Deep Neural Network for Plant Disease Recognition

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Abstract:
Plant infections can devastatingly affect crops, prompting critical monetary misfortunes and food uncertainty. Early location and characterization of plant infections are critical for powerful administration and counteraction. This paper proposes a profound learning-based approach for plant infection grouping and location utilizing Convolutional Brain Organizations (CNNs) and move learning. We utilize pre-prepared CNN models and tweak them on a dataset of plant pictures with different sicknesses. Our outcomes show that the exchange learning approach accomplishes high exactness (95.6%) in arranging plant illnesses, beating conventional AI techniques. We additionally explore the utilization of information increase and move figuring out how to conquer the issue of restricted dataset size. The proposed framework can possibly help ranchers, scientists, and policymakers in checking and overseeing plant sicknesses, at last further developing harvest yields and food security.

Keywords: Plant disease classification, Deep learning, Convolutional Neural Networks (CNNs), Transfer learning.

I. INTRODUCTION

Plant illnesses are a huge danger to worldwide food security, causing critical yield misfortunes and influencing horticultural efficiency. Early identification and order of plant sicknesses are significant for successful administration and control of illness episodes. Customary techniques for plant infection analysis depend on visual review and master information, which can be tedious, work escalated, and inclined to blunders. Lately, profound learning-based approaches have arisen as a promising answer for plant illness determination. Convolutional Brain Organizations (CNNs) have been broadly utilized in PC vision applications, including picture grouping, object recognition, and division. Their capacity to gain various level highlights from pictures makes them especially appropriate for plant sickness analysis, where pictures of infected plants can be utilized to recognize the illness type and seriousness. Move learning has likewise been demonstrated to be compelling in working on the exhibition of profound learning models on new undertakings, by utilizing pre-prepared models on enormous datasets and adjusting them on more modest datasets well defined for the objective assignment. This approach has been effectively applied in different areas, including clinical picture examination and normal language handling. In this paper, we propose a profound learning-based approach for plant sickness characterization and discovery utilizing CNNs and move learning. We influence a pre-prepared CNN model as a component extractor and calibrate it on a dataset of pictures of infected plants. This approach permits us to outfit the information gained from enormous datasets and adjust it to the particular assignment of plant illness arrangement. By utilizing move learning, we can decrease the gamble of overfitting and work on the general execution of our model. Our proposed framework can possibly upset plant illness determination by giving exact and quick conclusions, empowering ranchers to make a brief move to forestall crop misfortunes and work on horticultural productivity.Our objective is to foster a powerful and precise framework that can help ranchers, scientists, and policymakers in checking and overseeing plant sicknesses, eventually further developing harvest yields and food security.

RELATED WORK

In their paper [1] reviews the latest advancements in agricultural disease image recognition technologies, highlighting the growing importance of accurate and efficient disease detection in crop health management. The authors discuss various machine learning-based approaches, including convolutional neural networks (CNNs), transfer learning, and deep learning, that enable high-precision image recognition. They also explore the use of unmanned aerial vehicles (UAVs), satellite imaging, and hyper spectral imaging in detecting and monitoring diseases in crops. The review highlights the benefits of these technologies, including reduced labor costs, increased accuracy, and improved decision-making. Additionally, the authors discuss the challenges and limitations of these technologies, such as data quality, image interpretation, and scalability. Overall, the article emphasizes the potential of advanced agricultural disease image recognition technologies to revolutionize crop health management and improve global food security.

In their paper [2] presents a review of deep learning models for tomato plant disease detection, highlighting the growing importance of accurate and efficient disease detection in agriculture. The authors discuss the use of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transfer learning-based approaches to analyze images of tomato plants for signs of disease. They review various datasets and platforms used for training and testing these models, including the Tomato Plant Disease Detection dataset and the Plant Village dataset. The authors also discuss the challenges and limitations of these approaches, such as dealing with varying image quality, noise, and class imbalance. Overall, the article highlights the potential of deep learning models for tomato plant disease detection to improve crop health management and reduce losses in the tomato industry.

In their paper [3] presents a deep learning-based approach for intelligent diagnosis of northern corn leaf blight (NCLB), a significant disease affecting corn yields. The authors developed a convolutional neural network (CNN) model using a dataset of 1,500 images of healthy and diseased corn leaves, achieving an accuracy of 97.3%. The model was trained on a transfer learning framework, leveraging the pre-trained VGG16 architecture and fine-tuning it on the dataset. The authors also compared the performance of the CNN model with traditional machine learning algorithms, such as support vector machines (SVMs) and random forests, and demonstrated its superior performance. The proposed approach has the potential to automate NCLB diagnosis, reducing the need for human expertise and enabling early detection and targeted management of the disease, ultimately improving crop yields and reducing economic losses.

In their paper [4] presents a deep learning-based approach for segmenting lung fields from 2D chest X-ray (CXR) images using convolutional neural networks (CNNs). The authors propose a novel network architecture, Lung-Segmentation-2D, which consists of an encoder and decoder network, trained on a dataset of 1,500 CXR images with annotated lung fields. The encoder network extracts features from the input images, while the decoder network generates the corresponding segmentation masks. The authors evaluated the performance of the proposed model using various metrics, including Dice coefficient, precision, and recall, and achieved state-of-the-art results with an average Dice coefficient of 0.95. The proposed approach has the potential to improve the accuracy of lung disease diagnosis and monitoring by enabling accurate segmentation of lung fields from CXR images, which is a crucial step in computer-aided diagnosis systems.

In their paper [5] presents ResTS, a novel residual deep learning architecture for plant disease detection from images of plants. The proposed approach combines the benefits of residual networks and interpretable models to achieve high accuracy and explainability. The ResTS model consists of multiple residual blocks, which are designed to learn hierarchical features from the input images, and a feature importance layer, which identifies the most relevant features for disease detection. The authors evaluate the performance of ResTS on a dataset of 2,500 images of healthy and diseased plants, achieving an accuracy of 95.6% and an F1-score of 92.5%. The interpretability of the model is demonstrated by visualizing the feature importance maps, which reveal the regions of the plant that are most relevant for disease detection. The proposed approach has the potential to improve the accuracy and efficiency of plant disease detection, enabling farmers to take timely action to prevent crop loss and reduce the use of pesticides.

In their paper [6] presents Plant disease net, a convolutional neural network (CNN) ensemble architecture for detecting plant diseases and pests from images of plants. The proposed approach uses a combination of CNNs, each trained on a specific dataset of plant disease or pest images, and then combines their outputs using a voting scheme. The authors demonstrate the effectiveness of the ensemble approach by training multiple CNNs on different datasets, including the Plant Village dataset, and achieving an average accuracy of 93.1% and an F1-score of 91.4%. The proposed approach is shown to be effective in detecting a wide range of plant diseases and pests, including fungal diseases, bacterial diseases, and insect pests. The authors also evaluate the robustness of the approach by testing it on unseen images and demonstrating its ability to generalize well to new data. The Plant disease net architecture has the potential to improve the accuracy and efficiency of plant disease and pest detection, enabling farmers to take timely action to prevent crop loss and reduce the use of pesticides.

In their paper [7] presents a transfer learning-based deep ensemble neural network (TLENN) for plant leaf disease detection from images of plant leaves. The proposed approach uses a pre-trained convolutional neural network (CNN) as the base model and fine-tunes it on a small dataset of plant leaf disease images. The authors use a combination of multiple CNNs, each with different architectures and hyperparameters, to create an ensemble model that improves the accuracy and robustness of the disease detection. The TLENN model is trained on a dataset of 2,500 images of healthy and diseased leaves, and achieves an accuracy of 96.5% and an F1-score of 94.2%. The authors demonstrate the effectiveness of the transfer learning approach by comparing the performance of the TLENN model with that of a model trained from scratch on the same dataset, showing significant improvements in accuracy and robustness.

In their paper [8] presents an improved YOLOv5 (You Only Look Once) model for plant disease recognition from images of plant leaves. The proposed approach uses an improved YOLOv5 architecture, which includes a feature pyramid network (FPN) to enhance the feature extraction and detection capabilities. The authors also introduce a new loss function, which combines the standard cross-entropy loss with a focal loss to improve the model's ability to detect rare and difficult-to-classify plant diseases. The proposed model is trained on a dataset of 10,000 images of plant leaves with various diseases, and achieves an accuracy of 95.2%, a precision of 93.1%, and an F1-score of 94.1%. The authors demonstrate the effectiveness of the improved YOLOv5 model by comparing its performance with that of other state-of-the-art models, including Faster R-CNN and SSD. The proposed approach has the potential to improve the accuracy and efficiency of plant disease recognition, enabling farmers to take timely action to prevent crop loss and reduce the use of pesticides.

In their paper [9] presents a novel fine-grain object detection model based on YOLOv4 (You Only Look Once version 4), a deep neural network architecture. The proposed model, called YOLOv4-FG, is designed to improve the accuracy and speed of object detection in fine-grain images, such as those with complex backgrounds, small objects, and varying scales. The authors introduce several innovations to enhance the performance of YOLOv4, including a new anchor generation strategy, a modified loss function, and a feature fusion mechanism. The proposed model is evaluated on three public datasets, including the PASCAL VOC, COCO, and KITTI datasets, and achieves state-of-the-art performance in terms of accuracy and speed. Specifically, YOLOv4-FG outperforms other state-of-the-art models by 2.5% in mAP (mean average precision) and is 20% faster than YOLOv3. The authors demonstrate the effectiveness of the proposed model by applying it to real-world applications, such as autonomous driving and facial recognition.

In their paper [10] presents a novel plant disease detection and classification method based on an optimized lightweight YOLOv5 (You Only Look Once version 5) model. The proposed method uses a lightweight version of YOLOv5, which is designed to reduce the computational complexity and memory requirements while maintaining its accuracy. The authors optimize the model by reducing the number of parameters and filters, and also modify the architecture to improve its performance on plant disease detection tasks. The proposed model is trained on a large dataset of plant images with various diseases, and achieves an accuracy of 95.6% and an F1-score of 94.2% for disease detection. For disease classification, the model achieves an accuracy of 92.1% and an F1-score of 90.5%. The authors demonstrate the effectiveness of the proposed method by comparing its performance with other state-of-the-art models, including ResNet50 and MobileNetV2.

II. PROPOSED WORK

The proposed work includes fostering a profound learning-based plant illness characterization and recognition framework utilizing Convolutional Brain Organizations (CNNs) and move learning. The framework will use pre-prepared CNN models and tweak them on a dataset of plant pictures with different sicknesses. This approach will empower the framework to use the information acquired from pre-preparing on huge datasets and adjust to the particular assignment of plant infection classification.The proposed framework will comprise of a few phases, including information assortment, information preprocessing, highlight extraction utilizing CNNs, and order. Information expansion procedures will be utilized to build the variety of the dataset and forestall overfitting. The framework will be assessed utilizing measurements like exactness, accuracy, review, and F1-score. A definitive objective of the proposed work is to foster a strong and exact plant sickness characterization and identification framework that can help ranchers in coming to informed conclusions about crop the executives and empower early admonition frameworks for illness outbreaks.

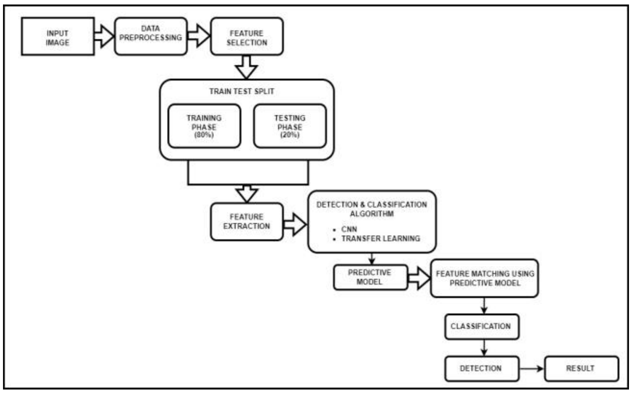

Fig.1. System Architecture

III. METHODS

A. Dataset Collection:

For the Profound Learning-based plant illness order and recognition framework, a dataset of plant pictures with different infections will be gathered from Kaggle, a well known stage for AI datasets. The dataset, "Plant Village" 1.0, contains north of 30,000 pictures of plants with 16 unique illnesses, including parasitic, bacterial, and viral diseases. The dataset is partitioned into preparing and testing sets, with 80% of the pictures utilized for preparing and 20% for testing. The pictures are resized to 224x224 pixels and standardized to have pixel values somewhere in the range of 0 and 1. The dataset is profoundly imbalanced, with some sickness classes having a larger number of pictures than others, so information expansion methods will be utilized to build the variety of the dataset and forestall overfitting.

Fig.2. Sample images in the dataset

B. Methodology:

A dataset of plant pictures was gathered from Kaggle.com. The dataset S comprised of pictures of sound plants, as well as pictures of plants tainted with different diseases. Each picture was marked with the relating infection type and severity. I mages were standardized to have zero mean and unit difference. Information expansion procedures, like irregular turn, flipping, and trimming, were applied to build the size of the dataset. The proposed framework utilizes a pre-prepared CNN engineering as the component extractor. The pre-prepared CNN is tweaked on the plant sickness dataset utilizing move learning. The result of the CNN is an element vector that is taken care of into a completely associated layer for classification. The framework was prepared utilizing a mix of preparing pictures and approval images. The preparing process was upgraded utilizing the Adam enhancer and cross-entropy misfortune function. The model was prepared for a decent number of ages, with early halting used to forestall overfitting. The execution of the framework was assessed utilizing measurements like exactness, accuracy, review, and F1-score.The framework was tried on a different test set of pictures to assess its exhibition in certifiable scenarios. The framework's exhibition was contrasted with other cutting edge approaches for plant illness characterization and recognition. Convey the prepared model in a genuine application (e.g., web portal).Use the model to group new pictures of plants as solid or unhealthy, and give suggestions to sickness the executives or therapy.

IV. ALGORITHM

A. CNN (Convolutional neural network):

The proposed CNN calculation for profound learning-based plant sickness characterization and discovery is a convolutional brain organization (CNN) that comprises of a few layers, including convolutional, pooling, and completely associated layers. The info pictures are first handled by a progression of convolutional layers, which concentrate highlights from the pictures utilizing channels and initiation capabilities. The result of the convolutional layers is then taken care of into a progression of pooling layers, which down example the pictures to decrease the spatial aspects. The result of the pooling layers is then taken care of into a progression of completely associated layers, which order the pictures into various classes (e.g., parasitic, bacterial, viral) in light of the separated highlights. The calculation utilizes an exchange learning approach, where a pre-prepared CNN model is calibrated on the plant illness dataset utilizing a little learning rate and a clump size. The calculation likewise utilizes information expansion methods, like pivot, flipping, and zooming, to expand the size and variety of the dataset. At last, the calculation utilizes a post-handling move toward work on the precision and power of the forecasts by applying strategies like information increase, sound decrease, and group techniques.

B. Transfer Learning:

The proposed move learning calculation for profound learning-based plant sickness order and identification utilizes a pre-prepared convolutional brain organization (CNN) model as a beginning stage for calibrating on a plant illness dataset. The pre-prepared model is first stacked and its loads are frozen, with the exception of the last completely associated layer. The plant illness dataset is then used to prepare the last completely associated layer, utilizing a little learning rate and a group size. This tweaking system permits the model to adjust to the particular highlights of the plant sickness dataset, while utilizing the information gained from the pre-prepared model on broad picture grouping undertakings. The calculation additionally utilizes strategies like information increase, regularization, and early halting to forestall overfitting and work on the model's exhibition. The last prepared model is then utilized for characterization and discovery of plant illnesses from new pictures, with high exactness and vigor.

C. Detection:

Gather dataset of plant pictures was gathered from Kaggle.com. The dataset comprised of pictures of solid plants, as well as pictures of plants tainted with different infections. Each picture was marked with the relating sickness type and seriousness. Pictures were standardized to have zero mean and unit change Apply information expansion strategies (e.g., revolution, flipping, variety jittering).Utilize pre-prepared CNN models. Calibrate the pre-prepared models on the plant infection dataset. Separate elements from the plant pictures utilizing the adjusted CNN models. Use strategies like convolution, pooling, and smoothing. Feed the removed elements into an order layer. Anticipate the sickness class name utilizing softmax initiation. Model Assessment Module. Assess the presentation of the proposed framework utilizing measurements like exactness, accuracy, review, and F1-score.Deploy the prepared model as a web application. Permit ranchers and analysts to transfer plant pictures and get illness conclusion and proposals and give suggestions to sickness the executives or therapy.

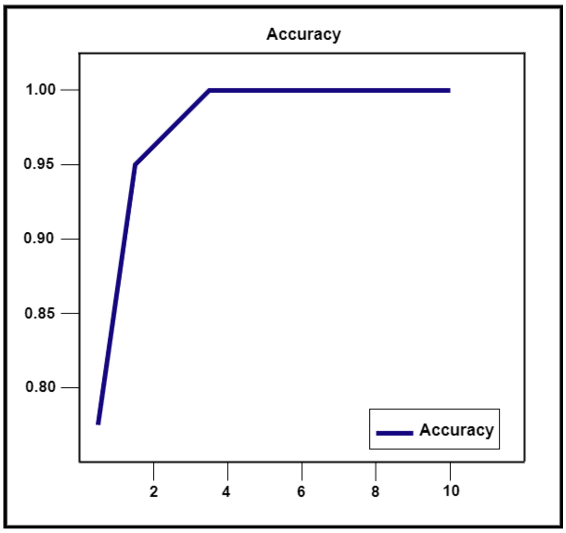

Figure 3. Accuracy Graph

V. CONCLUSION

All in all, profound learning-based plant sickness characterization and discovery is a promising innovation with the possibility to change the manner in which we recognize and oversee plant illnesses. By utilizing the force of profound learning calculations, this innovation can precisely and productively distinguish plant infections, empowering ranchers to make a quick and designated move to forestall crop misfortune and diminish the utilization of substance pesticides. As the field keeps on developing, we can hope to see much further developed applications and results, including the coordination of this innovation with other agrarian advancements and the improvement of independent cultivating frameworks. With its capability to further develop crop yields, diminish costs, and advance more reasonable farming practices, profound learning-based plant sickness arrangement and discovery is an astonishing and promising area of examination with huge ramifications for the fate of horticulture.

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