

Investigating Profound Learning Systems for Potato Disease Characterization

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Abstract— Given the swift advancements in agricultural technology and the escalating integration of artificial intelligence in identifying plant diseases, there is a pressing need for conducting practical research to further the progress of sustainable agriculture. To preserve food safety and enhance product quality, it is crucial to identify and classify potato flaws. Identifying the early stages of potato leaf diseases can be difficult because of the differences among crop species, variations in symptoms of crop diseases, and the influence of environmental factors. Detecting potato leaf diseases in their initial stages presents a challenge due to these variables. In the proposed model The early and late blight on potato leaves must be identified using a deep learning technique. In the proposed model the plant village datasets are used which comprise 2152 photos that were downloaded and included in the collection for potato leaves. The accuracy of the proposed model is 98%.

Index Terms— Deep Learning, Plant Disease, Image Classification, Machine learning.

I. INTRODUCTION

Potatoes are the fifth highest-produced commodity used for human consumption. The total worldwide production of potatoes in the year 2018 was 388,192,000 tonnes. (Source: FAOSTAT, 2019).

Infection during the growth of the plant or infection by the harvesting and use of chemicals can make potatoes defective which has low nutritional value that affects potato prices and consumers also.

The disease in the plant can be due to biotic factors like bacteria, algae, and fungi. Or due to other natural factors like rainfall, moisture, soil moisture content, temperature, and nutrition. The demand for the food supply will be 70% more by the year 2050 and the annual crop yield loss will be around 16% due to diseases. Therefore the diagnosis of the plant disease is essential to reduce the loss.

Numerous approaches exist for diagnosing plant diseases. One of the conventional methods involves visualization, relying significantly on the farmer's experience and often resulting in uncertainty and unreliability. Also, the manual visualization approach is very time- taking and requires a great amount of human labor. Some other approaches are spectroscopy methods and remote sensing methods or by extracting the DNA of the leaves by using a polymerase chain reaction. But these methods require expert operations and are not very economical, which is not feasible for a normal farmer who is indulged in the production. But the rapid development in technology like deep learning and image classification makes the detection of plant diseases automated. These techniques can detect the defect in the plant without the intervention of the human in less time and more certainly and economically than other methods. In recent years, various models based on machine learning(ML) /

Deep learning have been proposed to classify diseases in the plant.

The convolutional neural network (CNN) is commonly acknowledged as the most prevalent technique. These supervised deep learning models exhibit remarkable performance relative to other methods, drawing inspiration from both the biological nervous system and the visual system. Unlike Artificial Neural Networks (ANNs), CNNs employ fewer neurons and incorporate multiple convolution layers to capture features., although they do require a substantial training dataset. Several methods have been created in the last decades to identify leaf diseases in a variety of crops. In the majority of the techniques, features were fed into a classification algorithm after being extracted using image processing techniques.

To detect tomato leaf disease, [1] suggested a two- level deep-learning method. By applying residual learning, the authors utilized the first model to pinpoint significant features, while incorporating the second deep learning model as an attention mechanism. Subsequently, they identified late blight, early blight, and leaf mold diseases affecting tomato crops based on the Plant Village dataset. The application of deep learning approaches has a lot of issues. The primary issue is that the current approach lacks precision for different regions in the world as different regions have differences in the plants and the current practice is trained only on the plant village dataset which has only 152 healthy images. Let's say that the ratios of 80%, 10%, and 10% are used to divide the photos in the training, validation, and testing sets, respectively. And we have 1000 images of each disease which may lead to the model being over-fit to train. It is necessary to develop a dataset based on the regions so that the model can provide precise outputs for the plants of the different regions.

II. LITERATURE SURVEY

To identify and categorize potato diseases, new technologies like RGB imaging, x-ray, ultrasound, multispectral analysis, and hyperspectral analysis have been developed. Earlier, many researchers suggested using conventional image processing techniques like LBP, which stands for clustering, to find diseases in potato leaves. [2].utilized the Back Propagation Neural Network algorithm to detect and categorize diseases present in leaf images, achieving an impressive classification accuracy of 92%. Their methodology consisted of utilizing a segmentation technique that employed K Means Clustering on various features extracted from samples of potato leaf images. These features encompassed aspects such as color, texture, area, among others

In order to encompass a range of image attributes such as contrast, correlation, energy, homogeneity, mean, standard deviation, and variance, [3] implemented image segmentation as a technique for feature extraction. Following the extraction of these attributes, a neural network was employed as a classifier to detect and categorize diseases found on the leaves of two distinct plant species: cotton and tomato. Through this methodological approach, they attained a classification accuracy rate of 92.5%.

According to [4] a model employing deep convolutional neural networks was utilized to assess the infection of 13 folios while taking tomato and apple flora into account. The technique was utilized to separate 13 different ailments among healthy and damaged leaves.

A new experimental finding on a model created by [4] Employing convolutional neural networks (CNNs), the method can identify 13 various disease types alongside five different plant diseases. Through their investigation and study, they achieved an average accuracy rate of 96.3%.

[5] employed a multiclass Support Vector Machine to classify diseases on segmented images, using image segmentation principles specifically focused on the potato leaf category within the Plant Village dataset. This method led to a classification accuracy of 95%.

To confirm the hypotheses regarding potato diseases, [5] employed a multi-class Support Vector Machine model, utilizing a collection of 300 different images. The investigator then assessed the model's effectiveness by examining various operational metrics, including sensitivity, precision, F1-score, and recall.

[6].used the same technique but a different architecture to create a disease diagnosis system for cucumber plants using the Convolutional

Neural Network technique, achieving an average accuracy of 82.3%.

The Plant Village database, provided by [7], contains 2000 maize leaf photographs, which researchers utilized to classify three different types of illnesses using a multiclass SVM (Support Vector Machine) approach and various variables. Furthermore, they assessed the accuracy and precision of this method, In comparison to the histogram method and feature- based grey level co- occurrence, the experimental findings showcased the higher accuracy achieved by the SVM multiclass approach.

In their research, [8] applies segmentation through K-means clustering to identify the affected area of the plant. Following this, they extract color and texture features from the image. Data classification is conducted using the Support Vector Machine (SVM) method, resulting in an accuracy rate of 88.89%.

III. MATERIALS AND METHODS

A. Materials

Dataset

The proposed CNN was utilized for classifying specific test images sourced from the Plant Village dataset, which served as the foundation for model development. This dataset, widely utilized in plant disease research, comprises 1000 images each depicting fungal early blight disease and fungal late blight disease, alongside 152 images representing healthy plants. However, it lacks data from other regions, as the visual characteristics of potatoes may vary across different areas. All images in the dataset are standardized to dimensions of 256 * 256 pixels. A depiction of the dataset is presented in Figure 1.

B. Methods

In this research, a convolutional neural network is employed to classify fungal diseases affecting potato plants. A prominent attribute of CNNs is their capacity to autonomously learn and extract relevant features from raw input data. This ability is accomplished by a set of computational layers, comprising convolutional layers, pooling layers, and fully connected layers.

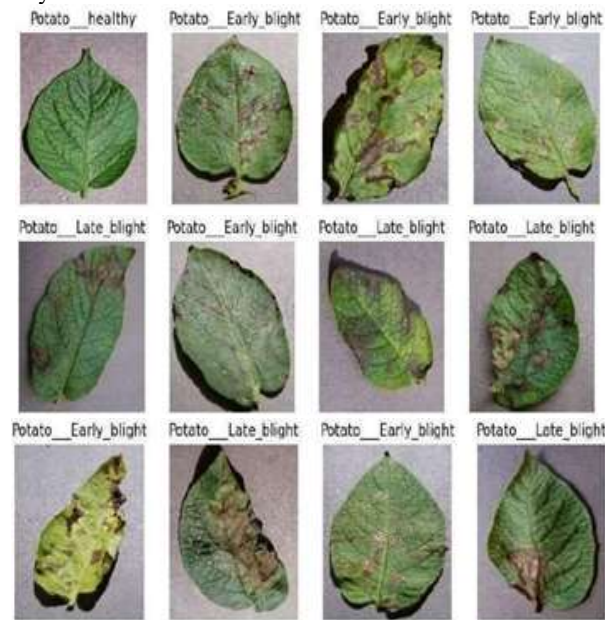


Fig.1. Sample dataset

Convolutional layers are fundamental elements within CNNs. They utilize a set of adaptable filters, or kernels, to perform a convolution operation on the input data, extracting spatial features such as edges, textures, and patterns. This method involves the element-wise multiplication of the filter weights with the input data, followed by a summation process. As a result, feature maps are generated, capturing distinct aspects of the input.

Pooling layers are utilized to decrease the spatial dimensions of feature maps., effectively managing computational complexity and mitigating overfitting. Among the various pooling operations, max pooling is the most commonly employed, selecting the maximum value from each local neighborhood within the feature map.

Fully connected layers are typically situated at the end of the CNN architecture. They receive high- level features from preceding layers and translate them into class scores or predictions. Each neuron in a fully connected layer connects to every neuron in the previous layer, resembling the structure of a traditional neural network.

Proposed Algorithm for the CNN Model.

1. Data set Collection.
2. Creating three categories out of the dataset of potato leaf images: training (80%), testing (10%), and testing (10%).

3. The training photos are subjected to preprocessing and data augmentation.
4. Auto-resize the dimensions of the annotated photos.
5. Upload the dataset to Google Cloud.
6. Using a jupyter notebook, train and validate the data.
7. Utilize the dataset training images to assist in training the CNN model.
8. Utilize the validation photos to check the dataset after training.
9. Save the CNN model for identifying potato diseases.
10. Using the testing images from the dataset testing is conducted on the trained saved model.

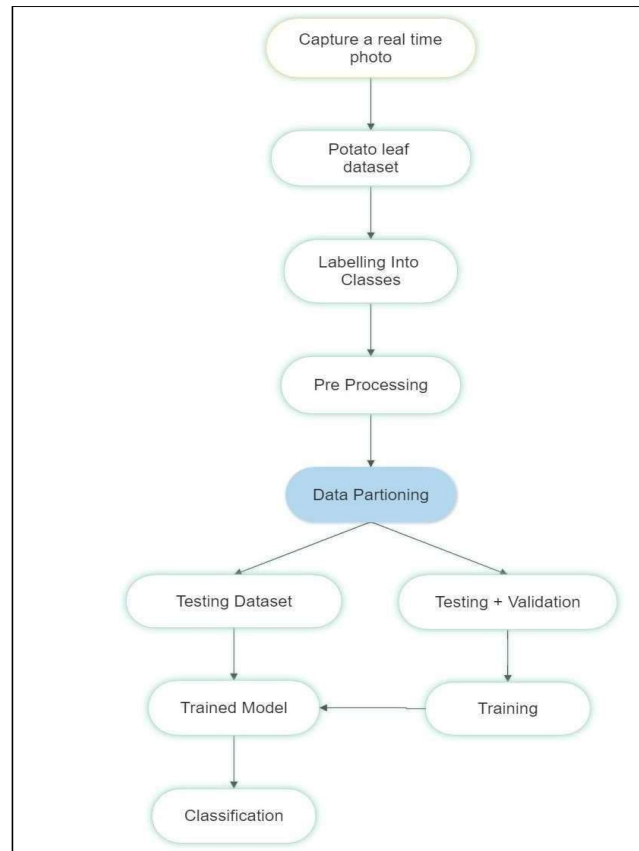


Fig.2. Workflow for the proposed system

Image preprocessing

Image preprocessing refers to the preparatory steps undertaken on visual data prior to its in-depth analysis. This preliminary stage involves a series of techniques designed to enhance the quality and utility of images, enabling more accurate subsequent analysis. These techniques encompass a range of actions such as noise reduction, contrast adjustment, resizing, and normalization. By refining the raw image data through preprocessing, researchers and analysts can subsequently extract more meaningful insights from the images, thereby facilitating more robust and accurate conclusions in various fields of study.

Data augmentation

The data augmentation technique makes the dataset more robust and is used to increase the dataset by adding some minor changes in the existing data set. Like changing the orientation of the image like horizontal flip or vertical flip or adjusting the contrast of the images. Data augmentation also adjusts the pixels and rotates the images by some specific angle.

In order to develop a successful model, it is crucial to train the model on specific training datasets and evaluate its accuracy using a validation set. The potato disease dataset is divided into three parts: training, validation, and testing, distributed in proportions of 80%, 10%, and 20% respectively.

In the plant village dataset, a total of 2152 images 1722 images are used for the testing and 215-215 images are used the in the validation and testing. The splitting of datasets is shown in Fig -3.

Different data augmentation techniques, including rescaling, width shifting, height shifting, horizontal flipping, and vertical flipping, are applied to the training sets. The current CNN model utilizes Adam optimization for the research. To maintain the 80% ratio, the model selects training images from the categories of early blight, healthy, and late blight, while keeping the remaining 20% of the data unchanged. This untouched portion of the data is subsequently divided into validation and testing sets to evaluate the performance of the developed and trained model.

```

In [16]: train_ds = dataset.take(54)
         len(train_ds)
Out[16]: 54

In [17]: test_ds = dataset.skip(54)
         len(test_ds)
Out[17]: 14

In [18]: val_size=0.1
         len(dataset)*val_size
Out[18]: 6.800000000000001

In [19]: val_ds = test_ds.take(6)
         len(val_ds)
Out[19]: 6

In [20]: test_ds = test_ds.skip(6)
         len(test_ds)
Out[20]: 8

```

Fig.3. Splitting of the dataset

IV. RESULTS

A. Proposed CNN Model Performance

The CNN model is trained using 80% of the data in the data set and the experiment used Adam optimizer technique and batch size of 32 and 50 epochs. In the result, the proposed CNN model provides an accuracy of 99% and when we run the scores command it shows an accuracy of 1.00 which means 100% for the given datasets. It is shown in the Figure 4.

The training and validation accuracy, along with the training and validation loss of the CNN model, are depicted in graphs presented in Figure-5. Additionally, Figure-6 exhibits the confidence graph.

```

Epoch 36/50
54/54 [=====] - 10s 178ms/step - loss: 0.0431 - accuracy: 0.9844 - val_loss: 0.0217 - val_accuracy: 0.9948
Epoch 37/50
54/54 [=====] - 10s 178ms/step - loss: 0.0353 - accuracy: 0.9896 - val_loss: 0.0092 - val_accuracy: 1.0000
Epoch 38/50
54/54 [=====] - 9s 173ms/step - loss: 0.0206 - accuracy: 0.9936 - val_loss: 0.0079 - val_accuracy: 1.0000
Epoch 39/50
54/54 [=====] - 9s 171ms/step - loss: 0.0307 - accuracy: 0.9913 - val_loss: 0.0209 - val_accuracy: 0.9896
Epoch 40/50
54/54 [=====] - 9s 175ms/step - loss: 0.0143 - accuracy: 0.9948 - val_loss: 0.0240 - val_accuracy: 0.9896
Epoch 41/50
54/54 [=====] - 9s 170ms/step - loss: 0.0196 - accuracy: 0.9936 - val_loss: 0.0441 - val_accuracy: 0.9844
Epoch 42/50
54/54 [=====] - 9s 173ms/step - loss: 0.0382 - accuracy: 0.9832 - val_loss: 0.2912 - val_accuracy: 0.9271
Epoch 43/50
54/54 [=====] - 9s 172ms/step - loss: 0.0416 - accuracy: 0.9832 - val_loss: 0.0425 - val_accuracy: 0.9896
Epoch 44/50
54/54 [=====] - 9s 171ms/step - loss: 0.0162 - accuracy: 0.9948 - val_loss: 0.0567 - val_accuracy: 0.9792
Epoch 45/50
54/54 [=====] - 9s 170ms/step - loss: 0.0990 - accuracy: 0.9653 - val_loss: 0.0892 - val_accuracy: 0.9688
Epoch 46/50
54/54 [=====] - 9s 171ms/step - loss: 0.0243 - accuracy: 0.9919 - val_loss: 0.0174 - val_accuracy: 0.9948
Epoch 47/50
54/54 [=====] - 9s 170ms/step - loss: 0.0476 - accuracy: 0.9844 - val_loss: 0.0217 - val_accuracy: 0.9896
Epoch 48/50
54/54 [=====] - 9s 170ms/step - loss: 0.0184 - accuracy: 0.9931 - val_loss: 0.1227 - val_accuracy: 0.9635
Epoch 49/50
54/54 [=====] - 10s 184ms/step - loss: 0.0298 - accuracy: 0.9884 - val_loss: 0.0528 - val_accuracy: 0.9844
Epoch 50/50
54/54 [=====] - 11s 196ms/step - loss: 0.0189 - accuracy: 0.9948 - val_loss: 0.0064 - val_accuracy: 1.0000

scores = model.evaluate(test_ds)
8/8 [=====] - 1s 14ms/step - loss: 0.0063 - accuracy: 1.0000

```

Fig.4. The statistics regarding accuracy and loss of the model on the data

B. Training and Validation

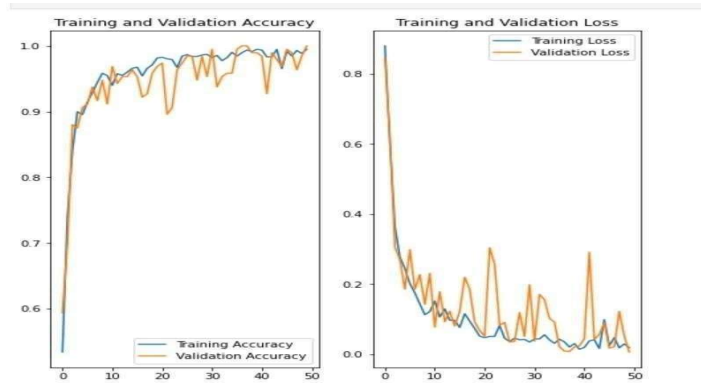


Fig.5 Accuracy of the model

Training accuracy serves as a gauge of a model's performance on the same dataset it was trained on. It signifies the model's capacity to predict the known outcomes within the training dataset accurately. A high training accuracy suggests that the model effectively accommodates the training data, captures underlying patterns, and fine-tunes its parameters to minimize discrepancies. Nevertheless, achieving a high training accuracy does not guarantee good performance on unseen data and could result in overfitting if the model becomes too specialized in the training dataset. Throughout training, the training loss measures the disparity between the model's predictions and the actual values within the training dataset. As the model improves its ability to fit the training data, the training loss decreases. A lower training loss signifies a better alignment with the training data. Validation accuracy measures the model's capability to generalize to fresh, unseen data. It quantifies the model's accuracy on a distinct validation dataset that was not part of the training process. The objective is to attain high validation accuracy, indicating that the model can make precise predictions when exposed to new, real-world data. A substantial disparity between training and validation accuracy could be indicative of overfitting, suggesting that the model may not generalize effectively. While Validation loss quantifies the model's error when applied to a separate dataset. It aids in detecting overfitting and evaluates the model's ability to generalize to new data. An increasing validation loss concurrent with a decreasing training loss may signal overfitting and limited generalization capacity.

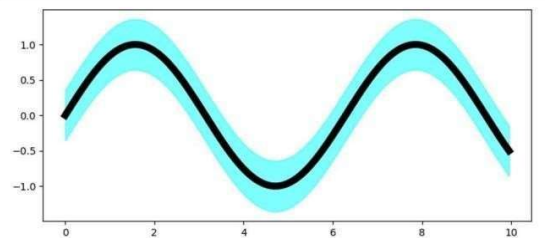


Fig-6 Confidence graph of the model

A confidence graph is a useful visual tool that is mostly used in classification jobs to evaluate the accuracy of predictions made by a model. Each prediction is given a confidence or probability score by the model, indicating how confident it is in the corresponding class or label. The graph offers information about the performance and behavior of the model by showing these confidence scores. This visualization can be used by researchers to assess the consistency and correctness of the model, which will help in decision-making. Additionally, it provides the option to set confidence thresholds, improving the model's usefulness for a variety of applications.

V. CONCLUSION AND FUTURE WORK

Deep learning proves to be a significantly very useful and essential technique in automating the classification of disease. The proposed plant disease classification CNN model is a straightforward model of deep learning which uses the data set of the plant village and uses data augmentation for pre-processing and was

able to provide 99% accuracy in the training while the existing manual traditional techniques have a high false ratio.

In the future, the work can be extended to creating a model which can detect multiple diseases on the single leaf images and use it like devices to collect the images from the field and create a more user- friendly interface that can be used by normal people which do not have much knowledge about the technology and devices which uses real-time monitoring and triggers whenever there is a disease developed on the plant.

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