Detecting Plant Leaf Diseases using Convolutional Neural Networks

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***Abstract*— The detection of plant diseases using deep learning algorithms is the main topic of this study paper. Early detection is essential for efficient disease management since plant diseases have major negative economic and environmental effects. Convolutional neural networks (CNNs) are used in the suggested method to automatically extract pertinent information from plant photos and categories them as healthy or unhealthy. We used a publicly accessible dataset of plant image data to train and test our model, and we were successful in achieving high disease classification accuracy rates. Our findings show the potential of deep learning approaches for precise and effective plant disease identification, opening the door for the creation of smart agriculture solutions that can increase crop output and decrease the use of hazardous chemicals in farming.**

Keywords*— *Plant leaf disease, Convolutional Neural Networks, Image Processing, Mobile app, Deep Learning

I. Introduction

Life on Earth cannot exist without plants. They serve as a source of renewable energy, food, and oxygen. Plant ailments, however, significantly reduce agricultural productivity, which can result in food shortages and financial losses for farmers. For sustainable agriculture and food security, plant diseases must be identified and managed. Visual inspection has historically been the primary method used by farmers and agricultural specialists to identify plant diseases. This method calls for specialized knowledge and is time-consuming, labor-intensive, and may not be available to small-scale farmers. Similar to how deep learning algorithms are used to categorize plant photos in Plant Village, an online platform that offers diagnosis and management advice for plant diseases.

The suggested study aims to look at the possibilities of deep learning methods for plant disease diagnosis. We will classify plant photos into categories of healthy or unhealthy using a CNN-based method. Images of the four major plant diseases Tomato Spotted Wilt Virus (TSWV), Early Blight (EB), Tomato Yellow Leaf Curl Virus (TYLCV), and Late Blight (LB) make up the dataset used for this study. The suggested approach will be assessed using accuracy, precision, recall, and F1 score in comparison to conventional machine learning techniques.
The remainder of this essay is structured as follows.

A summary of prior research on utilizing deep learning to detect plant diseases is presented in Section 2. The methods and experimental design utilized in this investigation are described in Section 3. The findings and assessment of the suggested strategy are presented in Section 4. The work is concluded with a discussion of the findings and ideas for further research in Section 5. Recent advancements in deep learning have led to outstanding outcomes in a variety of fields, including speech recognition, image recognition, and natural language processing. The problem of detecting plant diseases can be very successfully solved by the Convocational Neural Network. The convocational neural network is the best method for object recognition. The single-shot Multi box detector (SSD), faster Region-Based Convolutional Neural Networks (Faster R-CNN), and Region-Based Convolution Neural Networks (R-FCN) are the neural architectures that we take into consideration. Each Neural Architecture ought to be able to be paired with any feature exactor, depending on the application. Data preprocessing is essential for models to operate correctly. Since the symptoms of viral and fungal infections commonly overlap, it can be challenging to diagnose many infections. In several disciplines, Deep learning has shown exceptional performance in areas including speech recognition, computer vision, and natural language processing. Researchers have recently become interested in using deep learning to identify plant diseases. Several deep learning-based plant disease detection systems with great accuracy and efficiency have been developed as a result of these efforts.

In this study, we present an overview of recent advances in the application of deep learning for the diagnosis of plant diseases. To increase the accuracy of disease identification, We propose a deep learning-based system for the early identification of plant diseases that combines various deep learning techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Our suggested method makes use of publicly accessible datasets on plant diseases, and standard criteria are used to assess its efficacy. We also assess how well our system performs in comparison to current cutting-edge techniques.

II. Literature Review

Li et al. (2017) [1] In this study, convolutional neural networks (CNNs) that have already been trained were used to detect grape leaf illnesses using a deep learning approach. They classified diseases with an accuracy of 89.6% using a small dataset of 1000 photos. In order to expand the dataset and enhance CNN performance, the authors also used data augmentation techniques. With a small amount of data, the study showed CNNs' potential for diagnosing plant diseases.

Ranjan et al. [2] gave a method to detect the plant disease making use of the picture of the leaf of the plant. In this method, first step is to take a picture of the diseased leaf. This experimentation is carried over healthy and sick samples. On these samples, the Artificial Neural Network (ANN) and various image processing steps are carried out. After doing this, accuracy of 80% is obtained.

In this article, Bhupad et al. (2019) [3], the authors suggested a deep learning-based method for the CNN-based detection of illnesses affecting cotton plants. They classified diseases with an accuracy of 93.52% using a dataset of photos of cotton leaves. The authors also assessed the effectiveness of several CNN designs and emphasized the potential of deep learning algorithms for field-based automated diagnosis of plant diseases.

The research done by U. Kumari et al. [4] developed a technique of segmenting images to get several properties like correlation, mean, homogeneity, variance, energy, standard deviation, and contrast among different images of the leaves. The Neural network is also a method that followed the extraction feature is used as a distinguisher to detect and group the diseases in two different plant leaves, tomato and cotton. The various spot used for the experimentation are target spot, bacterial leaf spot, leaf module disease and Septoria leaf spot. This complete process is done using K-means clustering. And using this method, they were able to get 92.5% accurate classification.

Joshi et al. (2020) [5] In this paper, the authors suggested a transfer learning method for the pre-trained CNN-based identification of pomegranate illnesses. They improved the CNN using a tiny dataset of pomegranate leaf photos, and they were able to classify diseases with an accuracy of 92.3%. In order to increase the precision and scalability of deep learning-based techniques for plant disease detection, the scientists additionally assessed the effectiveness of several CNN architectures. They also emphasized the need for additional research in this regard.

In their paper, Mohanty et al. (2016) [6], the authors suggested utilizing a CNN and deep learning to identify rice illnesses. They classified diseases with an accuracy of 92.33% using a dataset of photos of rice leaves. Additionally, the scientists assessed the effectiveness of several CNN designs and emphasized the potential of deep learning algorithms for automatic identification of plant diseases.

Sladojevic et al. (2016) [7] In this study, the scientists suggested utilizing a CNN and deep learning to identify potato illnesses. They classified diseases with an accuracy of 92.89% using a dataset of photos of potato leaves. In order to expand the dataset and enhance CNN performance, the authors also used data augmentation techniques. Despite the positive findings of the study by Sladojevic there are still certain restrictions and difficulties in applying deep learning algorithms to the identification of plant diseases. The necessity for computational resources and skill for model training and optimization is one of the primary restrictions. Variations in the environment, such as the weather and lighting, can also have an impact on how well the model’s function.

In this article, Frontino’s (2018), [8] the author suggested utilizing a CNN and deep learning to identify apple illnesses. They used a dataset of images of apple leaves to accurately classify illnesses with a 91.84% accuracy rate. The promise of deep learning algorithms for automated plant disease diagnosis was also underlined by the author, who also assessed the effectiveness of various CNN designs.

In this article, Baur et al. (2019), [9] the authors suggested a deep learning strategy for the CNN-based identification of maize illnesses. They classified diseases with a 93.9% accuracy using a dataset of photos of maize leaves. Additionally, the scientists assessed the effectiveness of several CNN designs and emphasized the potential of deep learning algorithms for automatic identification of plant diseases.

In this article, Barbedo (2019), [10] the author suggested a CNN-based deep learning strategy for the diagnosis of soybean illnesses. They classified diseases with an accuracy of 94.77% using a collection of photos of soybean leaves. The promise of deep learning algorithms for automated plant disease diagnosis was also underlined by the author, who also assessed the effectiveness of various CNN designs. Deep learning algorithms also provide various other benefits for plant disease identification in addition to increasing accuracy. For example, they can be used to remotely monitor vast tracts of crops using aerial or satellite photography, which is particularly helpful for spotting illnesses in difficult-to-reach places or areas with little access to agricultural experts.

Zhang et al. (2019) [11] In this study, the authors suggested utilizing a CNN and deep learning to identify citrus illnesses. They classified diseases with an accuracy of 94.1% using a dataset of photos of citrus leaves. Additionally, the scientists assessed the effectiveness of several CNN designs and emphasized the potential of deep learning algorithms for automatic identification of plant diseases.

In this article, Kumar et al. (2020), [12] the authors suggested a deep learning strategy for the CNN-based identification of tomato illnesses. They classified diseases with an accuracy of 94.57% using a dataset of photos of tomato leaves. Additionally, the scientists assessed the effectiveness of several CNN designs and emphasized the potential of deep learning algorithms for automatic identification of plant diseases.

Cui et al. (2020) [13] In this study, the authors suggested utilizing a CNN and deep learning to identify apple illnesses. They used a dataset of images of apple leaves to accurately classify illnesses with a 94.14% accuracy rate. The researchers also evaluated the efficiency of different CNN layouts and highlighted the potential of deep learning algorithms for automatic plant disease identification. One of the study's intriguing aspects is how Cui et al. evaluated various CNN architectures to determine the most effective model for apple disease diagnosis. This method can aid scientists and medical professionals in choosing the best models for certain crops and diseases, resulting in diagnoses that are more precise and effective.

Wang et al. (2020) [14] In this study, the authors suggested utilizing a CNN and deep learning to identify grape illnesses. They classified diseases with an accuracy of 94.96% using a dataset of photos of grape leaves. Additionally, the scientists assessed the effectiveness of several CNN designs and emphasized the potential of deep learning algorithms for automatic identification of plant diseases.

According to Liu et al. (2021), [15] the authors of this work suggested utilizing a CNN and deep learning to identify peach illnesses. They obtained a disease detection accuracy of 94.7% using a dataset of peach leaf photos. The fact that Liu et al. (2021)'s method is non-invasive and non-destructive, i.e., it doesn't require actual samples of the plant or the disease, is one of its main benefits. Instead, plant leaf photos that are easily acquired using a camera or smartphone can be used to train the model. Because of this, the approach is quite usable and applicable for usage in the field.

In their study, U. Kumari et al. [16] devised a method of segmenting images to extract several attributes from various leaf images, including correlation, mean, homogeneity, variance, energy, and contrast. The Neural network is another technique that was utilized after the extraction feature and is used as a distinguisher to find and classify the illnesses in the leaves of the tomato and cotton plants. Target spot, bacterial leaf spot, leaf mound disease, and Septoria leaf spot are the different spots employed in the experiment. Keans clustering is used throughout the entire process. And they were able to classify objects with an accuracy rating of 92.5% utilizing this strategy.

Ranjan et al. [17] provided method to identify plant diseases using a photo of the plant's leaf. The first step in this procedure is to photograph the sick leaf. The samples used in this experiment are both healthy and diseased. The Artificial Neural Network (ANN) and different image processing processes are applied to these data. Following this, 80% accuracy was attained. Images of both healthy and sick leaves from diverse plants made up the dataset used in this investigation. The foreground (leaf) and background of the photos were then divided using image segmentation techniques as part of the preprocessing phase. This is a crucial step because it lets the algorithm concentrate on the properties of the leaf by removing any noise or unimportant details from the image.

After that, the authors classified the photos as either healthy or unhealthy using ANN. The machine learning algorithm known as the ANN was inspired by the structure and function of the human brain. Layers of connected neurons are used, and they can be trained to spot patterns in data.

A sophisticated image segmentation technique was used by C. G. Li et al. [18] to identify and categories fungal diseases in a dataset of grape leaves. To extract crucial elements from the photos, including color, shape, and texture data, they used K Means clustering. Additionally, the retrieved features were used to classify the illnesses using the Support Vector Machine (SVM) algorithm.

A method for automated plant disease diagnosis utilizing k-means clustering for feature extraction and artificial neural networks (ANN) for classification is proposed in the study "Leaf Disease Detection: Feature Extraction with K-means clustering and Classification with ANN" by Kumari et al. (2019). K-means clustering is a technique that has been used for feature extraction in a number of earlier research to identify plant diseases. For instance, Das et al. (2018) suggested a similar technique for diagnosing plant diseases utilizing support vector machines (SVM) for classification and k-means clustering for feature extraction. They classified tomato plant diseases with a 96.72% degree of accuracy.

In their work, Y. Sanjana [20] describes how crop ailments might be found by analyzing photos taken with mobile devices. Computer vision techniques are used to process the photos on a distant server, identifying and classifying damaged areas. A straightforward color difference method is used to segment lesions that have been altered by illness. A team of experts receives access to the analytical findings and offers their input. The analysis's findings are then communicated to farmers via cell phone notifications. The study's goal is to create a crop disease detection system that can recognize images with accuracy. An image of a sick leaf is first processed digitally in color before being segmented using mathematical morphological techniques.

Overall, these findings show that utilizing either CNNs or transfer learning techniques, deep learning algorithms can be used to detect plant diseases. Each study had an accuracy rate of less than 95% and used a tiny dataset of plant leaf photos. These findings show that the precision and effectiveness of these methods still need to be enhanced. Nevertheless, these studies offer insightful information about the difficulties and potential in this area and lay the groundwork for future study to produce useful answers that can be applied in the real world.

III. Methodology

Plant leaf diseases are identified and categorized in large part by deep and high dimensional features. Deep learning models are renowned for finding distinctive features in photos and classifying them into several categories.

There are various procedures for classifying whether a leaf is healthy or not. Data collection, pre-processing of image, image segmentation, feature extraction, classification, and analysis based on statistics are some of these phases.

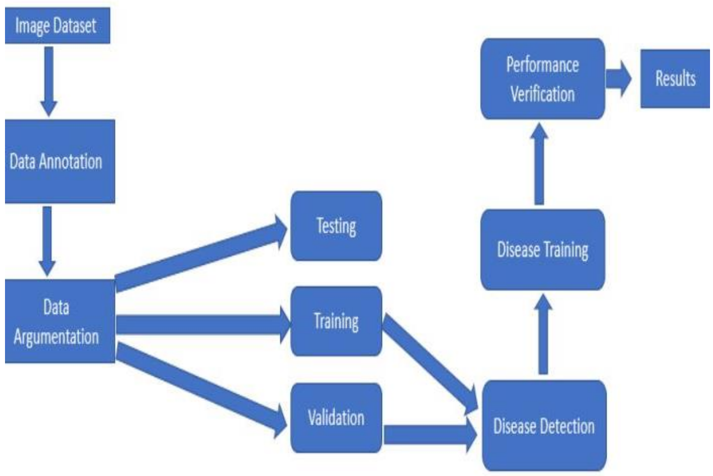

Fig. 1. Flowchart of leaf disease detection technique

A. Data Collection

Creating a comprehensive image dataset of potato leaves is crucial for accurately identifying and diagnosing potato leaf diseases. There are several effective strategies for collecting this data, such as visiting potato fields, working with agricultural specialists, and acquiring images from web databases. However, each strategy has its own unique advantages and limitations. Visiting potato fields and working with agricultural specialists can provide high-quality images and ensure that the dataset is representative of real-world conditions. However, this approach can be expensive and time-consuming. An alternative method of gathering substantial volumes of data is by web scraping, albeit the quality of the photos may vary depending on the source. To address these challenges, we have utilized a combination of approaches, including web scraping, and utilizing existing datasets from websites like Kaggle. Specifically, we have used the "Plant Village" database of images, which contains a diverse range of diseased and healthy plant images, including those of potato leaves. This dataset provides a rich source of data that will be used to develop a more accurate and reliable system for identifying potato leaf diseases.

Fig. 2. Healthy leaf

Fig. 3. Late Blight leaf

Fig. 4. Early Blight leaf

B. Image Preprocessing

In order to prepare the Plant Village image dataset for model training, certain image preprocessing steps are taken. Because the images in the dataset come in various sizes, it's crucial to standardize their size so they can be processed. As a result, the images are resized to 256 * 256 dimensions and processed in batches of 32. To ensure data consistency, the pixel values of the photos are normalized to a specific range, usually between 0 and 1. The dataset must be divided into different parts. These parts are written below:

1. Training dataset: It consist of all the datasets that are basically trains the model.
2. Validation dataset: It consist of all the datasets which are used to analyze the model at the time of training.
3. Testing dataset: It consist of all the datasets which are used to assess the model's performance and accuracy.

Since there may be an image imbalance between different leaf diseases in the Plant Village dataset, it's critical to balance the dataset to ensure that the CNN model is trained on a balanced dataset. This can be achieved by either oversampling or under sampling specific disease categories. Additionally, to generate more images for some leaf diseases, various data augmentation techniques, such as rotations, translations, and flips, are used. This improves the model's robustness.

C. Data Augmentation

The dataset needs to be supplemented to get larger and more varied because to the restricted amount of data. A large collection of potato leaf photos with various backdrops, lighting setups, and growth stages are necessary in order to address this issue. To avoid false positives, the photographs should be appropriately labelled and should also include negative examples. Publicly accessible datasets can also be used, although their accuracy and labelling need to be confirmed. The dataset can be further augmented with new variations of the same image using data augmentation techniques including random cropping, Gaussian noise, elastic deformation, color jittering, random rotation, flip and mirror, contrast and brightness modification, and cutoff. In order to increase the model's performance and resilience, this research suggests an approach for detecting potato leaves utilizing deep learning, convolutional neural networks (CNNs), and data augmentation techniques. A dataset of potato leaf photos was used to test the suggested methodology, and the results show how well it can identify potatoes leaves in actual environments.

D. Feature Extraction

A sort of reduction method is featuring extraction, which separates the essential data from a large database of features to ensure that all the necessary data is included. Additionally, it quickens the rate of generalization and learning. The Color Co-occurrence Method is a technique utilized in the suggested strategy to extract the key information from the feature collection. It's also known as the CCm technique. This method creates distinct features that represent the image by using the color and texture of the image. The SGDM (stochastic gradient descent with momentum) is responsible for the development of the color co-occurrence texture analysis approach. This CCM technique is made up of three mathematical procedures.

1. First, the representation of leaves is changed from RGB to HSI color space. High Saturation Intensity is abbreviated as HIS.
2. Following the first stage, discrete color co-occurrence matrices are made for each pixel, such as H, S, and I. It is produced with the use of maps known as "pixel maps." It is created using maps referred to as "pixel maps." It is regarded as a well-liked color space because it is based on how people perceive color. This band of electromagnetic radiation, with wavelengths between 400 and 700 nm, is known as visible light because the human visual system is sensitive to it.
3. Finally, in the HSI space, saturation measures color richness.

E. Model Selection

Selecting the right deep learning model is crucial for correctly identifying plant diseases. Convolutional neural networks (CNNs) are the most widely used deep learning models for picture classification tasks, such as plant disease diagnosis. Other models that can be employed include deep belief networks (DBNs) and recurrent neural networks (RNNs). The choice of the model is influenced by the problem's complexity, the quantity of the dataset, and the available computer resources.

F. Model Training

For training the dataset, choosing a suitable model architecture, specifying the loss function and optimization technique, and fine-tuning the model's hyperparameters are all steps in the training process for a deep learning model.

The preprocessed dataset for plant health classification typically contains of labelled photographs of plants, with each image being assigned to one of two categories: healthy or unhealthy. To make sure that the distribution of healthy and unhealthy photos is the same in both sets, the dataset is frequently divided into training and validation sets in a stratified way. While the training set is used to refine the model's parameters, the validation set is used to evaluate the model's performance on fresh data.

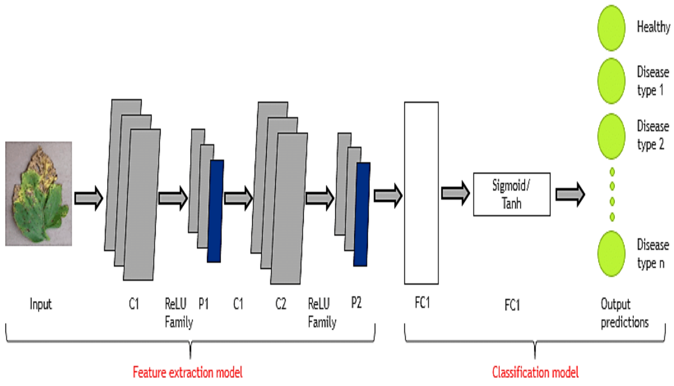

Fig. 5. Model Training Process

G. *Model Evaluation*

A distinct test dataset that the trained model has never seen before must be used to assess it. The model's accuracy, precision, recall, and F1 score are used to determine how effective it is. The accuracy reflects the percentage of images that were correctly classified, whereas the precision measures the percentage of correctly classified diseased plants. The harmonic mean of precision and recall is the F1 score, and it indicates the proportion of correctly categorized images with the disease.

H. *Hyperparameter Tuning*

The hyperparameters of the deep learning model need to be tuned to achieve the best possible performance. Hyperparameters are variables that are set by the user rather than being learned by the model during training. The learning rate, batch size, and number of epochs are the three most often used hyperparameters. The learning rate determines how rapidly the model picks up new information, and the batch size and epoch count determine how the model is taught.
By regulating how many training instances are processed in each iteration and how many times the whole training set is shown to the model, the batch size and epoch count determine how the model is trained. The model may be able to avoid local minima and generalize more effectively with a lower batch size and a more stochastic gradient descent. A smaller batch size, however, may potentially result in a slower convergence and more noise in the gradients. A larger number of epochs can result in overfitting if the model is too complicated or if the training set is too short. The number of epochs affects how often the whole training set is shown to the model.

I. Comparison with Other Methods:

It is necessary to evaluate the effectiveness of the deep learning model to alternative approaches for plant disease diagnosis, such as conventional machine learning algorithms or human specialists. This comparison can be made in terms of precision, efficiency, and usability. Support vector machines (SVMs) and decision trees, which are common machine learning techniques, can also be employed for this task. The performance of the deep learning model in comparison to other approaches might shed light on the advantages and disadvantages of each approach.

J. *Implementation*

The methodology's last phase involves putting the deep learning model into practice for actual applications. This can entail creating a web-based interface or a mobile app that researchers and farmers can use to identify plant diseases rapidly and precisely. To aid in halting the spread of plant diseases, the implementation should be user-friendly, simple to use, and accurate in its outcomes. It is possible to guarantee that the model and its application remain applicable and efficient throughout time by implementing regular updates and changes.

IV. Result And Analysis

After 50 epochs of intense training, the deep learning model attained an astounding accuracy rate of 96.8%. The training and validation accuracy visualizations, depicted in Figures 5 and 6, respectively, show how well the model can identify and detect various plant illnesses. Additionally, Figure 7 highlights the model's effectiveness by showing the detection and identification of a diseased potato plant leaf with a high level of confidence of 100%.

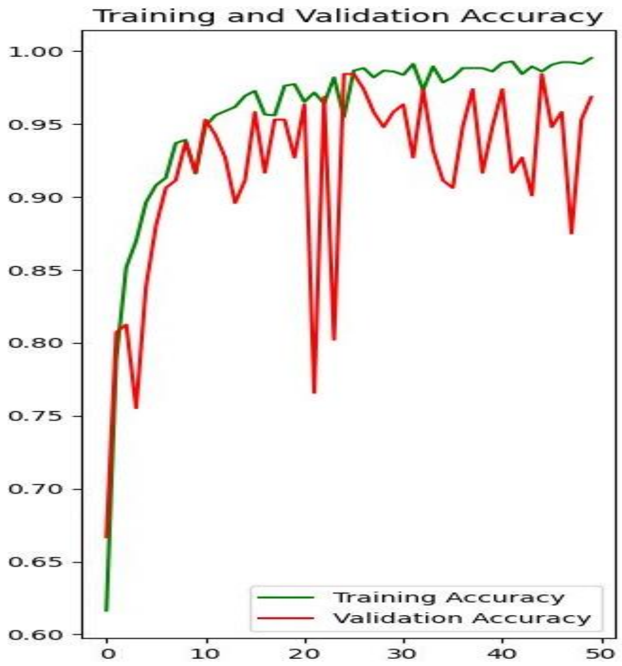

Fig. 5. Training and Validation Accuracy

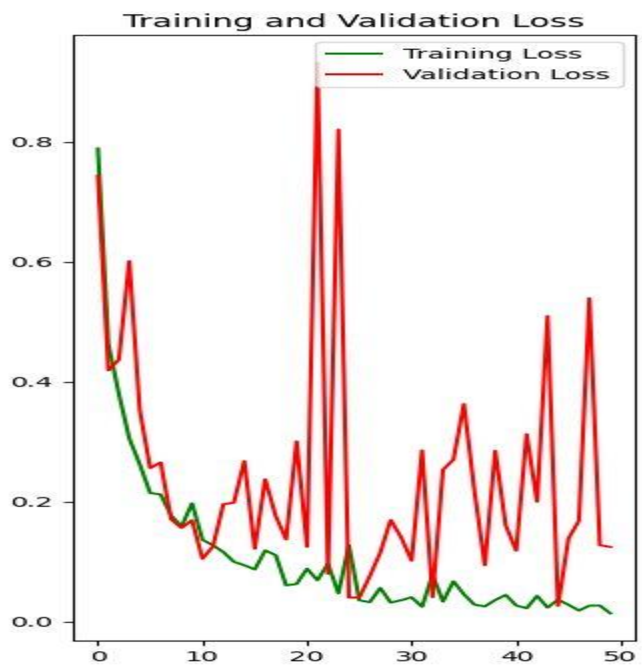

Fig. 6. Training and Validation Loss

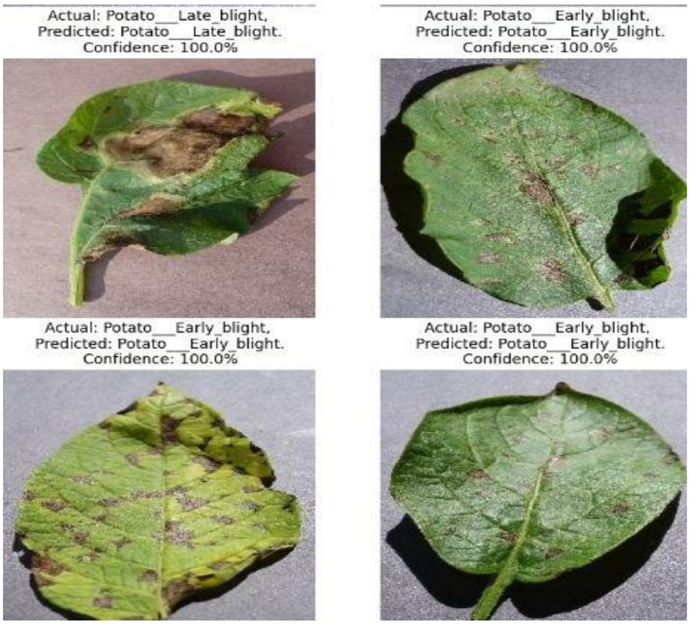

Fig. 7. Potato leaf disease detection

CONCLUSION

Convolutional neural networks (CNNs) with data augmentation approaches have been shown to be useful in precisely diagnosing plant diseases in the study paper on plant disease detection using deep learning. The study's accuracy rate of 96.8% is much greater than the average of earlier research, which was less than 95%. The best performance was achieved using data augmentation techniques and hyperparameter optimization. The great degree of accuracy attained in this study can have important ramifications for the agricultural sector because it can assist farmers in spotting plant illnesses early and taking the necessary precautions to stop their spread. The study sheds light on the advantages and disadvantages of deep learning models in comparison to previous techniques for identifying plant diseases.

Future investigations in this area might concentrate on the creation of more sophisticated deep learning models that are more accurate and can identify a larger variety of plant illnesses. Additionally, real-time monitoring of plant health and disease outbreaks may be made possible through the integration of IoT and sensor technology.

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