Abstract

Plant diseases pose a significant challenge for food production and safety. Therefore, it is indispensable to correctly identify plant diseases for timely intervention to protect crops from massive losses. The application of computer vision technology in phytopathology has increased exponentially due to automatic and accurate disease detection capability. However, a deep convolutional neural network (CNN) requires high computational resources, limiting its portability. In this study, a lightweight convolutional neural network was designed by incorporating different attention modules to improve the performance of the models. The models were trained, validated, and tested using tomato leaf disease datasets split into an 8:1:1 ratio. The efficacy of the various attention modules in plant disease classification was compared in terms of the performance and computational complexity of the models. The performance of the models was evaluated using the standard classification accuracy metrics (precision, recall, and F1 score). The results showed that CNN with attention mechanism improved the interclass precision and recall, thus increasing the overall accuracy (>1.1%). Moreover, the lightweight model significantly reduced network parameters (~16 times) and complexity (~23 times) compared to the standard ResNet50 model. However, amongst the proposed lightweight models, the model with attention mechanism nominally increased the network complexity and parameters compared to the model without attention modules, thereby producing better detection accuracy. Although all the attention modules enhanced the performance of CNN, the convolutional block attention module (CBAM) was the best (average accuracy 99.69%), followed by the self-attention (SA) mechanism (average accuracy 99.34%).

Introduction

Tomato is an important vegetable crop in the world, with a per capita consumption about 20 kg per year, accounting for around 15% of the total vegetable consumption . The global annual output of fresh tomato exceeds 170 million tons, ranking first in vegetable crop production . According to the survey data of the Food and Agriculture Organization of the United Nations, tomato disease is the main reason for the decrease in global tomato production, with an annual loss rate of as high as 8%–10% . . Automatic identification of tomato leaf diseases accurately can help to improve the management of tomato production and provides a good growth environment.

Traditional expert diagnosis on tomato leaf disease has a high cost and has a subjective misjudgment risk. With the rapid development of computer technology, computer vision, machine learning, and deep learning are widely used in crop disease detection . The Convolutional Neural Network (CNN) is a high-performance deep learning network; it abandons complex image preprocessing and feature extraction operations, and adopts an end-to-end structure, which greatly simplifies the recognition process compared to its learning . Several studies have been carried out to use deep learning technology to improve the survival rate of vegetables, fruits, and field crops through early disease detection and subsequent disease management.

Plant disease identification by visual way is a tedious task and less accurate and can be done only in limited areas. If automatic detection technique is used it will take less efforts, time and gets more accurate. In plants, some general diseases seen are brown and yellow spots, early and late scorch, and others are fungal, viral and bacterial diseases. Convolutional Neural Network (CNN) model used for apple leaf disease detection and classification. The dataset used in proposed system consist of 3642 images of apple leaves. Proposed system includes splitting the dataset into test data and training dataset. Conv2d neural network applied to train the CNN model. Model Achieved 90.2% accuracy with 30 epochs.

LITERATURE SURVEY

1. **Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition**

This paper proposes to identify the Tomato Plant Leaf disease using image processing techniques based on Image segmentation, clustering, and open-source algorithms, thus all contributing to a reliable, safe, and accurate system of leaf disease with the specialization to Tomato Plants.

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# Deep Learning for Plant Diseases: Detection and Saliency Map Visualisation

The current limitations and shortcomings of existing plant disease detection models are presented and discussed in this paper. Furthermore, a new dataset containing 79,265 images was introduced with the aim to become the largest dataset containing leaf images. Images were taken in various weather conditions, at different angles, and daylight hours with an inconsistent background mimicking practical situations. Two approaches were used to augment the number of images in the dataset: traditional augmentation methods and state-of-the-art style generative adversarial networks.

# A Lightweight Attention-Based Convolutional Neural Networks for Tomato Leaf Disease Classification

1. This work proposed a Deep Convolutional Neural Network (DCNN) model for image-based plant leaf disease identification using data augmentation and hyperparameter optimization techniques. The DCNN model was trained on an augmented dataset of over 240,000 images of different healthy and diseased plant leaves and backgrounds. Five image augmentation techniques were used: Generative Adversarial Network, Neural Style Transfer, Principal Component Analysis, Color Augmentation, and Position Augmentation. The random search technique was used to optimize the hyperparameters of the proposed DCNN model.

# AlexNet Convolutional Neural Network for Disease Detection and Classification of Tomato Leaf

1. In this study, the authors attempt to implement the function of AlexNet modification architecture-based CNN on the Android platform to predict tomato diseases based on leaf image. A dataset with of 18,345 training data and 4,585 testing data was used to create the predictive model. The information is separated into ten labels for tomato leaf diseases, each with 64 × 64 RGB pixels. The best model using the Adam optimizer with a realizing rate of 0.0005, the number of epochs 75, batch size 128, and an uncompromising cross-entropy loss function, has a high model accuracy with an average of 98%, a strictness rate of 0.98, a recall value of 0.99,

# Tomato plant disease detection using transfer learning with C-GAN synthetic images

 In this work, the authors reviewed the latest CNN networks pertinent to plant leaf disease classification,summarized DL principles involved in plant disease classification. Additionally, they summarized the main problems and corresponding solutions of CNN used for plant disease classification. Furthermore, discussed the future development direction in plant disease classification.

# Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition

1. This paper proposes to identify the Tomato Plant Leaf disease using image processing techniques based on Image segmentation, clustering, and open-source algorithms, thus all contributing to a reliable, safe, and accurate system of leaf disease with the specialization to Tomato Plants.

# Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks

1. This study review recent work where DL principles have been utilized for digital image–based plant stress phenotyping. it provide a comparative assessment of DL tools against other existing techniques, with respect to decision accuracy, data size requirement, and applicability in various scenarios. Finally, it outline several avenues of research leveraging current and future DL tools in plant science.

# A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition

1. In this work, specific CNN architectures were trained and assessed, to form an automated plant disease detection and diagnosis system, based on simple images of leaves of healthy and diseased plants. The available dataset contained images captured in both experimental (laboratory) setups and real cultivation conditions in the field

# A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition

1. In this paper, we review existing implementations and show that deep learning has been used successfully to identify species, classify animal behaviour and estimate biodiversity in large datasets like camera-trap images, audio recordings and videos. We demonstrate that deep learning can be beneficial to most ecological disciplines, including applied contexts, such as management and conservation.

# Deep learning models for plant disease detection and diagnosis

1. In this paper, we present a comprehensive review of research dedicated to applications of machine learning in agricultural production systems. The works analyzed were categorized in (a) crop management, including applications on yield prediction, disease detection, weed detection crop quality, and species recognition; (b) livestock management, including applications on animal welfare and livestock production; (c) water management; and (d) soil management. The filtering and classification of the presented articles demonstrate how agriculture will benefit from machine learning technologies. By applying machine learning to sensor data, farm management systems are evolving into real time artificial intelligence enabled programs that provide rich recommendations and insights for farmer decision support and action.

# A review on the main challenges in automatic plant disease identification based on visible range images

1. this paper propose a deep learning-based approach that automates the process of classifying ba- nana leaves diseases. In particular, it make use of the LeNet architecture as a convolutional neural network to classify image data sets. The preliminary results demonstrate the effectiveness of the proposed approach even under challenging conditions such as illumination, complex background, different resolution, size, pose, and orientation of real scene images.

# Applications of computer vision techniques in the agriculture and food industry: a review

1. This paper presents a detailed overview of the comparative introduction, latest developments and applications of computer vision systems in the external quality inspection of fruits and vegetables. Additionally, the principal components, basic theories, and corresponding processing and analytical methods are also reported in this paper.

# Detection of gray mold disease and its severity on strawberry using deep learning networks

1. In this study, a lightweight convolutional neural network was designed by incorporating different attention modules to improve the performance of the models. The models were trained, validated, and tested using tomato leaf disease datasets split into an 8:1:1 ratio. The efficacy of the various attention modules in plant disease classification was compared in terms of the performance and computational complexity of the models. The performance of the models was evaluated using the standard classification accuracy metrics (precision, recall, and F1 score). The results showed that CNN with attention mechanism improved the interclass precision and recall, thus increasing the overall accuracy (>1.1%).

# Deep-plant: Plant identification with convolutional neural networks

1. this paper perform a survey of 40 research efforts that employ deep learning techniques, applied to various agricultural and food production challenges. it examine the particular agricultural problems under study, the specific models and frameworks employed, the sources, nature and pre-processing of data used, and the overall performance achieved according to the metrics used at each work under study.

# Plant recognition via leaf shape and margin features

1. In this paper, a set of features that depict leaf shape and margin are proposed to improve the performance of plant recognition. The proposed margin features utilize the area ratio to quantify the convexity/concavity of each contour point at different scales and such margin features are effective in capturing the global information and contour details. The area ratio is the ration of the disk to the inside of the contour. The proposed shape features use a combination of morphological features to characterize the global shape of the leaf, which has merits in preserving the geometric properties of leaf shape.

# Image-based deep learning automated sorting of date fruit

1. in this study, a deep learning neural network as a smart, real-time and non-destructive method was developed and applied to automate the identification of four economically important carp species namely common carp (Cyprinus carpio), grass carp (Ctenopharingodon idella), bighead carp (Hypophtalmichthys nobilis) and silver carp (Hypophthalmichthys molitrix).

# Evaluation Matrics

## RESULTS

### Evaluation Metrics :

For evaluating the proposed models we used precision , recall , F1 Score , support and accuracy.We have used classification report and confusion matrix , these metrics are widely used for evaluating supervised machine learning models for classification when the dataset is multi labelled . Suppose a multi-labeled dataset consists of N number of instances, where each instance Ni is given by (xi,yi) , where xi represents the set of attributes and yi represents the set of labels . Let us say that yi and yi’ represent the labels which are true and labels which are predicted respectively for the ith instance then the metrics can be described for the ith instance which are by the following formulae.

#### Precision :

It is the ratio of accurately predicted authors as hate speech spreaders or not to the total number of predicted authors. It is computed as given in the equation below. The range of precision varies between 0 and 1 , where 1 is the best value and 0 is the worst value.

Precision = Number of accurately predicted authors = | yi∩yi’ | Total number of predicted authors |yi’|

#### Recall :

It is the ratio of accurately predicted authors as hate speech spreaders or not to the total number of authors. It is computed as is given in the below equation. The range of recall varies between 0 and 1 , where 1 is the best and 0 is the worst value .

Recall = Number of accurately predicted authors = | yi ∩ yi’ | Total number of authors |yi|

#### F1-Score :

The harmonic mean between Precision and Recall is called F1-Score, which gives the balanced equation between them . It can be represented by the below equation . The range of F1-score varies between 0 and 1 , where 1 is the best and 0 is the worst value.

F1-score = 2 x Precision x Recall

Precision + Recall

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