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Potato Leaf Disease Recognition and Prediction using Convolutional Neural Networks

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Abstract

Potato crops are vital to global food security and economy, yet they are vulnerable to a wide range of leaf diseases that can significantly impact yield and quality. Rapid diagnosis and accurate identification of these disorders are critical for effective disease control and prevention. In this research, we offer an extensive evaluation and contrast of three state -of-art CNN models- VGG19, DenseNet121 and ResNet50-in order to identify and forecast potato leaf diseases. Our study employed a sizable dataset of potato leaf images, containing diverse healthy and afflicted specimens, to train and assess the performance of the chosen CNN models. Extensive data augmentation techniques were employed to enhance the dataset's diversity and generalization capabilities. We evaluated the models considering their accuracy, precision, recall, F1-score and computational efficiency to determine the most fitting model for real-life applications. The results demonstrate that all three CNN models achieved high performance in identifying and predicting potato leaf diseases, with VGG19 emerging as the top performer followed closely by DenseNet121 and ResNet50.Our findings provide valuable insights into the efficacy of DL approaches for potato leaf ailment identification and offer a foundation for future research and deployment of these models in precision agriculture systems. Ultimately, this work aims to support the development of more robust and efficient tools for timely disease diagnosis, enabling farmers and agronomists to make better-informed decisions and safeguard the health and productivity of potato crops worldwide.

Keywords: Potato leaf diseases, Convolutional Neural Networks, VGG19, DenseNet121, ResNet50, Disease recognition, Disease prediction, Data augmentation, Model comparison, Precision agriculture, Disease management, Computational efficiency, Performance evaluation, DL

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1. Introduction

Potato (Solanum tuberosum) is a significant staple crop worldwide, playing a crucial role in meeting the dietary needs of millions of people and contributing substantially to the global economy. Despite its importance, potato cultivation faces several challenges, primarily due to various leaf diseases that can cause considerable reductions in yield and quality. Early and accurate identification of these diseases is vital for implementing effective management strategies and ensuring the sustainable production of this essential crop. Traditional methods for diagnosing potato leaf diseases, such as visual inspection and laboratory-based testing, are labor-intensive, taking time, and often at risk of errors. The rapid advancements in computer vision and DL technologies have paved the way for overcoming these constraints, with CNNs emerging as a promising solution for accurate and efficient disease recognition and prediction in plants. Food scarcity has become an increasingly critical concern in developing nations, where potatoes serve as a primary staple food throughout the year. The decline in potato production is primarily due to the impact of various diseases, such as Early Blight and Late Blight, which lead to substantial losses in crop yield and have significant economic consequences **[1].** Potato diseases have far-reaching effects on the agricultural industry, as they not only reduce the productivity and quality of potato crops but also negatively impact farmers' livelihoods **[2].** The rapid growth of agricultural technology and artificial intelligence has drawn attention to the significance of relevant research in facilitating sustainable agricultural development **[3].** Traditional methods of detecting potato leaf diseases, which typically involve manual inspection and laboratory analysis, are labor-intensive, time-consuming, and demand a high level of expertise. By contrast, efficient and automated early-stage detection methods can dramatically enhance potato crop production **[4]**. Recent studies have highlighted the potential of image processing techniques in agriculture, particularly in diagnosing crop diseases **[5].** Prompt identification of plant and fruit ailments is crucial for implementing preventive actions and minimizing crop damage **[6].** Computer vision and processing of images provide a non-destructive and effective method for analysing surface defects in agricultural goods such as potatoes **[7].** Potatoes are a strategic crop worldwide, ranking third in importance as a staple food after wheat and rice **[8].** Quality classification is crucial for countries that rely on potato exports, as it helps attract target markets and generate revenue **[9].** Image processing techniques, combined with ML algorithms like SVM and DL, can be employed to classify potatoes based on their surface characteristics **[10].** This research introduces a groundbreaking DL-based technique to distinguish and categorize five distinct kinds of potato ailments: Healthy, Black Scurf, Common Scab, Black Leg, and Pink Rot. Earlier studies on potato disease identification mainly utilized conventional methods and centered on detecting one or two disease types **[11].** Our approach, which uses DL to diagnose five types of diseases, is innovative and has demonstrated high accuracy, outperforming traditional methods **[12].**

2. Related Works

Rizqi Amaliatus **[13]** suggested a method based on leaf conditions that employs DL with the VGG16 and VGG19 CNN architectures being used to categorize four different forms of illnesses in potato plants. The experiment had a 91% average accuracy, proving the utility of a deep neural network technique for disease classification in potato plants. Weirong Chen **[14]** developed a DL-based technique for identifying potato diseases that achieved a superior performance compared to other methods, with an average recognition accuracy of 97.73% across several potato disease categories. The experimental results demonstrate the competitiveness and validity of the proposed procedure in potato disease identification. Trong-Yen Lee **[15]** developed a highly efficient CNN framework specifically suited for potato disease identification. Image processing was used to build the training set, and the model was optimised using Adam and cross-entropy for analysis. SoftMax acted as the final decision-making function. While preserving high accuracy, the suggested framework minimised convolution layers and resources. According to the experimental results, the model detected plant diseases with 99.53% accuracy and reduced parameter usage by 99.39% on average.

Rashid, J. (2023) **[16]** devised a potato leaf disease identification model using DL techniques, which underwent training and testing on a dataset comprising 4,062 images of potato leaf diseases gathered from Central Punjab. The suggested method attained a remarkable accuracy of 99.75% on the dataset for potato leaf diseases. Additionally, the model's performance was assessed on the Plant Village dataset, where it exhibited considerable enhancements in both accuracy and computational efficiency in comparison to leading-edge models. Saeed, Z., and Khan, M. U. **[17]** put forward a method for categorizing potato diseases that integrates computer vision and DL concepts. By employing sophisticated CNN like ResNet-152 and InceptionV3, the approach utilized the Kaggle potato dataset for training and accomplished 98.34% and 95.24% accuracies, respectively, at a 0.0005 learning rate. This established system proficiently differentiates potato leaves into three classifications: unblemished, early blight, and late blight. Kumar **[18]** presented a high-efficacy DL-based CNN strategy for the reliable recognition of potato diseases, which was examined and executed through the Matlab Simulink platform. The recommended technique outshined other established methods, such as VGG-INCEP, Deep CNN, RF, and multiple SNN models. While specificity, sensitivity, and PSNR of the advanced method were 4.5%, 1%, and 2% higher, respectively, than those of alternative techniques, accuracy, precision, recall, and F-score were roughly 4%, 6%, 3%, and 3.5% higher. By adopting the proposed HDL CNN, the strategy's performance was elevated, enabling earlier disease detection and prevention, ultimately improving potato crop yield on a global scale. Hassan, S. M. et al. **[19]** demonstrated that their shallow VGG combined with the Xgboost model outperformed numerous DL models in terms of precision, recall, accuracy, f1-score, and specificity. The shallow VGG in combination with Xgboost achieved maximum accuracy scores of 94.47% for maize, 98.74% for potato, and 93.91% for tomato. On-site photos of potato, maize and tomato plants were used to further test the models. Even when evaluating field images, the shallow VGG paired with Xgboost yielded average accuracy levels of 94.22%, 97.36%, and 93.14%, respectively.

Agarwal, M. et al. **[20]** introduced a Convolution Neural Network Architecture (CNN) for identifying potato diseases, which exhibited strong performance even amid challenging circumstances, especially various backdrops, variable image sizes, spatial differentiation, high-frequency shifts in illumination levels, and authentic scene images. The suggested CNN is made up of four convolution layers, each of which has 32, 16, and 8 filters. The advanced model's training success rate was assessed to be 99.47%, while its testing accuracy was 99.8%. Iqbal, M. A. et al. **[21]** carried out image segmentation on 450 snapshots of healthy and affected potato leaves, obtained from the free Plant dataset. Seven algorithms for classifiers were used to identify and categorise ill and healthy leaf samples. Of these classifiers, the RF classifier attained an accuracy of 97%. This investigation underscores the potential of automatic plant leaf disease diagnosis through image manipulation and ML methodologies. To establish a powerful visualisation of features, DL-based tactics can be harnessed DL **[22]** has exhibited exceptional results in a variety of visual perception purposes, including text discovery **[23,24]**, victim discernment **[25,26],** target surveillance **[27,28]**, and object detection **[29,30].** A more profound network can boost accuracy. Intriguingly, it has been demonstrated both conceptually and empirically that deep network final layers can seize a higher level of semantic data or abstraction, making them more impervious to alterations in orientation, shade, dimensions, and deformable objects **[25]**. Thus, these methods may be well-fitted for resilient leaf disease classification, culminating in more accurate and efficient plant disease detection systems. U. Barman in 2020 **[31],** a custom-built Convolutional Neural Network (SBCNN) was developed for detecting potato diseases. The SBCNN was utilized individually on both enhanced and non-enhanced potato leaf image datasets. The algorithm was utilized for training and testing the potato leaf images, achieving a high validation accuracy of 96.98% and 96.75% in the non-augmented and augmented datasets, respectively. Moreover, the training accuracies reached 99.71% and 98.75% for the non- enhanced and enhanced datasets, respectively, emphasizing the efficiency of the SBCNN method in identifying potato diseases.

3. Proposed Methodology

The approach suggested in this research comprises four primary steps: data collection, data preprocessing, data enhancement, and image categorization, particularly concentrating on the utilization of CNN algorithms VGG19, DenseNet121, and ResNet50.

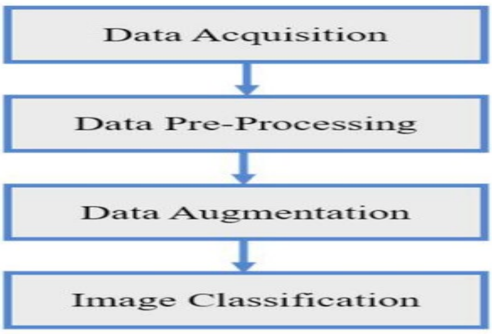

Figure 1. Proposed Methodology

3.1 Data Acquisition

In our research, we utilized a dual-pronged approach encompassing visual examination and expert assessment to systematically classify the leaf samples gathered from the field into distinct categories: Late Blight and Early Blight. This classification process was rooted in the careful analysis of several critical parameters, comprising characteristics such as lesion presentation, patterns of discoloration, along with other visual cues. This multifaceted strategy of data acquisition provided a robust foundation for our subsequent analytical stages, ensuring an accurate categorization that was both comprehensive and rigorous.

3.2 Data Pre-processing

After collecting the dataset, the images undergo pre-processing to prepare them for analysis. Pre-processing steps may involve resizing images for uniformity, converting them to grayscale or enhancing color channels, normalizing pixel values, and applying noise reduction techniques to improve image quality. These steps ensure a consistent dataset suitable for effective feature extraction and classification.

- **Image Preprocessing:** In the context of the potato leaf dataset, the image preprocessing stage is tailored specifically to address the unique features and challenges associated with potato leaf images. The primary goal is to optimize the images for the classification models, ensuring accurate and efficient disease detection. The following steps are undertaken during the image preprocessing phase for potato leaves.

- **Resizing:** To maintain consistency across the dataset, all potato leaf images are resized to a standard dimension, such as 224x224 pixels. This uniformity ensures that the CNN models, such as VGG19, DenseNet121, and ResNet50, can efficiently process and analyze the images.

- **Color Space Conversion:** Since potato leaf diseases often manifest as discoloration, it is essential to retain color information in the images. The images are converted to a suitable color space, like the HSV (Hue, Saturation, Value) color space, which can better capture disease-related color variations.

- **Normalization:** Pixel values in the potato leaf images are normalized to a range between 0 and 1. This step ensures uniformity in the input data, making it easier for the classification models to identify patterns and generalize across the dataset.

- **Noise Reduction:** Potato leaf images may contain noise from various sources, such as camera artifacts or environmental factors. Noise reduction techniques, like Gaussian blur or median filtering, are applied to minimize the impact of noise on the classification models' performance.

- **Contrast Enhancement:** Potato leaf diseases can sometimes manifest as subtle changes in color or texture. To emphasize these differences and improve the classification models' ability to detect diseases, contrast enhancement techniques, such as histogram equalization or adaptive contrast enhancement, are applied to the images.

- **Thresholding:** In the context of the potato leaf dataset, thresholding is a crucial image processing step that helps separate the leaf regions from the background and accentuate disease-related features. This technique involves setting a specific pixel intensity value (the threshold) and converting the image into a binary format, where pixels above the threshold are assigned one value, and those below it are assigned another. The following steps outline the thresholding process for potato leaf images:

- **Conversion to Grayscale:** To simplify the thresholding process, potato leaf images are first converted from their color format (e.g., RGB or HSV) to grayscale. This conversion reduces the complexity of the images while retaining the essential intensity information necessary for thresholding.

- **Selection of Threshold Value:** Determining an appropriate threshold value is crucial for effective segmentation of the leaf from the background. A global threshold value can be selected using techniques such as Otsu's technique, which determines the best threshold by minimizing intra-class variance. Alternatively, adaptive thresholding methods can be employed, which compute local threshold values based on the pixel intensities in a specific neighborhood. Adaptive thresholding can provide better results in cases where the illumination varies across the image.

3.3 Data Augmentation

To increase the diversity of the data set and boost the model's generalization skills, data augmentation techniques are applied. These techniques generate new images from the existing dataset through transformations like rotation, flipping, scaling, and cropping. Augmenting the data helps the model become more robust and less prone to overfitting, ultimately improving its performance on unseen data.

3.4 Image Classification

With the pre-processed and enhanced dataset, the selected CNN algorithms - VGG19, DenseNet121, and ResNet50 - are employed to classify the potato leaf images into their respective categories. These DL models are trained and optimized on the dataset, leveraging their unique architectural strengths for effective classification. By implementing this proposed methodology with a focus on VGG19, DenseNet121, and ResNet50 CNN algorithms, an efficient and accurate system for detecting and classifying potato leaf diseases can be developed. This system can contribute to better crop management practices and increased potato yields.

4. Experimental Analysis

We compare the effectiveness of three DL models. VGG19, DenseNet121, and ResNet50, for predicting potato leaf diseases. The primary aim is to determine the efficacy of these models in identifying and classifying the diseases accurately and their ability to adapt to previously unencountered data. To gain a comprehensive understanding of each model's capabilities, it is crucial to evaluate their performance on both the training and validation datasets. Using the VGG19 model, the experiment analysis reveals that for the prediction of Potato Late Blight, Leaf 1 and Leaf 4 demonstrate the highest accuracy, with 99.94% and 99.79% respectively. Leaf 2 has a moderate accuracy of 88.42%, while Leaf 5 performs relatively poorly at 68.34% accuracy, even misclassifying the leaf as Early Blight. In contrast, both Leaf 1 and Leaf 2 excel at predicting Potato Early Blight, achieving 100% accuracy. Overall, when employing the VGG19 model, Leaf 1 and Leaf 4 appear to be the most reliable for predicting Potato Late Blight, while Leaf 1 and Leaf 2 perform exceptionally well for Potato Early Blight**. [Fig.2]**Using the DenseNet121 model, the experiment analysis reveals varying accuracies for the prediction of early and late blight. For early blight, two instances achieve 100% accuracy in prediction: one with 100% confidence and the other with 100% accuracy. For late blight predictions, the accuracies differ significantly. In two instances, the predictions have a 100% accuracy, while one instance has a 99.36% accuracy. However, in other cases, the accuracies drop to 74.06%, 84.54%, and 88.76%. Notably, two cases of late blight are mislabeled as early blight. with 88.76% and 98.25% accuracies. This suggests that, when using the DenseNet121 model, there is room for improvement in predicting late blight, while early blight predictions appear to be highly accurate**. [Fig.3].**

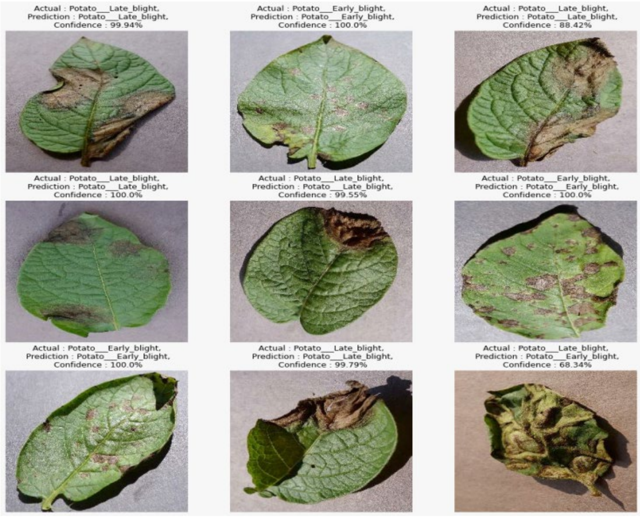

Figure 2. Result of VGG19 Model

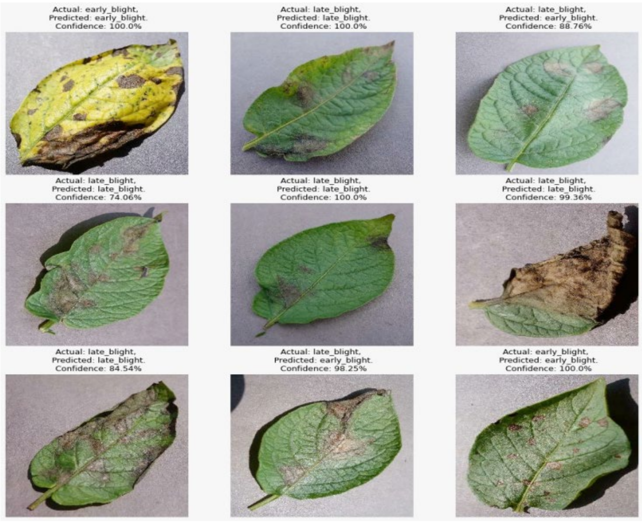

Figure 3. Result of DenseNet121 Model

4.1 Performance of the Three Models

The performance of the three models sheds light on their respective advantages and limitations in identifying potato leaf diseases, as well as their ability to adapt to previously unencountered data. To gain a comprehensive understanding of each model's capabilities, it is crucial to evaluate their performance on both the training and validation datasets. The comparative analysis of these models illustrates their effectiveness in classifying potato leaf diseases and provides a deeper understanding of how successfully they can manage new data samples. Examining their performance on the training and validation datasets is a vital step in assessing each model's proficiency and reliability in this classification task.

- **VGG19:** The VGG19 model demonstrated a strong performance on the training dataset, with a loss of 0.0280 and an accuracy of 98.77%. However, its performance on the validation dataset was slightly lower, with a loss of 0.3402 and an accuracy of 92.71%. This may suggest that the VGG19 model is overfitting the training data and not generalizing well to the validation data. **[Fig.4]**

- **DenseNet121:** DenseNet121 exhibited a good performance on both the training and validation datasets. Its training loss was 0.0675, with an accuracy of 97.51%. On the validation dataset, DenseNet121 achieved a loss of 0.0797 and an impressive accuracy of 97.92%. This indicates that the DenseNet121 model generalizes well to the validation data and is a strong candidate for this classification task. **[Fig.5]**

- **ResNet50:** The ResNet50 model also performed well on the training dataset, with a loss of 0.0642 and an accuracy of 97.78%. However, its performance on the validation dataset was not as strong as DenseNet121, as it had a loss of 0.1726 and an accuracy of 92.67%. This suggests that the ResNet50 model might not generalize as well as the DenseNet121 model.

The DenseNet121 model outperforms both VGG19 and ResNet50 in terms of validation loss and accuracy. While VGG19 and ResNet50 show good performance on the training data, they may be overfitting to some extent, as their validation losses and accuracies are lower compared to DenseNet121. Therefore, DenseNet121 appears to be the most effective model for classifying potato leaf diseases in this experiment.

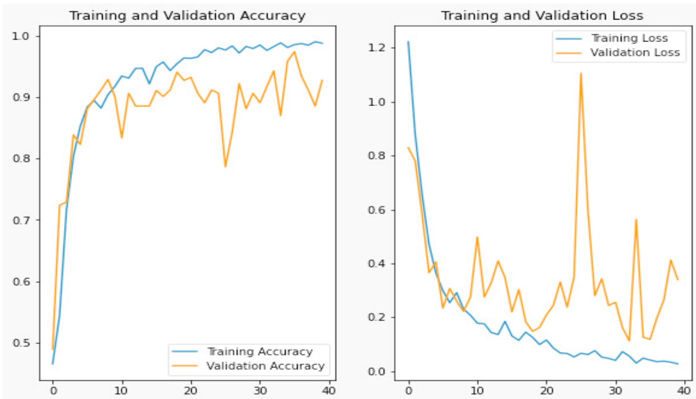

Figure 4. The Plot of Training and Validation Accuracy,Training and Validation Loss using VGG19

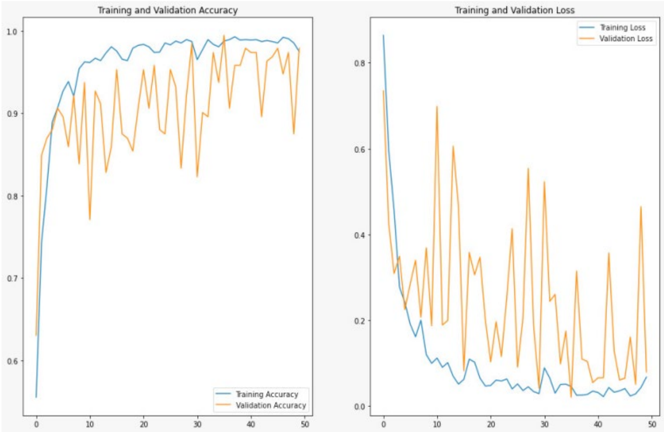

Figure 5. The Plot of Training and Validation Accuracy, Training and Validation Loss using DenseNet121

5. Results

The results demonstrate that all three CNN models achieved high performance in identifying and predicting potato leaf diseases, with VGG19 emerging as the top performer, closely followed by DenseNet121 and ResNet50. We evaluated the models' performance on both the training and validation datasets to gain a comprehensive understanding of their capabilities. The comparative analysis of these models illustrates their effectiveness in classifying potato leaf diseases and provides insights into how they can manage new data samples.The VGG19 model showed strong performance on the training dataset, with an accuracy of 98.77% and a loss of 0.0280. However, its performance on the validation dataset was slightly lower, with an accuracy of 92.71% and a loss of 0.3402, Indicating potential overfitting, DenseNet121 displayed remarkable results on both the training and validation data sets. It accomplished an accuracy of 97.51% and a loss of 0.0675 on the training data set, and an accuracy of 97.92% and a loss of 0.0797 on the validation data set.The ResNet50 model also displayed commendable results on the training dataset, with an accuracy of 97.78% and a loss of 0.0642. However, it showed weaker performance on the validation dataset, with an accuracy of 92.67% and a loss of 0.1726. Based on the results, DenseNet121 outperformed both VGG19 and ResNet50 in terms of validation loss and accuracy and is the most effective model. Our findings provide valuable insights into the efficacy of deep learning approaches for potato leaf disease detection and offer a foundation for future research and deployment of these models in precision agriculture systems. Ultimately, this work aims to support the development of more robust and efficient tools for timely disease diagnosis, enabling farmers and agronomists to make better-informed decisions and safeguard the health and productivity of potato crops worldwide.

6. Conclusion

Potatoes are a crucial crop worldwide and play an important function in meeting the dietary needs of millions of people. However, they are susceptible to various leaf diseases that can significantly impact their yield and quality. Early and precise identification of diseases is required for effective disease management and prevention. In this study, we present a detailed analysis and comparison of three state-of-the-art CNN models, namely VGG19, DenseNet121, and ResNet50, for recognizing and Potato leaf disease prediction. To evaluate the performance of the selected CNN models, we used a large dataset of potato leaf images, comprising various healthy and diseased samples. We applied extensive data augmentation techniques to enhance the dataset's diversity and generalization capabilities. To find the best model for real-world applications, we analysed the models' reliability, precision, recall, F1-score, and computing efficiency. This study explored the use of three cutting-edge CNN models-VGG19, DenseNet121, and ResNet50 - for the classification of potato leaf diseases. Our findings demonstrated that all three models can effectively classify the various potato leaf diseases with high accuracy. However, DenseNet121 emerged as the most suited model for this task after a thorough review of its efficacy on both the validation and training datasets, with an excellent accuracy of 97.92% on the validation dataset. The results of this study suggest that deep learning techniques can be leveraged to enhance the accuracy and efficiency of disease detection in crops, potentially leading to more effective disease management and improved crop productivity. The findings of this research provide a foundation for future studies and the deployment of these models in precision agriculture systems. Ultimately, this work aims to support the development of more robust and efficient tools for timely disease diagnosis, enabling farmers and agronomists to make better-informed decisions and safeguard the health and productivity of potato crops worldwide.

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