

CNN BASED IDENTIFICATION OF PLANT DISEASES FROM LEAF IMAGES

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Abstract: Plant study now uses an efficient and cost-effective method for identifying plant diseases from leaf images because of the development of plant phenomics. Convolutional neural networks (CNN) are the most widely used technology for identifying plant diseases due to their exceptional performance. However, dealing with small datasets remains a challenge to CNN's representation capability, which has a significant impact on its popularity. The paper proposes a new method called PiTLiD, which is based on a pre trained Inception-V3 convolutional neural network and transfer learning to identify plant leaf diseases from phenotype data of plant leaf with small sample size. The proposed method was evaluated on several datasets with small-scale samples, and the results show that PiTLiD performs better than compared methods. The study provides a plant disease identification tool based on a deep learning algorithm for plant phenomics.

Index Terms - Plant Phenomics, Convolutional Neural Networks (CNN), Plant Disease Identification, PiTLiD (Plant leaf disease identification), Inception-V3, Transfer Learning, Small Datasets, Deep Learning Algorithm, Leaf Image Analysis, Phenotype Data.

Keywords: Plant Diseases Identification, Convolutional Neural Network Model, Machine Learning, Leaf images, Deep Learning, Image Processing, Agriculture Technology, Transfer Learning, Plant Pathology, Feature Extraction

1. INTRODUCTION

Plant phenotype refers to plant phenol typictra it's for reflecting characteristics of crops such as the yield, quality, and stress resistance and so on. Current phenotypic analysis methods for plant diseases using handheld tools or visual observation with naked eyes were laborious, expensive, and time-consuming and experience dependent for the expert's judgment. As a

state-of-the-art deep learning approach, the convolutional neural network (CNN) has been proven to perform excellently in various aspects, such as face recognition, objection detection, machine translation, text classification, and cancer therapy. For the performances of CNN-based methods were nearly close to human level in computer vision tasks, a wide range of agricultural applications based on CNNs have been produced, such as plant disease diagnosis and detection, assessment of plant disease severity, plant organ detection and counting, and weed

recognition. These agricultural applications increase farm successful classification of plant diseases can help to improve the quality and/or quantity of agricultural products reduce the misuse of chemical sprayers such as fungicide/herbicide and protect the environment at the same time.

In recent years, the integration of Internet of Things (IoT) technologies into agriculture has witnessed remarkable advancements, particularly in the realm of plant phenotyping. The prospect of enhancing agricultural productivity and sustainability through innovative platforms is explored in scholarly works such as Fan et al.'s comprehensive analysis [1]. Additionally, Kolhar and Jagtap provide a nuanced review of machine vision applications for plant trait estimation and classification in phenotyping studies [2].

Automated plant phenotyping systems have emerged as invaluable tools, showcasing their potential in evaluating specific plant traits, such as salt tolerance in soybean, as exemplified by Zhou et al. [3]. The intersection of deep learning and agricultural IoT is evident in disease identification methodologies, exemplified by Zhang et al.'s application of deep learning for cucumber leaf disease detection [4], as well as Picon et al.'s exploration of convolutional neural networks for crop disease classification using mobile capture devices [5].

Furthermore, the integration of convolutional neural networks (CNNs) has demonstrated promising outcomes in detecting and classifying tomato leaf diseases [6][7]. Li et al. provide a comprehensive review of computer vision technologies for plant phenotyping, highlighting the evolving landscape of these innovative applications [8]. Transfer learning

techniques are harnessed by Sravan et al. for crop disease classification [9], while the prediction of plant biomass accumulation from image-derived parameters is explored by Chen et al. [10].

Conventional digital cameras have proven effective in assessing leaf area index and biomass [11], while advanced technologies such as terrestrial lidar data are leveraged for individual maize segmentation using deep learning algorithms [12]. Ubbens and Stavness present a deep learning platform, Deep Plant Phenomics, designed for complex plant phenotyping tasks [13]. A comprehensive survey of deep learning-based plant phenotype research in agriculture is encapsulated by Weng et al.'s work [14], and the temporal phenotype/genotype classification is addressed through deep phenotyping techniques [15].

In this rapidly evolving landscape, these studies collectively contribute to the foundation of knowledge shaping the future of IoT in agriculture, emphasizing the pivotal role of advanced technologies in revolutionizing plant phenotyping methodologies.

2. LITERATURE REVIEW

The literature on the application of Internet of Things (IoT) and machine learning techniques in agriculture, particularly focusing on plant phenotyping, presents a comprehensive overview of recent advancements in this field. The following literature survey provides a summary of key findings and methodologies from the referenced papers. The future of IoT in agriculture, as discussed by Fan et al. [1], emphasizes the significance of plant high-throughput phenotypic platforms. This research highlights the potential of IoT to revolutionize agriculture by leveraging

advanced technologies for high-throughput phenotyping.

Machine vision in plant phenotyping is explored in depth by Kolhar and Jagtap [2], who review plant trait estimation and classification studies. The paper emphasizes the role of machine vision in extracting valuable information about plant traits, contributing to the overall understanding of plant phenotypes. Zhou et al. [3] contribute to the literature with the development of an automated plant phenotyping system specifically designed for evaluating salt tolerance in soybean. The study demonstrates the practical application of technology in addressing specific agricultural challenges, showcasing the potential for automated systems in stress tolerance assessments.

Deep learning techniques for disease identification in crops are explored by Zhang et al. [4], Picon et al. [5], and others. These studies utilize convolutional neural networks (CNNs) for accurate detection and classification of various leaf diseases in crops, showcasing the potential of deep learning in precision agriculture. Similarly, the use of CNNs is also evident in the work of Tm et al. [6], Natarajan et al. [7], and Sravan et al. [9], where these studies focus on the detection of diseases in tomato plants. The papers collectively demonstrate the effectiveness of deep learning in disease identification, particularly in the context of limited sample sizes.

Li et al. [8] provide a comprehensive review of computer vision technologies for plant phenotyping. The paper surveys various methodologies and technologies employed in plant phenotyping, offering insights into the diverse approaches used in this evolving field. Chen et al. [10] contribute to the

literature by proposing a method to predict plant biomass accumulation from image-derived parameters. This research showcases the potential of image-based predictions in estimating plant biomass, providing valuable information for agricultural practices. The utilization of digital cameras for assessing leaf area index and biomass in cereal breeding is explored by Casadesus and Villegas [11]. This study showcases the versatility of conventional digital cameras in plant phenotyping, offering cost-effective solutions for assessing crucial plant parameters.

Deep learning is applied to terrestrial lidar data for maize segmentation in the work of Jin et al. [12]. The study introduces the use of Faster R-CNN and regional growth algorithms, highlighting the potential of deep learning in segmenting individual maize plants from complex data sources. Ubbens and Stavness [13] present a deep learning platform for complex plant phenotyping tasks, emphasizing the importance of deep plant phenomics. This paper introduces a platform that facilitates various phenotyping tasks, showcasing the versatility of deep learning in addressing complex plant biology challenges.

Weng et al. [14] conduct a survey on deep learning-based plant phenotype research in agriculture. The paper provides a comprehensive overview of the diverse applications of deep learning in plant phenotyping, summarizing the key methodologies and findings across different studies. Finally, Taghavi Namin et al. [15] explore deep phenotyping using deep learning for temporal phenotype/genotype classification. The paper introduces the concept of deep phenotyping, showcasing the potential for

temporal classification of plant phenotypes using advanced deep learning techniques. In conclusion, the literature survey highlights the diverse applications of IoT, machine learning, and deep learning in plant phenotyping and agriculture. The studies discussed collectively showcase the potential of these technologies in addressing various challenges in precision agriculture, disease detection, and biomass estimation. The integration of advanced technologies in agriculture opens up new possibilities for improving crop yield, resource efficiency, and overall sustainability.

3. METHODOLOGY

In literature they adapted Deep Residual Neural Network-based algorithm to deal with the detection of multiple plant diseases in real acquisition conditions where different adoptions for early disease detection have been proposed. This work analyses the performance of early identification of three relevant European endemic wheat diseases. In another work they aim detect diseases that occur on plants in tomato fields or in their greenhouses. For this purpose, deep learning was used to detect the various diseases on the leaves of tomato plants, and it was aimed that the deep learning algorithm should be run in real time on the robot. So the robot will be able to detect the diseases of the plants while wandering manually or autonomously on the field or in the greenhouse. So, the Deep learning architecture selection was the key issue for the implementation. So that, two different deep learning network architectures were tested first AlexNet and then SqueezeNet. For both of these deep learning networks training and validation were done on the

Nvidia Jetson TX1. They used Plant Village dataset for the training.

Drawbacks:

1. However, the models trained on this dataset such as PlantVillage have very low accuracies when running on field images with complex backgrounds and multiple leaves per image.
2. They did not use any hyperparameter tuning to find the best set of parameters.
3. They did not perform preprocessing stages, like residual connection, and batch normalization and data augmentation. So, it may leads to decrease in performance.

The proposed work in the paper titled "PiTLiD: Identification of Plant Disease From Leaf Images Based on Convolutional Neural Network" is a new method called PiTLiD, which is based on a pretrained Inception-V3 convolutional neural network and transfer learning to identify plant leaf diseases from phenotype data of plant leaf with small sample size. The proposed method aims to address the small sample size problem of the training data, without the demand of a large number of phenotype samples that traditional CNN requires. The paper demonstrates the effectiveness and feasibility of PiTLiD in phenotyping task of diseases classification. The proposed method eliminates effects of poor samples on image recognition and classification and got an overall accuracy of 99.45 AE 0.17%, which is the highest prediction accuracy in several phenotyping approaches.

Benefits:

1. In this work, we compared three different learning rate methods on validation set to decide the best one.
 2. To evaluate the robustness of the proposed method, the experiments on several datasets with small-scale samples were implemented.
 3. Our model used the parameters of the pre trained model which has already learned features from a massive dataset as initialization.
 4. The augmented training dataset was utilized to fine-tune whole model to learn properties of new images of our apple disease dataset so model can become more appropriate to the apple disease classification task.
 5. In our work hyper-parameters were tuned to find the best set.
- Data exploration: using this module we will load data into system
 - Image processing: Using the module we will process of transforming an image into a digital form and performing certain operations to get some useful information from it.
 - Model generation: Building the model - LeNet - Feature Extraction using LeNet - CNN - Voting Classifier (RF + DT) - InceptionV3 from Scratch-InceptionV3 Retraining -PiTLiD-Torch Inception-Torchvision with GoogleNet and Xception.
 - User signup & login: Using this module will get registration and login
 - User input: Using this module will give input for prediction
 - Prediction: Final predicted displayed

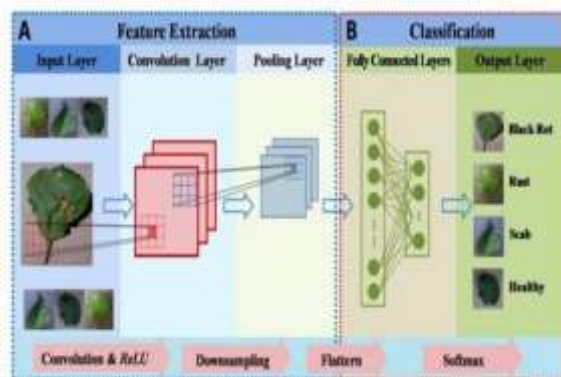


Fig 1 System Architecture

Modules:

The modules are:

4. IMPLEMENTATION

LeNet – LeNet is a convolutional neural network structure proposed by LeCun et al. in 1998.,[1] In general, LeNet refers to LeNet-5 and is a simple convolutional neural network. Convolutional neural networks are a kind of feed-forward neural network whose artificial neurons can respond to a part of the surrounding cells in the coverage range and perform well in large-scale image processing.

CNN – Convolutional neural network is a regularized type of feed-forward neural network that learns feature engineering by itself via filters optimization. Vanishing gradients and exploding gradients, seen

during backpropagation in earlier neural networks, are prevented by using regularized weights over fewer connections

Voting Classifier (RF + DT) – A Voting Classifier is a machine learning model that trains on an ensemble of numerous models and predicts an output (class) based on their highest probability of chosen class as the output.

InceptionV3 - Inception-v3 is a convolutional neural network that is 48 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

GoogLeNet - GoogLeNet is a convolutional neural network that is 22 layers deep. You can load a pretrained version of the network trained on either the ImageNet [1] or Places365 [2] [3] data sets.

Xception - Xception is a convolutional neural network that is 71 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals

5. EXPERIMENTAL RESULTS

Dataset Description:

This dataset consists of 70,000 high-quality images of diseased and healthy plant leaves from 9 different species. Each species has 3 data splits (train, test, and validation), with consistent categories across all

splits. This dataset is ideal for machine learning researchers and practitioners working on plant disease detection and classification, as well as for agricultural experts seeking to improve plant health and crop yields. The dataset is unique in its diversity, covering a wide range of plant species, diseases, and growth stages. With this dataset, we aim to accelerate research and development in the field of plant pathology and help farmers improve their crop health and productivity.



Fig 2 Anaconda prompt



Fig 3 URL

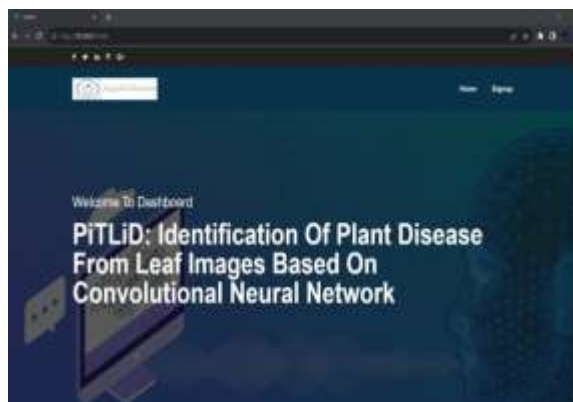


Fig 4 Home Page

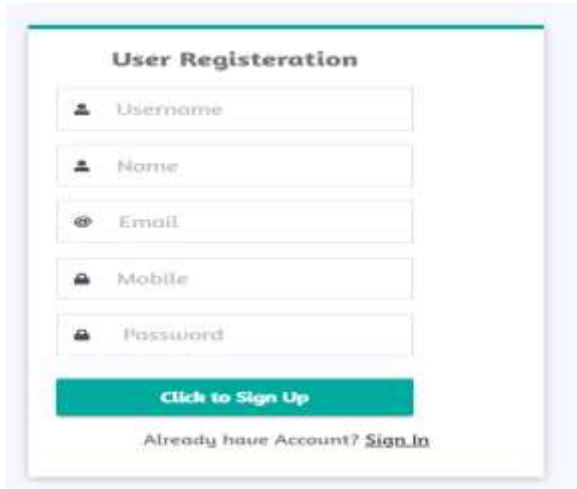


Fig 5 Registration page

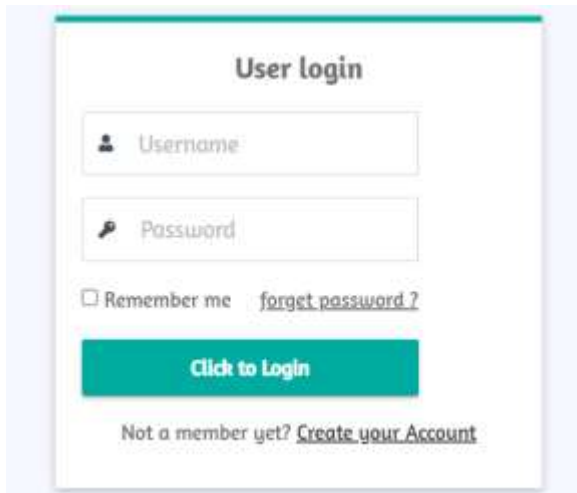


Fig 6 Login page

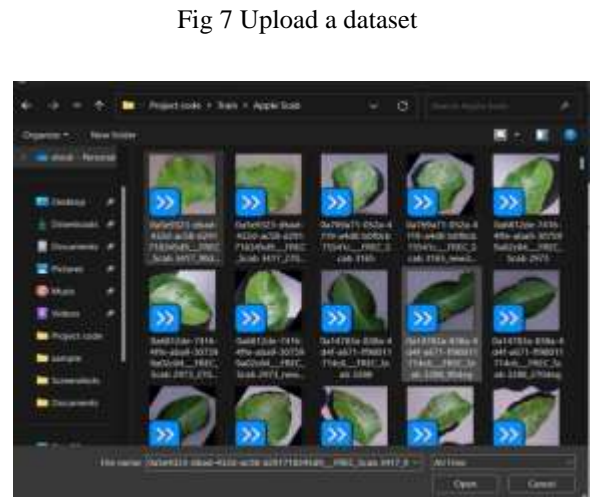


Fig 7 Upload a dataset

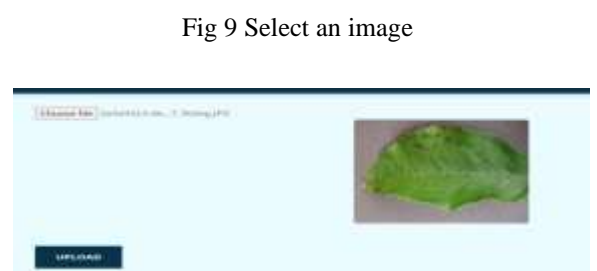


Fig 9 Select an image



Fig 10 Upload image

Fig 11 Predicted Output

6. CONCLUSION

In this work proposed a new method called PiTLiD, which is based on a pre trained Inception-V3 convolutional neural network and transfer learning to identify plant leaf diseases from phenotype data of plant leaf with small sample size. The proposed method was evaluated on several datasets with small-scale samples, and the results show that PiTLiD performs better than compared methods. The study provides a plant disease identification tool based on a deep learning algorithm for plant phenomics.

FUTURE WORK:

The paper concludes that PiTLiD is a promising method for plant disease identification and can be used as a tool for plant phenotyping. Future work may include the following three points. (1) Combining with other deep learning models, such as ResNet, DenseNet, SqueezeNet and so on to obtain extra performance. (2) Improving data augmentation techniques. Current data augmentation technologies largely depend on existing disease data and so how to use more advanced techniques to directly generate new data after learning disease images features. (3) Applying this approach to other fields to solve the problem that only a small number of training samples with accurate labels can be obtained

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