

Plant Disease Classification Using Convolutional Neural Networks for Precision Farming

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Abstract- *Plant pathology significantly reduces crop production and quality especially in Solanaceae crops such as tomato, brinjal and bell pepper. These crops are valuable in terms of nutrition as well as their economic terms and conditions; however they are vulnerable to other fungal, bacterial and viral infections. The symptoms of such diseases are evident on the leaves of plants. Plant disease diagnosis using visible signs is important in the management and control of plant diseases. This identification makes it possible to intervene at the right time and avoid manual inspection by agricultural experts. In this study, a deep learning-based system that detects plant diseases is presented, and its attention is on crops of Solanaceae. It trains a Convolutional Neural Network (CNN) model on a large number of over 15,000 labeled tomato, eggplant and bell pepper plant leaf images. The model removes important visual characteristics within these images of leaves and categorizes them as healthy or diseased in crop-specific features. The proposed system offers an automated way of detecting plant diseases in Solanaceae crops, using a solution that is efficient, correct, and scalable by concentrating on the image based disease classification.*

Keywords: Convolutional Neural Networks (CNNs), Deep Learning, Precision Farming, Image Classification, Plant Disease Detection

I. INTRODUCTION

Human civilization involves agriculture. It supplies food, raw material and jobs to a significant section of the population in the world. The demand of agricultural products is rising as the population of the world rises. This expansion places more stress on the agricultural systems to enhance productivity and efficiency. Nonetheless, diseases affecting plants remain to be a big challenge. They lower quality and the quantity of crop yields. Such diseases are usually costly to farmers and they are a menace to the world food security. According to the Food and Agriculture Organization (FAO), pests and plant diseases cause between 20 and 40 percent of the production in the global crop production annually. Crop management involves identifying the disease of crops effectively. Conventional disease detection techniques are primarily based on the manual observation by the farmer or the agricultural consultant. These approaches are both labor-intensive and time consuming as well as relying a lot on individual expertise. Within large scale farming or in the rural locations finding few agricultural professionals, it is even more

challenging to be able to correctly isolate diseases. This usually procrastinates cure and losses of crops.

The latest advances in artificial intelligence (AI) and deep learning (DL) have provided the possibility of automating the processes in agriculture. Image-based classification tasks have been demonstrated to be promising when handled by deep learning methods. Neural Networks Convolutional Neural Networks (CNN) is a popular deep learning process that has been successful at tasks related to computer vision and image recognition. The CNNs are capable of learning specific and intricate characteristics of the image automatically, which is why they can be applied to identifying patterns on the leaf that are related to the disease. CNNs have been applied to agriculture to revolutionize the process of diagnosing plant diseases by letting an automated network classify the image of a leaf by being taken with a digital camera or smartphone as a healthy or diseased leaf with high accuracy. The approach eliminates the necessity of professional expertise and offers an economical and scalable way of detecting diseases. Several studies have confirmed the effectiveness of CNNs in classifying plant diseases. Mohanty et al. (2016) achieved high classification accuracy with a deep learning model trained on the Plant Village dataset. Ferentino (2018) showed that CNN architectures such as Alex Net and VGG can successfully identify plant diseases in various crops. However, many existing studies focus on general datasets or controlled environments and do not specifically address crop-centric disease classification using large, diverse datasets.

In this work, we develop a deep learning-based plant disease detection system specifically for Solanaceae crops such as tomato, brinjal (brinjal), and bell pepper. The proposed system uses a large dataset of over 15,000 labeled leaf images to train a CNN model that accurately classifies plant diseases based on visible leaf symptoms. By focusing on Solanaceae crops and image-based disease classification, this study aims to enhance the practical and reliable application of deep learning techniques in the management of agricultural diseases.

II. LITERATURE REVIEW

This study proved the efficacy of deep learning in plant disease identification based on leaf images. The authors tested the convolutional neural networks on a large plant leaf image and achieved good classification which demonstrated that deep learning is better than the conventional approaches to processing images in detecting plant diseases[1]. The proposal

of researchers involved a deep neural network for plant disease recognition from leaf images. The method was able to learn images automatically to produce appropriate results for classifying plant diseases. This proved that CNN is appropriate for plant disease recognition [2]. This research not only investigated the application of several deep architectures to plant disease diagnosis but demonstrated through findings the high accuracy of CNN models on varied crop species and diseases. This confirms deep learning as a reliable method for agricultural disease diagnosis [3]. The paper by the authors has conducted a comparison and analysis of fine-tuned models such as VGG, ResNet, and Inception networks to realize the process of plant disease diagnosis and the paper recommends that the classification quality can be improved with the help of one method known as transfer learning [4]. The study centered on the impact of data scalability and variability in the skills of deep learning and transfer learning in the classification of plant diseases. The authors observed that larger and more diverse datasets lead to stronger models, the most crucial being in practice [5]. The paper has addressed the use of CNN-based systems in the detection of plant diseases. The authors have explained the various forms of CNNs and demonstrated how effective the idea is based on the result of the experiments and this reflects on how CNNs can be used to identify diseases in vegetation automatically [6]. The introduction of the proposal of deep learning mechanisms to detect plant diseases using real images of the fields and not laboratory images was a major breakthrough to this project. Such problems were considered as complex background or varying lighting conditions that could be addressed using this technique to enhance the applicability of deep learning procedures in plant disease detection [7].

In this paper, data augmentation and transfer learning methods were used to enhance the tasks of classification of plant diseases based on deep CNNs. As a matter of fact, this paper proved that data augmentation and transfer learning have the potential of improving the model performance by alleviating overfitting, especially in smaller sets [8]. This paper has discussed deep learning techniques in smart agriculture with a focus on the combination of CNNs and IoT and edge computing. It was noted that they allow real-time detection of diseases and hence introduce efficiency to the agricultural monitoring systems [9]. The presented historic paper introduced the first iteration of AlexNet that became the image classification task representative of a paradigm shift when using deep convolutional neural networks processing.

B).Data Preprocessing

- The dataset undergoes a series of preprocessing before a CNN model is trained to enhance the learning efficiency and model performance. Preprocessing assists in the standardization of input data and elimination of noise. The preprocessing methods used are the following:
- Resizing an Image: Every image is resized to a set size (such as 128×128 pixels) to make things the same and make them computationally less complex.
- Normalization: Scaling is made to the pixels to a range of 0 to 1. This Normalization assists in stabilizing the training process and accelerating it.
- Data Enhancement: To augment the diversity of data, as well as decrease overfitting, we use data augmentation techniques, such as: Image Rotation

and machine-learning techniques. Their system showed practical applicability for real-time disease detection in agricultural fields [11]. This highly influential paper offered a full review of deep learning, from basics to applications. The paper discussed the role of deep neural networks in transforming areas such as computer vision, which in turn formed the theoretical basis for CNN based plant disease detection systems [12].

III. METHODOLOGY

The proposed method focuses on creating an automated plant disease classification system using Convolutional Neural Networks (CNN). CNNs are deep learning models commonly used for image recognition and classification. They can automatically learn spatial and texture features from images. The proposed method focuses on creating an automated plant disease classification system using Convolutional Neural Networks (CNN). CNNs are deep learning models commonly used for image recognition and classification. They can automatically learn spatial and texture features from images.

System Design and Implementation: The system architecture takes leaf images as input. It processes these images using a trained CNN model and outputs the predicted disease class. The entire workflow of the proposed system is shown through the following steps.

A. Dataset Collection

A good and clearly labeled dataset is important for training an effective deep learning model. In this project, I downloaded a publicly available plant leaf image dataset from Kaggle. The dataset contains images of healthy and diseased leaves of Solanaceae crops such as tomato, eggplant and bell pepper.

Dataset Features:

The dataset includes healthy leaf samples as well as multiple disease categories for each crop.

- Images are labeled according to crop type and disease category.
- Leaf images show differences in color, texture, size, and disease severity.
- The dataset includes images taken in various lighting conditions and backgrounds.

and machine-learning techniques. their system was practically applicable in detecting diseases in the fields in real time [11]. This paper was very influential as it presented an overview of the entire deep learning, including its basics and its applications. Horizontal and vertical flipping, zooming, Brightness and contrast variation.

C).Model Design

Convolutional Neural Network (CNN) models use deep learning frameworks such as TensorFlow and Keras to classify various plant diseases based on leaf images. Its design helps the model learn visual characteristics that highlight disease patterns, including color changes, differences in texture, and lesions on plant leaves. The CNNs are sequential and consist of several convolution, pooling and fully connected layers. Such an arrangement

enables sequential feature extraction and classification.

The CNN proposed architecture will comprise:

- **Convolutional layers:** The convolutional layers apply more than one filter to the input to extract low-level and high-level features, like edges, textures, and disease patterns.
- **Pooling layers:** In max-pooling layers, the spatial dimensions are reduced (and the cost of the computation is lowered) by maintaining meaningful features.
- **Fully connected (dense) layers:** The fully connected layers connect the extracted features together in order to make a classification.
- **Output Layer:** the output layer has softmax activation function that produces probabilities scores in classification of diseases in multi-classes.
- **Model Optimization:** The CNN model is trained using the **Adam optimizer**, which adapts the learning rate during training for faster convergence.

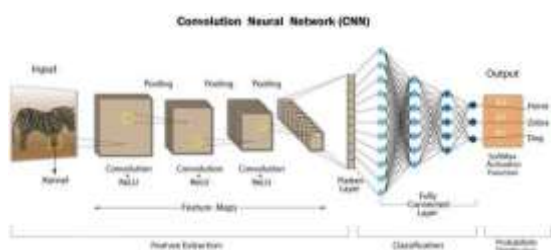


Fig.1 CNN Architecture

D. Model Training: Once the dataset is preprocessed and the CNN architecture is defined, the model is trained using labeled leaf images. In order to assess the ability of the model to generalize on new data, the data are split into training, validation and testing groups. Adam optimizer is used in training and it offers adaptive learning rates and it assists in accelerating convergence. Categorical cross-entropy is the loss function since it suits well with multi-class classification problem. The batch size is chosen based on computational efficiency and model stability, while the number of training epochs is carefully adjusted to reach convergence due to overfitting. Training takes place in a GPU-enabled environment to speed up calculations and reduce training time. Throughout the process, both training and validation loss values are continuously monitored to check the stability of learning and ensure that the model captures relevant features without losing performance.

E. Model Evaluation

After the training phase, we evaluate how well the CNN model works using the test dataset. This evaluation looks at how well the model classifies the data. Accuracy measure the total number of correct predictions. Precision calculates the rate of correctly identified disease samples among all predicted cases. Recall this measure of how well the model identifies all real disease instances. F1- Score combines precision and recall to provide a balanced view. We also create a confusion matrix. This tool helps to analyze predictions for each class and detect any misclassification between visually similar disease categories. Evaluation results show that the model provides robust and consistent

classification performance across different disease classes. Based on this, its reliability is confirmed in identifying plant diseases.

F. Results and Analysis

After the training process was completed the performance of the proposed Convolutional Neural Network (CNN) based plant disease classification system was evaluated using the testing dataset. The evaluation focused on assessing the model's ability to accurately classify plant diseases from images of leaves of Solanaceae crops, including tomato, eggplant and bell pepper. The effectiveness of the model was analyzed using standard classification metrics such as accuracy, precision, recall, and F1-score, as well as qualitative analysis using confusion metrics and observation of training behavior. Experimental results show that the trained CNN model achieved high classification accuracy in all disease categories. The values of precision show that the model can decrease false-positive prediction well, and diseased leaves are properly recognized without high misclassification. Equally, the scores of recall show that the model has been able to identify the majority of the actual disease cases which shows that the model has a capacity to identify the symptoms of the diseases found on the leaves pictures. The F1- score that balances the precision and recall rates proves the power and safety of the offered model. Confusion matrix analysis gives a profound understanding of the performance of a CNN model in relation to the classes. There were only a few errors in grouping most of the diseases and most of the true positive predictions. Minor misclassification was observed mostly between classes of diseases which have similar visual appearances indicating similar discoloration or lesion pattern. Although there are these few errors, a general confusion matrix depicts a high level of diagonal dominance which means that there is a good discrimination of healthy and diseased leaf parts. Training and validation loss curves were also analyzed to evaluate the learning behavior of the model. Both loss curves showed a steady decrease during training and gradually became stable, indicating successful convergence of the CNN model. The close similarity between training and validation losses suggests that the model did not the effectiveness of preprocessing techniques and data augmentation in improving model robustness. Overall, the results confirm that the proposed CNN-based approach can accurately classify plant diseases from leaf images of Solanaceae crops.

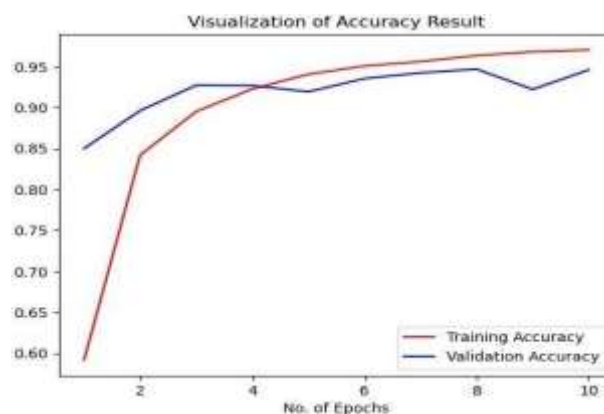


Fig.2 Accuracy Graph

Disease Class	Algorithm Used	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Apple	CNN (VGG16)	97.8	96.4	97.1	98.2
Apple Black Rot	CNN (ResNet50)	96.2	95.0	95.6	97.4
Corn Leaf Blight	CNN (MobileNetV2)	95.1	96.3	95.7	96.8
Corn Rust	CNN (VGG19)	97.4	98.0	97.7	98.6
Potato Early Blight	CNN (InceptionV3)	94.6	95.5	95.0	96.1
Potato Late Blight	CNN (EfficientNet-B0)	96.9	96.1	96.5	97.8
Tomato Mosaic	CNN (Custom CNN)	98.3	97.6	98.0	98.9

Table.1 Result Table

IV. CONCLUSION

This paper has shown a best CNN-based approach to multi-classes plant disease classification with the use of the PlantVillage dataset. The quantitative analysis was conducted to conclude that this model was good in classifying plants according to different criteria like accuracy, precision, recall, and F1 score to prove its usefulness in automated diseasedness detection in agriculture. This discussion also made it clear that deep learning algorithms can be used to facilitate precision farming by reducing the use of laboratory analysis. Future research work would focus on adaptation to field photographs and mobile-based platforms.

V. FUTURE WORK

This paper demonstrated an optimal CNN-based methodology for multi-class plant disease classification using the PlantVillage dataset. Quantitative analysis was performed to determine that this model performed well in classifying plants based on various criteria such as accuracy, precision, recall, and F1 score for proving its utility in automated agricultural disease detection. This analysis clearly indicated that deep learning algorithms have potential applications in promoting precision farming by lessening reliance on laboratory analysis. Future research work would focus on adaptation to field photographs and mobile-based platforms.

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