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Plant Disease Detection Using Deep Learning

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ABSTRACT:

Plant diseases pose a significant threat to global agricultural production, leading to reduced crop yields and economic losses. Traditional disease detection methods rely on manual inspection by experts, which is time-consuming, expensive, and often impractical for large-scale farming. To address these challenges, this project, Plant Disease Detection Using Deep Learning, leverages advanced deep learning techniques to automate the identification and classification of plant diseases. A large dataset of field plant images, including both healthy and diseased samples, is collected and preprocessed to train a Convolutional Neural Network (CNN)-based model. The model is designed to recognize patterns and features in plant leaves, enabling accurate classification of various plant diseases

Introduction

By the year 2050, the world's population is projected to reach a staggering 10 billion individuals. As a result, food production needs to accommodate the increasing population, even though there is a limited amount of arable land available. The United Nations Food and Agriculture Organization (FAO) recommends boosting the food supply by 70% to cater to the future population by 2050, while approximately one-third of all cultivated food is discarded due to plant diseases or disorders. Plant diseases have a significant economic impact, resulting in losses of around us$ 220 billion each year. Decline in agricultural productivity is a significant scientific inquiry. Plants perish if their leaves are unable to produce chlorophyll through photosynthesis due to diseases or disorders. Artificial intelligence (ai) has been extensively studied to address the issue of crop yield loss, particularly in the fields of computer vision and machine learning. As a result, numerous deep convolutional neural networks (cnn) have been suggested by researchers for the identification and classification of plant diseases. The objective of these solutions is to assist farmers in detecting plant diseases promptly and recommending preventive measures to prevent crop damage.

Literature Review

Plant diseases pose significant threats to agricultural productivity, impacting food security and economic stability. The advent of deep learning has revolutionized disease detection, offering automated, accurate, and efficient solutions. This note synthesizes findings from key studies in 2021-2025, focusing on recent reviews from 2023 to 2025, to provide a detailed overview of the field as of April 16, 2025. It addresses the approaches, achievements, and limitations of various models, while exploring ongoing advancements and their implications for precision agriculture. The study, "DHBP: A dual-stream hierarchical bilinear pooling model for plant disease multi-task classification" (ScienceDirect), introduced a model leveraging fine-grained image recognition and multi-task learning with homoscedastic uncertainty optimization. It achieved 84.71% accuracy for plant classification and 75.06% for disease classification under complex field conditions, facing challenges with computational complexity and limited scalability.

 MobileNet-Based Approach by Elhoucine Elfatimi and Recep Eryigit et al. (2022)
Titled "Beans Leaf Diseases Classification Using MobileNet Models" (IEEE Xplore), this study focused on bean leaf disease classification, achieving over 97% training accuracy and 92% test accuracy. The efficiency of MobileNet models is notable, but it risks overfitting and lacks feature interpretability.
 EfficientNetV2 with U2-Net by Sunil C. K. and Jaidhar C. D. et al. (2022)
The study, "Cardamom Plant Disease Detection Approach Using EfficientNetV2" (IEEE Xplore), combined U2-Net preprocessing with EfficientNetV2, attaining 98.26% accuracy for cardamom and grape diseases, but struggles with computational complexity and interpretability.

- **End-to-End Deep Learning Model by Hassan Amin and Ashraf Darwish et al. (2022)**

The study, "End-to-End Deep Learning Model for Corn Leaf Disease Classification" (IEEE Xplore), developed a model combining EfficientNetB0 and DenseNet121, achieving 98.56% accuracy for corn leaf disease identification, facing potential computational complexity during feature fusion.

- **Novel CNN by Sk Mahmudul Hassan and Arnab Kumar Maji et al. (2022)**

The paper, "Plant Disease Identification Using a Novel Convolutional Neural Network" (IEEE Xplore), introduced a model with inception layers and residual connections, achieving 99.39% accuracy on PlantVillage, with challenges in scalability and generalization.

- **Robust Detector by Alvaro Fuentes and Sook Yoon et al. (2021)**

The study, "A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition" (MDPI), evaluated Faster R-CNN, R-FCN, and SSD with VGG net and ResNet, achieving effective recognition of nine disease and pest types, but facing sensitivity to image variations.

- **Overview by Manivarsh Adi and Abhishek Kumar Singh et al. (2021)**

The study, "An Overview on Plant Disease Detection Algorithm Using Deep Learning" (IEEE Xplore), explored ANN and CNN with pre-trained models, highlighting computational constraints and sensitivity to environmental factors.

- **Cassava Mosaic Disease Detection by David Opeoluwa Oyewola and Emmanuel Gbenga Dada et al. (2021)**

The study, "Detecting cassava mosaic disease using a deep residual convolutional neural network with distinct block processing" (NCBI), introduced a DRNN, outperforming plain CNN by 9.25% on the Kaggle Cassava Disease Dataset, with dependency on diverse training data.

- **Imbalanced Datasets by Mobeen Ahmad and Muhammad Abdullah et al. (2021)**

The paper, "Plant Disease Detection in Imbalanced Datasets Using Efficient Convolutional Neural Networks With Stepwise Transfer Learning" (IEEE Xplore), achieved 99% accuracy on Pepper and 99.69% on PlantVillage, addressing class imbalance with challenges in fine-tuning hyperparameters.

- **Review by Lili Li and Shujuan Zhang et al. (2021)**

The review, "Plant Disease Detection and Classification by Deep Learning—A Review" (IEEE Xplore), presented advancements in deep learning for crop leaf disease identification, noting variability in environmental conditions and computational requirements.

Modules:

MobileNet is a streamlined convolutional neural network architecture specifically optimized for mobile and embedded vision applications. It leverages depthwise separable convolutions to reduce computational cost and model size, enabling efficient performance on devices with limited processing power and low latency requirements.
VGG-16 is a deep convolutional neural network comprising 16 layers, originally trained on the large-scale ImageNet dataset, which contains over a million images. The pre-trained model is capable of recognizing a wide array of objects, including tools like keyboards and mice, stationery items like pencils, and various animal species.
Inception-ResNet-v2 is a hybrid neural network architecture combining elements of Inception modules with residual connections, and it spans 164 layers. Trained on the ImageNet dataset, this model can categorize images into 1,000 different object classes, covering a diverse range of categories such as electronic devices and animals.
Inception-v3 is another deep learning model in the Inception family, consisting of 48 layers. With training on over a million images from ImageNet, this model can accurately classify images into 1,000 unique categories, including everyday objects and living organisms.
Xception, short for Extreme Inception, is a highly advanced convolutional neural network made up of 71 layers. It is trained on the ImageNet dataset and offers the ability to classify images into 1,000 different object categories, ranging from common items like electronics and stationery to various animal species.

4 Architecture

A Data Flow Diagram (DFD), often referred to as a bubble chart, is a straightforward graphical representation used to illustrate how data enters a system, the processes that act upon it, and the resulting output data produced by the system.

The DFD is a fundamental tool for system modeling, helping to describe various components of a system. These components include system processes, the data utilized within those processes, external entities that interact with the system, and the flow of information throughout the system.

A DFD visualizes the movement of data within a system and shows how it is altered through a sequence of processing steps. It serves as a graphical method for representing data flow and the changes it undergoes from input to output.

Also known as a bubble chart, a DFD can be used to model a system at different levels of detail. It can be broken down into multiple layers or levels, each offering a deeper view of the data flow and functionality within the system.

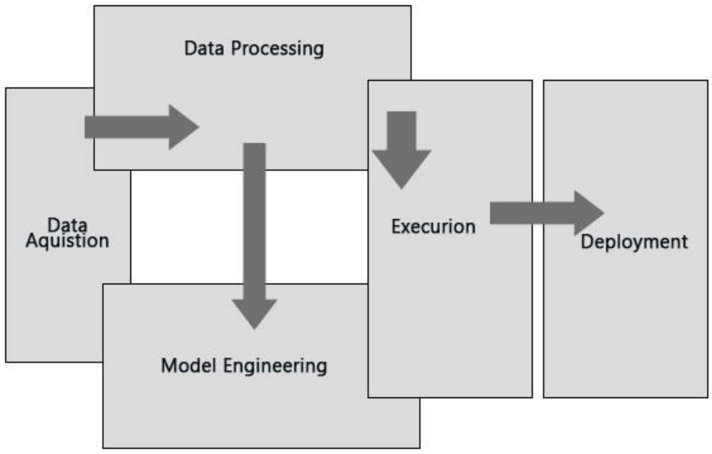

Fig 1. Architecture

5. Conclusion

In this study, we have introduced a novel and comprehensive dataset consisting of 5,170 annotated images of plant diseases, meticulously collected from real-world field conditions across various plantations. Unlike many existing datasets that rely on lab-controlled or synthetic environments, our dataset comprises exclusively of natural field images, thereby capturing the complexity and variability of real agricultural scenarios. Each image in the dataset has been carefully examined and annotated by expert plant pathologists, ensuring high-quality, reliable ground truth labels.

One of the key contributions of our dataset is that it includes the **first annotated images of cassava diseases**, making it a valuable resource for the study and management of diseases in this economically significant crop. The FieldPlant dataset holds substantial potential to advance research in plant pathology, particularly in developing machine learning and deep learning models for plant disease detection, classification, and monitoring in real-world applications.

Our evaluation of several state-of-the-art deep learning models for both classification and object detection tasks reveals that FieldPlant enables **better classification performance** compared to other widely-used datasets like **PlantVillage** and **PlantDoc**. This suggests that the natural variability and real-world context of FieldPlant provide a more robust and challenging benchmark for training and evaluating plant disease detection systems.

Moreover, while the dataset already covers a range of diseases, we recognize that it can be further enriched by expanding it to include **additional disease classes and crop varieties**. This would not only enhance the diversity and applicability of the dataset but also support the development of more generalizable and effective diagnostic tools.

sustainable and technology-driven agriculture.

8 REFERENCES:

1. Tian et al. (2020) conducted an extensive review on the use of computer vision technologies for automating agricultural practices, highlighting the growing role of AI in improving efficiency across farming tasks.
2. Hughes and Salathé developed an online platform designed to offer plant health imagery, enabling researchers and developers to build mobile applications for diagnosing crop diseases.
3. Greg (2019) reported on how computer vision has emerged as a promising solution to minimize post-harvest losses by offering real-time insights into crop conditions.
4. Singh et al. introduced "PlantDoc," a dataset designed specifically for training models to visually detect plant diseases. It was shared during a leading data science and management conference.
5. Adi et al. (2021) presented a comprehensive overview of deep learning algorithms tailored to detect plant diseases, and evaluated their effectiveness using various datasets.
6. The AI Labs at Makerere University and NaCRRI (2020) launched “iBean,” a digital project providing tools and datasets that support AI-based crop monitoring and disease detection.
7. Sharif and his team (2018) proposed a technique for detecting citrus plant diseases using a combination of segmentation and optimized feature extraction to improve classification accuracy.
8. Sethy (2020) released a curated set of rice leaf disease images on an open-access platform to support training and validation of deep learning models in agricultural diagnostics.
9. Oyewola et al. (2021) applied a deep residual CNN model integrated with block-based processing for the detection of cassava mosaic disease, demonstrating its performance on real-world plant samples.
10. AI Challenger (2018) made publicly available a series of annotated datasets geared towards training machine learning models for multiple AI tasks, including plant disease identification.
11. Ngugi and colleagues designed a deep learning-based image segmentation method for tomato leaves, optimized for mobile platforms to assist in real-time agricultural disease tracking.

12. Ahmad and Abdullah (2021) tackled the issue of unbalanced plant disease datasets using a customized CNN approach, leveraging stepwise transfer learning to enhance classification on limited samples.

13. Wang et al. proposed a dual-stream model using bilinear pooling for handling multiple classification tasks in plant disease diagnosis, which they evaluated using large agricultural image datasets.

14. Li, Zhang, and Wang (2021) reviewed the progress in plant disease identification using deep learning methods, outlining strengths, gaps, and potential improvements in the field.

15. Nagaraju and Chawla (2020) offered an analytical survey of deep learning frameworks applied to plant pathology, emphasizing model performance, dataset characteristics, and real-time deployment challenges.