Leaf Disease Detection by Convolutional Neural Network (CNN)

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Abstract. Effective plant disease detection is paramount for ensuring global food security and sustainable agricultural practices. This article presents a comprehensive exploration of utilizing machine learning, specifically Convolutional Neural Networks (CNNs), for accurate and timely plant disease classification. The research delves into the integration of diverse datasets, preprocessing techniques, and CNN architecture to create a robust disease detection model. The dataset, encompassing various crops and diseases, forms the foundation for training the model, while preprocessing ensures optimal data quality. The CNN architecture, meticulously designed, progresses through convolutional and pooling layers to extract hierarchical features from input images. The trained model achieves an accuracy of 92.23% on disease classification, showcasing the potential of such technology in agricultural innovation. The article underscores the pivotal role of machine learning in revolutionizing plant disease detection, thus contributing to global food security and sustainable agriculture.

Keywords: Machine learning; convolutional neural network; food security.

1. Introduction

Safe and nutritious food is the source of energy for the human body and the first line of defense against disease. Reliable access to food can have significant positive effects, however the United Nations estimates that between 720 million and 811 million people globally were food insecure in 2020 [1]. Over 30% of the world's population, or a startling 2.4 billion people, experienced moderate to severe food insecurity, meaning they frequently lacked access to enough food [1]. The COVID-19 pandemic is making the world's food systems more vulnerable and inadequate, and current forecasts indicate that the sustainable Goal of Zero Hunger is not on track to achieve by 2030 [1]. The world is showing a dangerous sign to us, what can we do to help solve this problem?

One possible solution is the crop disease detection phone app. What the app does is that a peasant could take a picture of their crop, upload it, and the app could automatically identify what crop is it and whether it has a disease or not. With this app, farmers can detect crop diseases in the early stage and react correspondingly therefore to reduce crop-loss due to diseases. However, relevant investigations are still limited, which make this issue to be of interest to academia. Currently, machine learning is introduced to this field, and achieved numerous achievements. Nevertheless, the accuracy needs improvement, which motivates the author to be involved with this interesting issue.

2. Literature Review

An early study on plant disease classification technique was done by Bashish et al in 2011. This study explores a method for identifying and categorizing leaf diseases in plants. The approach involves Neural Networks-based Classification. With the proposed method, Bashish et al was able to achieve an accuracy of 92.7% for disease image classification [2].

In 2015, a study done by Reddy et al proposed an electronic expert system in the form of an app. This app aims to assist farmers in making informed decisions and improving their farming experience while avoiding heavy losses [3]. In this study, Reddy et al discussed the need for an app-based expert system to help farmers make better decisions in their experimental farming endeavors, particularly in the context of disease detection and crop management.

The key to efficiently training machine learning models is having large and varied datasets. Images pertaining to plant health were published in an open-access collection by Hughes and Salathe in 2016

[4]. The 54,309 photos in this collection, which spans 14 crop species and 26 diseases, make up a total of 38 crop-disease pairs [4]. The availability of this dataset makes it much easier to develop and enhance mobile applications for identifying plant diseases. (See Fig. 1 as an example).

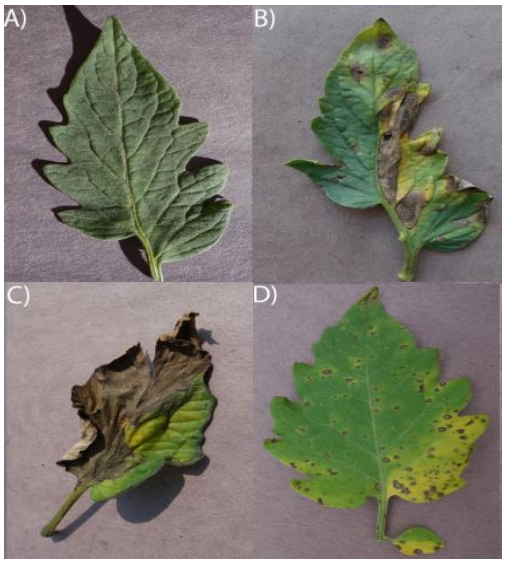


Fig 1. Examples of different plant images in the data set.

A further approach for image segmentation technique that is utilized for automatic detection and classification of plant leaf diseases was presented by Singh and Misra in 2016 [5]. With the algorithm, Singh and Misra achieves an accuracy of 97.6%, which is 4.9% higher than their previous accuracy result, 92.7% [5]. Moreover, Singh and Misra also discussed several possible plant disease classification techniques that could possibly be applied in the future.

Later in 2016, Hughes et al explored the application of deep learning techniques for detecting plant diseases based on images. Their study focuses on leveraging the capabilities of deep learning models to achieve accurate and efficient plant disease diagnosis. The authors delve into various deep learning architectures and approaches to demonstrate the efficacy of this method. On a test set, the trained model achieves an accuracy of 99.35%, demonstrating the viability of this strategy [6]. By harnessing the power of deep learning, the authors aim to contribute to advancements in plant disease detection, potentially leading to improved agricultural management practices and crop health.

Both Hughes and Salathe work in the team "Plant Village," and the team released their plant disease classification app "PlantVillage Nuru" in 2018. TensorFlow, an open-source software for numerical computation utilizing data flow graphs, is incorporated into the program; and it is initially created by Google's Machine Intelligence Research team for the purposes of performing machine learning and deep learning research [7].

Another study on image classification technique was done by Singh and Misra. The paper explores the use of image segmentation techniques and soft computing methods to identify and classify these diseases [5] with the algorithm, Singh and Misra achieves an accuracy of 97.6%, which is 4.9% higher than their previous accuracy result, 92.7% [5]. Image segmentation is applied to extract meaningful features from plant leaf images, while soft computing techniques such as neural networks or fuzzy logic may be employed for disease classification [5]. Singh and Misra also discussed several possible plant disease classification techniques that could possibly be applied in the future.

The use of deep learning algorithms for the aim of identifying and categorizing plant diseases was addressed by Saleem et al in 2019 [8]. The article offers a thorough analysis of the various deep learning models and techniques used in the field of plant disease detection. The authors demonstrate the importance of deep learning in advancing agricultural practices by highlighting its potential to precisely diagnose and categorize numerous plant diseases. The publication advances techniques for effective plant disease management and mitigation by providing a complete viewpoint.

In recent years, a method for leveraging transfer learning to train the deep learning model with just a few dozen illness photos has been discovered. In a few-shot learning framework, Argüeso et al, proposed a unique method for categorizing plant diseases [9]. The study focuses on utilizing images captured directly from the field to train the classification model, which is particularly important for real-world scenarios. The authors explore the challenges associated with limited data and propose a few-shot learning method to address these limitations. This innovative approach has potential implications for accurate and timely disease diagnosis in agricultural settings, offering a promising solution to enhance plant disease management practices.

Siddiqua et al evaluated all of the major plant disease classification apps in 2022 based on the quality, performance, and limitations of these mobile applications.

The incorporation of machine learning techniques has largely been contributing to the impressive advancements in the identification and classification of plant diseases. Many pioneers have carried out significant research on the use of different machine learning techniques for precisely diagnosing and categorizing plant diseases. These techniques enable the early diagnosis and efficient management of plant diseases, which has important consequences for agricultural sustainability.

In conclusion, the convergence of machine learning techniques with plant disease detection and classification has paved the way for remarkable advancements in agriculture [10]. They reviewed various existing plant disease detection apps, assess their accuracy, usability, and overall effectiveness. They also discussed shortcomings and limitations encountered in these applications. The paper aims to provide insights into the current landscape of mobile apps for plant disease detection, offering valuable information for researchers, practitioners, and developers working in the field of agricultural technology and plant health management [10].

3. Methodology

3.1. Dataset

A dataset is a collection of data points that are used to train, validate, and test a machine learning model. The quality and composition of the dataset have a profound impact on the performance of the resulting model. Machine learning models learn patterns and relationships from data. A diverse and representative dataset allows the model to learn these patterns more effectively, leading to better generalization to unseen data.

The dataset used in this study is the open-source image dataset released in 2016. [4] However, due to the hardware limitation, only half of the images (30170 images) are used in this study, which would ultimately lead to a down grade to the quality of prediction.

3.2. Preprocessing Images

Preprocessing is a crucial step in image classification pipelines. It involves preparing and cleaning the raw image data before feeding it into a machine learning model. Proper preprocessing can significantly improve the performance of the image classification model.

Images in the dataset are bare images without labels, so the first step in the preprocessing is to assign tags or categories to each image in a dataset. These labels provide ground truth information that machine learning algorithms use to learn patterns and relationships between visual features and their corresponding classes. Paths to images, their labels, and the class names are stored within a panda's data frame for later processing.

After labeling, the dataset is divided into two main subsets: the training set and the test set. These subsets play crucial roles in training the model and testing the accuracy of the model. 'train_test_split' method is used to split the data into 80% train set (24136 images) and 20% test set (6034 images).

A generator function is used to create batches of training data on-the-fly. Images are resized into 150 * 150 pixels to reduce the memory need. Images are then normalized and categorized for training.

3.3. Model Construction

Convolutional Neural Networks (CNNs) are a subclass of deep learning models that were created expressly for processing and interpreting grid-like input, such as image data. Due to their capacity to automatically identify hierarchical features from unprocessed pixel data, they have revolutionized image classification and a number of other computer vision applications. In this work, the Keras library is used to build a CNN model for picture categorization.

Conv2D layer with 16 filters, 3x3 kernel size, and "relu" activation is the model's foundation. The dimensions of the images being used for this layer are (150, 150, and 3), where 150 is the size of the resized image and 3 is the number of RGB color channels.

Following the Conv2D layer is a MaxPooling2D layer with a pool size of (2, 2) that shrinks the feature maps' spatial dimensions while preserving crucial data.

To gradually extract features from the input photos, three further pairs of Conv2D and MaxPooling2D layers are added with increasing filter counts (64, 128, and 128).

The 2D feature maps are transformed into a 1D vector via a "Flatten" layer after the convolutional layers before being fed into a fully connected neural network.

Then, two 512-unit dense layers with a'relu' activation and a 0.3 dropout rate dropout layer are added to each layer. Dropout, which involves randomly removing a portion of neurons during training, helps prevent overfitting.

The output classes are represented by the final dense layer's 39 units, which corresponds to the number of classes. It provides class probabilities using the'softmax' activation function.

4. Result and Discussion

4.1. Model Result

The training data and testing data are fed into the CNN structure constructed in the previous step. With 30 epochs, the model is able to reach 92.23% of accuracy with the final loss to 0.2683, which is satisfactory (Details are shown in the following Fig. 2).

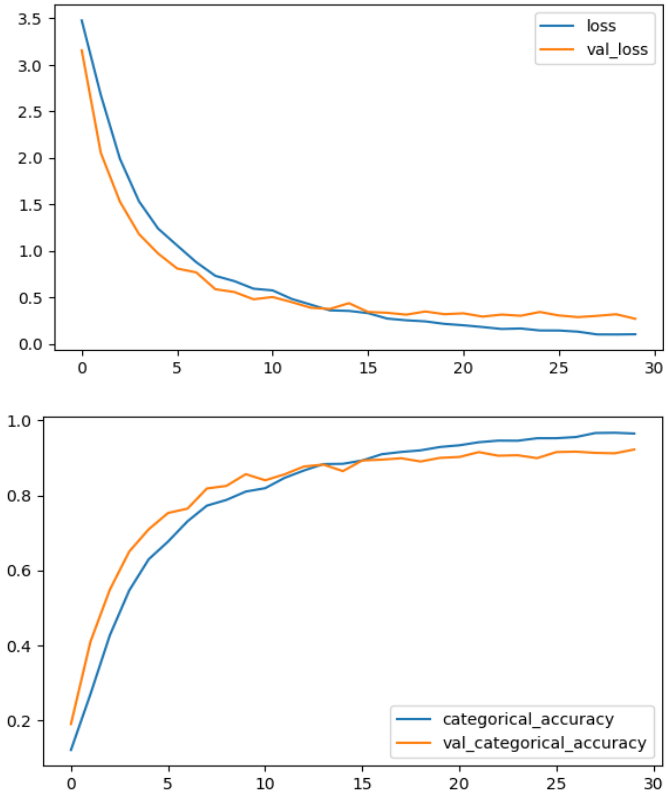


Fig 2. Loss and Accuracy Progress with Epochs.

4.2. Discussion and Future Investigation

The utilization of machine learning, specifically Convolutional Neural Network (CNN), in plant disease detection holds tremendous promise for revolutionizing agricultural practices. This study successfully achieves an accuracy of 92.23% on disease classification demonstrates the potential of such techniques in aiding farmers and improving crop yield. However, several important aspects deserve consideration and further exploration.

4.2.1. Data

The dataset used in this study is rather incomplete already compared to the opensource dataset released in 2016. Using the full dataset would lead to more accurate and robust disease detection systems.

Moreover, to improve the model's generalization to various crops, diseases, and environmental conditions, collecting a broader range of images from different geographic regions and climates is essential. A possible way could be to incorporate more crop disease images as users are uploading their images to the app.

4.2.2. Real-world Implementation Challenges

While the application of CNN in disease detection is promising, real-world implementation can present challenges. Variability in lighting conditions, weather, and plant growth stages can impact the accuracy of disease detection models. Fine-tuning and adaptation of models to different environmental conditions will be necessary for robust deployment. Additionally, the availability of reliable and consistent internet connectivity in remote areas where farming is prevalent can affect the feasibility of using mobile apps for disease detection.

4.2.3. Continual Model Improvement

The success of any machine learning model depends on continuous learning and improvement. The model presented here achieved an impressive accuracy, but there's always room for enhancement. Regular updates to the dataset with new images of various disease stages, different crops, and changing environmental conditions will contribute to a more comprehensive and accurate model.

5. Conclusion

The study’s successful application of Convolutional Neural Networks for plant disease classification underscores the potential of machine learning in addressing critical challenges in agriculture. As the world grapples with increasing demands for food production and the need to alleviate hunger, technological solutions like disease detection apps can be crucial components of a comprehensive strategy. By continuously refining models, adapting to real-world conditions, and ensuring accessibility for farmers, these advancements can contribute significantly to achieving sustainable agricultural practices and moving closer to the goal of zero hunger.

In summary, while challenges exist, the progress made in the realm of plant disease detection through machine learning offers hope for a more resilient and food-secure future. As researchers, technologists, and policymakers work collaboratively, the impact of such solutions can be amplified, leading to more effective and efficient agricultural practices worldwide.

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