Potato Disease Classification Using Densent121

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***Abstract*— Image processing-based approaches for plant disease recognition and classification is an important area of current study. Such applications can detect diseases in plants in real-time. Plants are most vulnerable to fungal, bacterial, and viral infections. This study acknowledged five primary potato diseases: Early Blight, Late Blight, and Healthy Potato Plant Leaf. Colour, shape, and texture data extracted from healthy and ill potato plant photos are used to classify the plants. The feature extraction method is used after the segmentation step. The classification model was fed features extracted from segmented images. Finally, these five different types of classifications were used to classify diseases. Using five different types of potato photos resulted in an overall classification accuracy of 98%. Various studies have also been discovered to establish a more open approach to detecting potato diseases.**

***Keywords— Potato, Conv2D, NumPy, Convolutional Neural Networks (CNN), DenseNet***

##### introduction

Plant diseases that interrupt normal plant growth and cause crop yield losses are unusual. Suitable environmental conditions and crop types determine these diseases' prevalence and spread. To alleviate these losses, many plant disease control strategies have been created. In recent decades, significant progress has been achieved in identifying and diagnosing plant diseases. Early and precise disease detection may aid in implementing preventive measures to limit output loss and retain high-quality crops. Image recognition technology to identify plant diseases has grown in popularity, accelerating the development of visual applications and digital technologies.

Many publications have proposed and investigated image-processing algorithms for automatically detecting and measuring plant diseases. These ideas aim to develop a system that can detect plant diseases without needing domain experts. The condition can be identified using image processing techniques by extracting typical features from the damaged regions of infected plant pictures. Pattern recognition technologies such as neural networks (references number) and support vector machines (references number) are frequently used to detect disease-infected plants. Colour, shape, texture, and other properties are among the characteristics derived from plant disease digital pictures.

This research aimed to recognize various diseases that commonly affect horticultural plants to automate the identification and evaluation of plant diseases using image processing. The study examined photographs of potato plant leaves concerned with Early Blight, Late Blight. There were seven techniques for identifying potato plant infections in this study. Step 1: Load a total of three different types of photos. Step 2: Develop training and testing datasets. Step three is to segment the training and testing datasets. Steps 4 and 5 extract colour, shape, and texture information from segmented photos of healthy and sick potato plants. Load training data into the classification model in step 6. Step 7: Use a confusion matrix to visualise the outcome. The primary purpose of this classification model is to create an efficient architecture that's capable of reliably predicting potato diseases.

The research highlights the need for automated methods to detect and classify plant diseases, which can help identify early situations and prevent crop yield losses. The authors explicitly target two important tomato diseases and healthy potato plant leaves.

1. The colour, shape, and texture properties of healthy and diseased potato plants are extracted using segmented pictures. The collected features are then fed into a DenseNet classification model. Conv2D, MaxPooling2D, Resize, Rescalar, and Flatten are included in the model architecture, which is followed by SoftMax and Relu activation functions for multi-class classification.
2. The authors report an overall classification accuracy of 98% on the dataset used in their study, as well as research gaps and future directions, such as collecting larger and more diverse datasets, improving model interpretability, and incorporating other imaging modalities for accurate disease detection.
3. The publication includes A literature review that examines the use of DenseNet and transfers learning approaches in potato disease classification and problems and limitations in the field. It also evaluates the planned architecture's accuracy compared to other relevant works.

Finally, the research discusses a DenseNet-based strategy for potato disease classification and its potential benefits for farmers in automated disease identification. The suggested architecture achieves excellent accuracy and provides a feasible and efficient disease control strategy.

##### related work

Md co-authored him. Asif Iqbal and Kamrul Hasan Talukder, "Detection of Potato Disease Using Image Segmentation and Machine Learning," In August 2020, it appeared in conference paper form. The scientists used a publicly accessible plant village database to gather 450 photos of healthy and sick potato leaves. Hu Moments, Haralick Texture, and the Color Histogram were only a few of the global feature descriptors that were put to use throughout the feature extraction process. In addition, the authors used seven classifier methods to determine which leaves were healthy and which were infected, including Random Forest, Logistic Regression, k-Nearest Neighbors, Decision Trees, Naive Bayes, Linear Discriminant Analysis, and Support Vector Machine. The research showed that the Random Forest classifier could correctly detect and categorize illnesses affecting potato leaves with an accuracy of 97%. Overall, the study provides a strategy based on image processing and machine learning for autonomous diagnosing diseases in potato leaves. [1]

The paper by Ali Arshaghi, Mohsen Ashourian, and Leila Ghabeli titled "Potato diseases detection and Classification using deep learning methods" examines deep learning techniques. In July 2022, the work appeared in the Multimedia Tools and Applications journal. Five illnesses affecting potatoes are examined here using convolutional neural network (CNN) techniques: Healthy, Black Scurf, Common Scab, Black Leg, and Pink Rot. The research team used a dataset of 5,000 photos of potatoes to evaluate how well their suggested deep learning technique performed compared to existing methods, including AlexNet, GoogLeNet, VGG, R-CNN, and Transfer Learning. The paper's findings indicate that deep learning performed better than the other approaches and successfully classified potato illnesses more accurately. The authors claim 100% and 99% precision across all illness types.[2]

By Nour Eldeen M. Khalifa, Mohamed Hamed N. Taha, Lobna M. Abou El- Maged, and Aboul Ella Hassanien. In this study, we describe a suggested architecture that uses a deep convolutional neural network to differentiate between healthy potato leaves, leaves affected by early blight, and leaves affected by late blight. The authors found that the overall testing accuracy had significantly improved after using augmentation procedures to extend the dataset size from 1,722 to 9,822 photos. The suggested architecture has been tested and shown to have a mean accuracy of 98%. [3]

In the article "Detection of Potato Diseases Using Image Segmentation and Multi-class Support Vector Machine," the authors develop a method that combines image processing and machine learning approaches. The suggested way successfully classified illnesses on potato leaves in experiments, achieving an accuracy of 95%. While alternative methods for illness identification need costly hyperspectral imaging gear or computationally complex deep learning algorithms, the authors of this study emphasize the benefits of their RGB imaging-based approach. [4]

Previous studies have shown that deep learning methods help identify and categorize agricultural diseases in various crops. Bolle et al. presented a system that uses computer vision and machine learning. Other research has Artificial intelligence, specifically deep understanding, explored in the context of disease classification. This paper focused on particular crops, such as applying deep learning techniques to segment and classify banana leaf diseases. [5]

"Potato Disease Classification Using Convolution Neural Networks" was written by D. Oppenheim and G. Shani. This paper explores the potential of deep learning and computer vision for illness diagnosis in potatoes. For example, after training on 90% of the data, the top model attained a 96% accuracy in classification when evaluated on the remaining 10%. According to the study, a more extensive training set leads to more accurate categories. It also includes a confusion matrix study that shows how well CNN can categorize potato illnesses. [6]

##### methodology

Potato crops play a crucial role in global food security and agricultural economies. However, diseases significantly threatened potato production, leading to yield losses and decreased quality. Therefore, accurate and timely disease detection is essential for effective disease management strategies. In recent years, computer vision techniques, and intense learning models like CNN and DenseNet, have shown promising results in automating the detection and classification of potato diseases.

1. *Image Acquisition*

We have used two downloaded datasets. Combining them, we have taken 5403 images of size 256\*256 from Kaggle across three labels: Early Blight, Late Blight, and Healthy. The images used for each category are displayed below in Fig. 1. Table 1 gives the image count for each label.

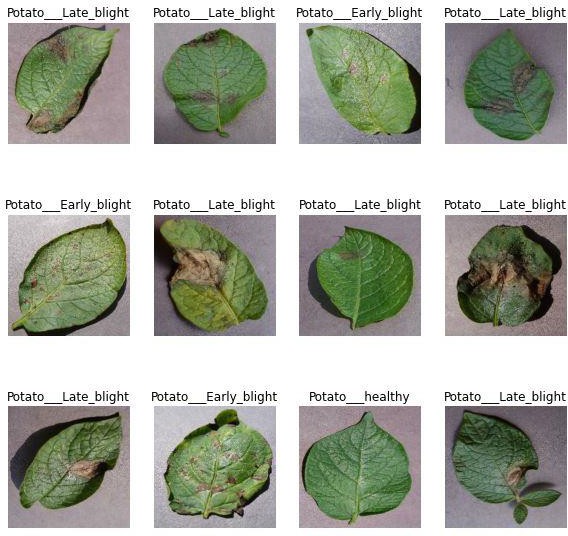


Fig. 1: Leaves Sample

|  |  |
| --- | --- |
| **Label Name** | **Number of Images** |
| Early Blight | 2303 |
| Late Blight | 2132 |
| Healthy | 968 |
|  |  |

Table 1: Label List

1. *Image Pre-Processing*

We loaded the images with the cv2.imread function and resized the photos into 64\*64. After resizing, we converted the images into a NumPy array and modified the pixel value from 0-255 to 0-1. This makes it easier for our model to train.

1. *Proposed Methodology*

Any image application can benefit from pre-processing methods that enhance image quality and characteristics. Detecting plant diseases is no different. The collection contains images with irrelevant context for identifying potato diseases in leaves. We convert the picture from RGB color space to a NumPy array to get around this. Then we balanced the pixel value. The model is pre-trained on the ImageNet dataset, which provides a good starting point for various computer vision tasks. Next, an input layer is defined to accept image data with specific dimensions, represented by SIZE and N\_ch. This allows the model to process images of varying sizes and channel depths. To adapt the DenseNet121 model to the specific problem at hand, a Conv2D layer is added as the first layer after the input.

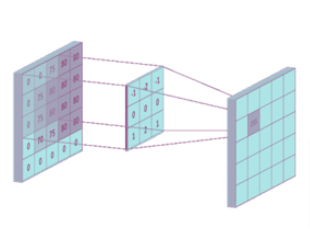


Fig. 2: NumPy Array

This layer performs convolutional operations on the input image, enhancing its representation and extracting relevant features. The pre-trained DenseNet121 model is then applied to the output of the Conv2D layer. This allows the model to leverage the learned features from the pre-trained layers and further refine the representation of the input image. Compared to related projects, the additional model layers are stacked on top of the initial DenseNet121 layers. To minimize the output's spatial dimensions, we use a GlobalAveragePooling2D layer, and then we add BatchNormalization and Dropout layers to boost generalization and stop overfitting. Suggested architecture fared better in tests.

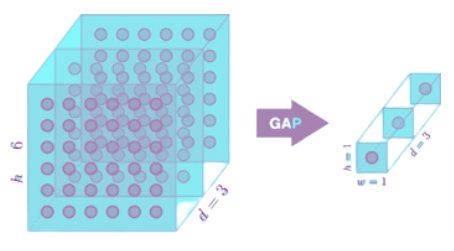


Fig. 3: Layer

A fully connected layer with 256 units and ReLU activation is included, followed by more BatchNormalization and Dropout layers for regularization. The final layer of the model is a dense layer with three teams and SoftMax activation, which outputs probabilities for three classes.

This indicates that the model is designed for a multi-class classification problem, aiming to classify input images into one of the three classes. The model is then compiled with the Adam optimizer, a commonly used optimization algorithm. The loss function is set to categorical cross-entropy, suitable for multi-class classification, and accuracy is chosen as the evaluation metric. Finally, the model summary is printed, summarizing the model architecture and the number of trainable parameters.

The following flowchart provides an overview and more detail on the subsequent topics. The simplified workflow is shown in Fig. 4 below.

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Description automatically generated

Fig. 4: Proposed Model

1. *Experimental Setup*

Python is utilized in the model, which typically aims towards a less-complicated, more straightforward language while providing programmers with a workaround, utilizing Keras. In addition, it has been decided to use the deep learning architecture. To compute mathematical operations, we use NumPy, and to Visualize our datasets, we have used pandas.

##### result and discussion

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Description automatically generated Infectious diseases of crops pose a global danger to agricultural production. Nevertheless, these risks may be controlled and eradicated at early stages with the help of artificial intelligence's advancements in detection and categorization. To classify potato leaf blight, the authors of this article recommended using a Densenet121 architecture. One Conv2D layer, one GlobalAveragePooling2D layer, two Batch Normalization layers, two Dropout levels, one Dense layer, and one Dense output layer comprise the suggested architecture's eight layers. By applying augmentation methods to a larger number of photos in the dataset, we were able to boost the accuracy of our tests significantly. A mean testing accuracy of 98% was attained by the suggested design. In this study, we give a confusion matrix detailing the many sorts of accuracy and the computed and reported performance measurements. Finally, a comparison of the suggested architecture's testing accuracy to that of similar works was offered. When compared to related projects, the proposed architecture fared better in tests.

Fig. 5: Actual vs. Predicted Graph

##### conclusion

This work uses the Denset121 architecture to build a user-friendly and self-service platform. With little computer work, the two most devastating potato diseases—late blight and early blight—can be diagnosed. Our approach will offer farmers a feasible, efficient, and timesaving way of disease identification. We plan to integrate more diseases of various species of plants into the system. Our future works will automatically estimate the detected disease's severity.

**Table 2 Comparison results of related works and the proposed architecture**

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Year** | **Description** | **Accuracy (%)** |
| [1] | 2020 | Random Forest | 97.00 |
| [2] | 2022 | CNN | 99.00 |
| [3] | 2017 | Support Vector Machine (SVM) | 95.00 |
| Proposed Architecture | 2023 | Densenet121 | 98.00 |

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