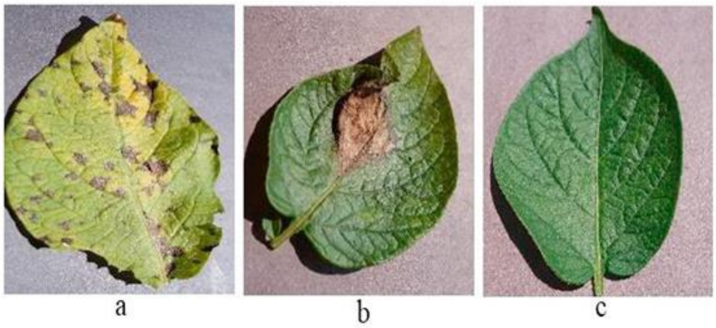
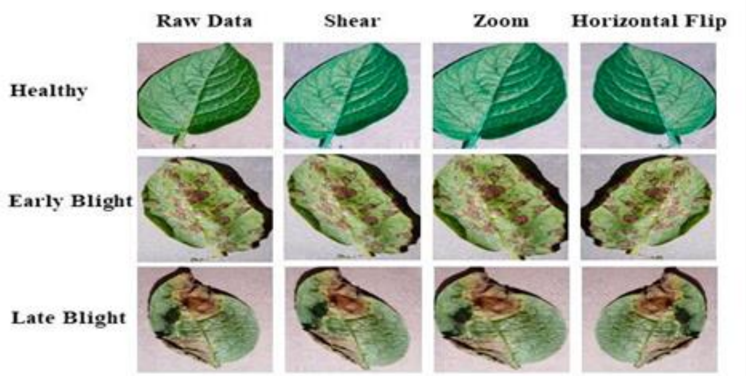
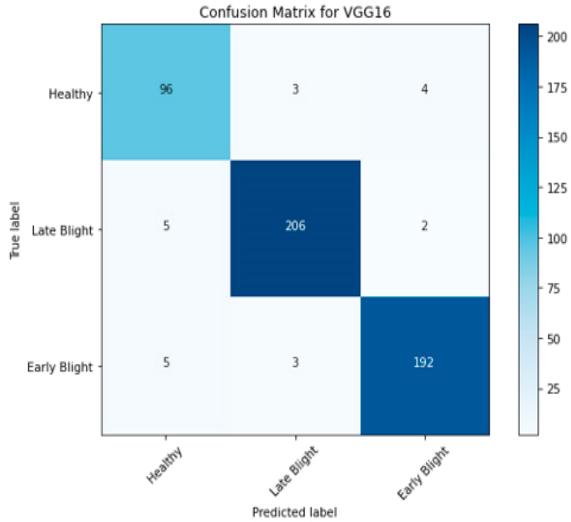




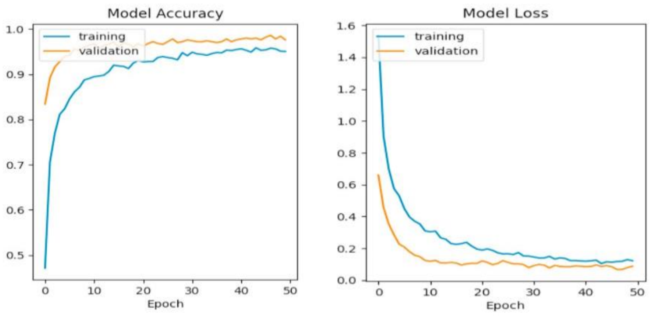
Research on the use of water in agricultural product assessment and monitoring, as well as early detection of illnesses that manifest on leaves, is crucial. Every year, chemical treatments are employed in the field to manage weeds and pests. It is necessary to take action to decrease environmental health and boost the usage of these materials. The usage of images is growing daily in the modern society. agriculture, weather, robots, medicine, etc. This subject has seen a great deal of study, and these domains make extensive use of its applications. Imaging technology is being used in agriculture for more purposes than only field inspection and crop disease detection. In agriculture, the application of artificial intelligence and image processing to identify and categorize plant and fruit pests and illnesses is growing, and the topic is always being researched.
In this research, we also assess five categories of potato illnesses (grouper, black spot, scab, black leg, and red rot) using convolutional neural networks (CNN). A database containing five thousand photos of potatoes is used. We evaluate our approach against other impractical approaches including transfer learning, R-CNN, VGG, Alexnet, and Googlenet. The outcomes demonstrate that the suggested deep learning approach has a greater accuracy than other ongoing initiatives.
agricultural chores [19] in order to get a deeper understanding of the circumstances the crop is growing in. Farmers are able to identify ongoing field operations without physically being in the field thanks to the current sensor and communication technologies, which give a detailed image of the field. Wireless sensors monitor the crops with greater precision and discover problems at early stages. This typically facilitates the employment of smart instruments from the initial planting of crops all the way up to the harvest [20].

III. LITERATURE REVIEW

Categorize photos using Clustering and to forecast page rank, we employ three classification techniques: VGG19, ResNet50, and VGG16. Every model undergoes 50 training sessions. The confusion matrix of the optimal model, VGG16, is displayed in Figure 7, and Table 3 displays the models' performance with respect to various parameters. Additionally, we computed performance measures, including accuracy, precision, recall, F1 score, and confusion matrix, for different K value possibilities.



Using VGG16, VGG19, and ResNet50 models without data augmentation, we achieved an accuracy of 0.954, 0.906, and 0.643, respectively. Data augmentation can enhance the performance of any deep neural network [25]. As a result, we employed several enhancements that enable the identification of abnormal photos within the dataset. Using VGG16, VGG19, and ResNet50 models, we were able to get accuracies of 0.959, 0.925, and 0.632 following augmentation. Development led to improvements in the vgg16 and vgg19 models' performance.
At K=3, the VGG16 model has the highest accuracy (97%) of all. For our dataset, two other models, achieve 95% and 67% accuracy, respectively. The accuracy and loss curves for the VGG16 model are displayed by period in Figure 8. We were able to acquire an accurate model after augmentation.



IV. APPLICATIONS

1. Image Recognition for Disease Identification:

Deep learning models, particularly convolutional neural networks (CNNs), can be trained on large datasets of potato plant images to recognize patterns associated with different diseases. This enables automated identification of diseases such as late blight, early blight, and bacterial wilt.

2. Precision Agriculture:

Combining deep learning with remote sensing technology such as drones or satellite imagery can help monitor large areas of land. These systems detect diseases in the potato crop, allowing farmers to focus treatments on specific areas rather than applying them everywhere.

3. Early Detection and Monitoring:

Deep learning models can be used to monitor crops regularly to detect early symptoms. The system regularly analyzes images or sensor data and provides early warning, allowing farmers to take precautions before the disease spreads.

4. Disease Severity Estimation:
Deep learning algorithms can not only detect the presence of disease, but also predict the severity of the disease. This information is useful for farmers in determining the suitability of interventions such as treating pesticides or herbicides.

5. Mobile Applications for Farmers:
Building mobile apps with deep learning models could allow farmers to assess the health of their potatoes. Farmers can take photos of their plants using their smartphones, and the app can analyze the images to detect diseases and offer treatment recommendations.

V. CONCLUSION

In this study, we investigate the use of image processing and neural networks for the identification and categorization of potato flaws. Our technique yields good results. Compared to other approaches, the CNN-based approach has a greater accuracy rate. We employ our method's undefinable potatoes, such as R-CNN, VGG, Alexnet, and Googlenet. We contrast it with other approaches. In our experiment, we were able to categorize potatoes with 100% and 99% accuracy. The confusion matrix effectively classifies the majority of potyviruses. Black spot, scab, black leg, red rot, and other illnesses are known to affect potatoes. This article presents a new study on the detection of five illnesses in potatoes. The majority of earlier research has split subjects into categories like healthy and ill groups. With 5000 photos utilized in the potato data set, these figures demonstrate the method's effectiveness. In certain categories, we attain accuracy rates of 100% and 99%.

V. FUTURE SCOPE

1. Enhanced Accuracy with More Data:
As more data becomes available, deep learning models for potato disease prediction will likely become more accurate. Larger and more diverse datasets can contribute to better model generalization and performance.

2 . Prior Training and Transfer Learning
Pre-trained models on general plant diseases or related crops can be fine-tuned specifically for potato diseases, speeding up the training process and improving performance, especially when data is limited.

3. Integration with IoT and Sensor Technologies:
The integration of deep learning models with Internet of Things (IoT) devices and sensor technologies can provide real-time monitoring of environmental conditions, soil health, and disease presence. This integration allows for more comprehensive and timely predictions.

4. Edge Computing for On-site Processing:
Implementing edge computing solutions can enable on-site processing of data, reducing the need for transmitting large amounts of information to centralized servers. This is especially beneficial in remote agricultural areas with limited connectivity.

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