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PLANT LEAF DISEASE-BASED CNN WITH RESNET 50

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Abstract

The agriculture field has a high impact on our lives. Agriculture is the most important sector of our Economy. Proper management leads to a profit in agricultural products. Farmers do not have expertise in leaf disease so they produce less production. Plant leaf disease detection is important because profit and loss depend on the production. CNN is the solution for leaf disease detection and classification. The main aim of this research is to detect apple, grape, corn, potato, and tomato plants leaf diseases. Plant leaf diseases are monitoring of large fields of crops disease detection, and thus automatically detected some feature of diseases as per that provide medical treatment. The proposed Deep CNN model has been compared with popular transfer learning approaches such as Resnet50. Plant leaf disease detection has a wide range of applications available in various fields such as Biological Research and Agriculture Institute. Plant leaf disease detection is one of the required research topics as it may prove beneficial in monitoring large fields of crops, and thus automatically detect the symptoms of diseases as soon as they appear on plant leaves.

Keywords: CNN with Resnet50, Plant leaf disease, Agriculture Research

1. Introduction

Agriculture is the most significant economic sector in our country. Numerous illnesses harm plant leaves and have an impact on crop yields in that area. The diagnosis of leaf diseases is crucial. The profit in agricultural products is the result of regular maintenance of plant leaves. Farmers produce less because they lack knowledge about leaf disease. Because productivity determines profit and loss, leaf disease identification is crucial. In order

to identify diseases in the leaves of tomato, apple, grape, corn, potato, and plant [11], deep learning techniques are used here. Twenty-four thousand leaf photos are used in it, along with twenty-four different types of leaf illnesses [13]. There are a total of 24 different types of labels for apple, grape, corn, potato, and tomato plants. Some of the categories include Apple scab, Black rot, apple rust, and healthy. Grape label namely: Black rot, Esca, healthy, and Leaf blight. Corn label namely: Corn Cercospora spot Gray spot, Corn rust, Corn healthy, Corn Northern Blight[11][13]. Potato labels namely: Early blight, healthy, and Late blight. Tomato labels namely: bacterial spot, early blight, healthy, late blight, leaf mold, septoria leaf spot, spider mite, target sport, and mosaic virus[11][13]. The dataset consists of 31,119 images of apples, grapes, potatoes, and tomatoes, all Images are resized into 256 x 256, and the images are divided into two parts training and testing dataset[11][13].
1. Apple scab 2. Grape Esca 3. Corn leaf spot 4. Potato Early 5.Tomato Bacterial Blight Spot

Fig.1 Leaves with Disease part [11]

Fig. 1 shows damaged portions of several vegetable and fruit leaves, including those from potatoes, tomatoes, corn, apples, and grapes. Deep learning methods make it simple to identify this illness [13]. Resnet50-enabled convolutional neural networks (CNNs) were used to identify this illness. 224 x 224 is the new image size[13].

Literature Survey

Robert G. de Luna, Elmer P. Dadios, Argel A. Bandala [1] Argel A. Bandala, Robert G. de Luna, and Elmer P. Dadios [1] Utilizing the required infrastructure, smart farming systems are a cutting-edge technology that contribute to raising the nation's tomato output levels and quality. Diseases are unavoidable in tomato plant growing since several factors, including soil, sunlight, and environment, must be taken into account. Camera-captured tomato leaf disease has been made achievable by the current state of advanced computer system innovation enabled by deep learning. This research produced a novel method for accurately identifying diseases in tomato plants. To identify and diagnose leaf diseases, a motor-controlled image-capturing box was built to take images from all four sides of each tomato plant. A specific breed of tomato which is Diamante Max was used as the test subject. The system was designed to identify the diseases namely Phroma Rot, Leaf Miner, and Target Spot. Dataset leaves containing diseased and healthy plant leaves are collected. Then train a deep convolution neural network to identify three diseases. The system used a Convolution Neural Network to identify which of the tomato diseases is present on the monitored tomato plants. The F-RCNN-trained anomaly detection model produced a confidence score of 80% while the Transfer Learning disease recognition model achieved an accuracy of 95.75%. The automated image capturing system was implemented in actual and registered 91.67% accuracy in the recognition of the tomato plant leaf diseases

Sunku Rohan, Triveni S Pujar, Suma VR Amog Shetty, Rishabh F Tated [2] Agriculture field has a high impact on our lives. Agriculture is the most important sector of our Economy. Farmers find it difficult to identify the leaf disease so they produce less production. Though, videos and images of leaves provide a better view agricultural scientists can provide a better solution. So that can solve the problem related to crop disease [2]. It is required to note that if the productivity of the crop is diseased then, it has a high risk of providing good nutrition [2]. Due to the improvement and development in technology where devices are smart enough to recognize and detect plant diseases. Acknowledge the disease's faster treatment to lessen the negative impacts on harvest [2]. This paper focuses on plant disease detection using image processing techniques [2]. This paper accessed open dataset images that consisted of 5000 images of healthy and diseased plant leaves, and they used semi-supervised techniques for crop types and detecting the disease of four classes[2].

Bin Liu, Peng Jiang, Yuehan Chen, Dongjian He, Chunquan Liang [3] This paper contains five types of apple leaf disease that are, aria leaf spot, Brown spot, Mosaic, Grey spot, and Rust. That is affected by Apple [3]. This paper used deep learning techniques to improve convolution neural networks (CNNs) for the detection of apple leaf diseases [3]. In this paper, the apple leaf disease dataset (ALDD) is used, which consists of complex images and laboratory images, and the rest constructed via data augmentation and image annotation technologies to create a new apple leaf disease detection model that uses deep-CNNs is by using Rainbow concatenation and Google Net Inception structure[3]. In the testing dataset using 26,377 images of apple leaf disease, the proposed INAR- model is trained and then detects five common apple leaf diseases [3]. The experimental results show that the INAR- SSD model realizes 78.80% detection performance, with a high-detection speed of 23.13 FPS [3]. The results demonstrate that the novel INAR-SSD model provides a high-performance solution for the early diagnosis of apple leaf diseases that can perform real-time detection of these diseases with higher accuracy and faster detection speed than previous methods [3].

Geetharamani G., Arun Pandian J [4] In this paper, plant leaf disease identification using deep learning technique in convolution neural network (CNN). The Convolutional neural network model is trained using an than 39 different classes of open datasets of plant leaf diseases, and background images [4]. That contains six types of data augmentation methods that are used for gamma correction, image flipping, principal component analysis (PCA) color augmentation, rotation, noise injection, and scaling[4]. The whole is notice that using data augmentation. That can increase the performance of the model. The model was trained using different training ranges of epochs, batch sizes, and dropouts [4]. Then CNN is compared with transfer learning approaches, the proposed model achieves better results. When using the validation data [4]. Though the simulation proposed model achieves 96.46% classification accuracy [4]. The accuracy of the CNN is better than the accuracy of transfer learning approaches [4]

Rekha Chahar, Priyanka Soni [5] This paper contains vegetable, fruit, crops, and flowers Agricultural Images, and leaf disease [14]. The agricultural product type is associated with disease identification [14]. These diseases are specific to the product component which can be root, seed, and leaf [14]. This is helpful in the provide identification of diseases from remote labs [14]. The work is here divided into two steps. In the first step, the ring project-based segmentation model is defined to explore the features of leaf images [14]. Once the features are identified then work is applied for the PNN classifier to identify the existence of disease [14]. The work is about identifying the health and infected disease based on featured region identification [14]. The work is applied to randomly collected leaf images from the web for different plants [14]

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2. Proposed work

The proposed CNN method classifies 38 types of various plant leaf diseases with classification accuracy. Recognition of different leaf diseases through automatic techniques will be helpful for farmers to decrease the strenuous work of monitoring a big farm. Apply the Reset algorithm to the data set and generate a prediction model. The space complexity depends on the Presentation and visualization of discovered patterns has been reduced to design and implement a layered Convolutional Neural Network
(CNN) with the ResNet50 model along with transfer learning that improves the feature distinctiveness of the leaf image. Effectively detection of diseases not only for a particular plant but for multiclass plants. Determination of the best transfer learning technique to achieve the most accurate classification and optimal recognition accuracy for multi-class plant diseases; Resolution of distinct labeling and class issues in plant disease recognition by proposing a deep learning-based CNN model.

3. Methodology

DATASET DESCRIPTION

In the Plant leaf diseases dataset with augmentation data set, 39 different classes of plant leaf and background images are available. The data set contains 61,486 images. We used six different augmentation techniques for increasing the data set size. These techniques are 1)image flipping, 2) Gamma correction, 3) noise injection, 4) PCA color augmentation, 5) rotation, and 6) Scaling [11][13]. We use The Plant leaf diseases dataset with an augmentation dataset of only 30,052 images with 24 labels. The apple label namely: Apple scab, Black rot, apple rust, and healthy. Corn label namely: Corn Cercospora spot Gray spot, Corn rust, Corn healthy, Corn Northern Blight[13][11]. Grape label namely: Black rot, Esca, healthy, and Leaf blight. Potato labels: Early blight, healthy, and Late blight. Tomato labels namely: bacterial spot, early blight, healthy, late blight, leaf mold, septoria leaf spot, spider mite, target sport, mosaic virus, and yellow leaf curl viruses 2 Plant disease dataset

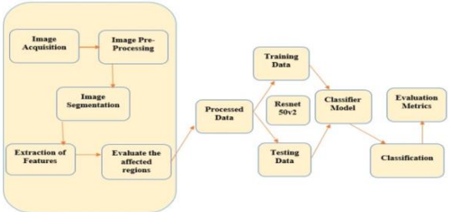

Fig 3 Flow on the Methodology

PREPROCESSING

In the pre-processing, images from their original size have been rescaled to the correct dimensions, if not the Keras library, is unable to manage such large-scale images. In the case of the plant village dataset no need to resize the dimensions because all the data are in a uniform size.
The Plant Village dataset has been extended dynamically to prevent overlapping the sample. This method raises the total dataset. Numerous methods change the training data and adjust the array representations so that the data mark stays the same as data increase techniques.

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IMAGE ACQUISITION FOR DATASET CREATION:

This step involves exploring various data sources from where data can be extracted for training the model and further how the test image input is to be provided.

FEATURE EXTRACTION

After segmentation, the Region of Interest is selected which has better image data, and various features are extracted using feature extraction techniques. This precisely describes the diseased region based on color, shape, and textural features. Various feature extraction methods such as color co-occurrence, contrast, correlation, etc. are used to extract the desired set of features.

TRANSFER LEARNING APPROACH

In general, it takes several days or weeks to train and tune most state-of-the-art models, even if the model is trained on high-end GPU machines. Training and building a model from scratch is time-consuming. A CNN model built from scratch with a publicly available plant disease dataset seemed to attain 25% accuracy in 200 epochs, whereas a pre-trained CNN model using a transfer learning approach attained 63% accuracy in almost half the number of iterations (over 100 epochs). There are various approaches to transfer learning methods; which one to use relies on the specifics of the dataset and the pre-trained network model to be used for classification.

BENEFITS OF TRANSFER LEARNING:

- ✓ Large number of variables can be processed at the same time.
- ✓ It can optimize variables with highly complex cost surfaces.

RESNET-50

ResNet-50 is a convolutional neural network that has 50 deep layers. The model has five stages, with convolution and identity blocks. These residual networks act as a backbone for computer vision tasks. ResNet [49] introduced the concept of stacking convolution layers one above the other. Besides stacking the convolution layers, they also have several skip connections, which bypass the original input to reach the output of the convolutional neural network.

Furthermore, the skip connection can be placed before the activation function to mitigate the vanishing gradient issue. Thus, deeper models end up with more errors, and to resolve these issues, skip connections in the residual neural network were introduced. These shortcut connections are simply based on identity mapping.

Let us consider x as the input image, F(x) as the nonlinear layers fitting mappings, and H(x) as the residual mapping. Thus, the function for residual mapping becomes:

$(x)=(x)+x(1)$

ResNet-50 has convolution as an identity block. Each identity block has three convolutional layers and over 23 M trainable parameters. Input x and shortcut x are the two matrices, and they can only be added if the output dimension from a shortcut and the convolution layer after the convolution and batch normalization are the same. Otherwise, shortcut x must go through a convolution layer and batch normalization to match the dimension.

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4. Results

```
/content/drive/My Drive/leafdisease dataset/Apple___Apple_scab
/content/drive/My Drive/leafdisease dataset/Apple___Black_rot
/content/drive/My Drive/leafdisease dataset/Apple___Cedar_apple_rust
/content/drive/My Drive/leafdisease dataset/Apple___healthy
/content/drive/My Drive/leafdisease dataset/Grape___Black_rot
/content/drive/My Drive/leafdisease dataset/Grape___Esca_(Black_Measles)
/content/drive/My Drive/leafdisease dataset/Grape___healthy
/content/drive/My Drive/leafdisease dataset/Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
/content/drive/My Drive/leafdisease dataset/Corn___Cercospora_leaf_spot Gray_leaf_spot
/content/drive/My Drive/leafdisease dataset/Corn___Common_rust
/content/drive/My Drive/leafdisease dataset/Corn___healthy
/content/drive/My Drive/leafdisease dataset/Corn___Northern_Leaf_Blight
/content/drive/My Drive/leafdisease dataset/Potato___Early_blight
/content/drive/My Drive/leafdisease dataset/Potato___healthy
/content/drive/My Drive/leafdisease dataset/Potato___Late_blight
/content/drive/My Drive/leafdisease dataset/Tomato___Bacterial_spot
/content/drive/My Drive/leafdisease dataset/Tomato___Early_blight
/content/drive/My Drive/leafdisease dataset/Tomato___healthy
/content/drive/My Drive/leafdisease dataset/Tomato___Late_blight
/content/drive/My Drive/leafdisease dataset/Tomato___Leaf_Mold
/content/drive/My Drive/leafdisease dataset/Tomato___Septoria_leaf_spot
/content/drive/My Drive/leafdisease dataset/Tomato___Spider_mites Two-spotted_spider_mite
/content/drive/My Drive/leafdisease dataset/Tomato___Target_Spot
/content/drive/My Drive/leafdisease dataset/Tomato___Tomato_mosaic_virus
X_data shape: (24000, 256, 256, 3)
```

Fig 5 labeled dataset images

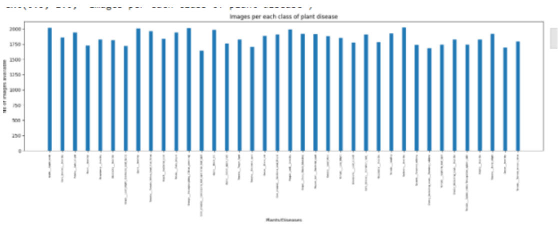
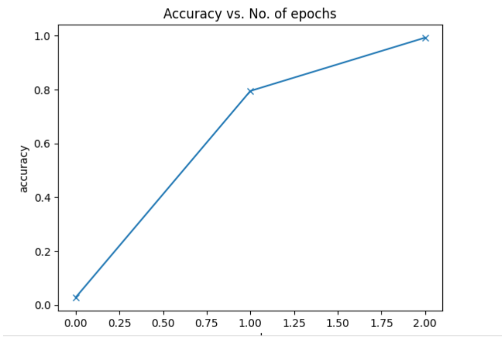


Fig 6 Each class of plant disease



5. Conclusion

We have studied about existing system feature-based approach. It's done by image processing technique in this we have studied steps like image Acquisition, image preprocessing, Image Segmentation, feature extraction, and classification. Proposed system to achieve this purpose, we have to use CNN and get an accuracy is 90.23%. We have also used the VGG16 model to detect leaf disease but in our case, CNN has better results than VGG16. In the future, we can add more classes of leaves and disease type

6. References

[1] Robert G. de Luna, Elmer P. Dadios,

Argel A. Bandala, "Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition," International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD) 2019.

[2] Suma VR Amog Shetty, Rishab F Tated, Sunku Rohan, Triveni S Pujar, "CNN based Leaf Disease Identification and Remedy Recommendation System," IEEE conference paper 2019.

[3] Peng Jiang, Yuehan Chen, Bin Liu, Dongjian He, Chunquan Liang, "Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolution Neural Networks," IEEE ACCESS 2019.

[4] Geetharamani, Arun Pandian, "Identification of plant leaf diseases using a nine-layer deep convolution neural network," Computers and Electrical Engineering 76 (2019).

[5] Robert G. de Luna, Elmer P. Dadios, Argel A. Bandala, "Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition," Proceedings of TENCON 2018 - 2018 IEEE Region 10 Conference.

[6] Omkar Kulkarni, "Crop Disease Detection Using Deep Learning," IEEE Access 2018.

[7] Abirami Devaraj, Karunya Rathan, Sarvepalli Jaahnavi and K Indira, "Identification of Plant Disease using Image Processing Technique," International Conference on Communication and Signal Processing, IEEE 2019.

[8] Velamakanni Sahithya, Brahmadevara Saivihari, Vellanki Krishna Vamsi, Parvathreddy Sandeep Reddy and Karthigha Balamurugan, "GUI based Detection of Unhealthy Leaves using Image Processing Techniques," International Conference on Communication and Signal Processing 2019.

[9] Balakrishna K Mahesh Rao, "Tomato Plant Leaves Disease Classification Using KNN and PNN," International Journal of Computer Vision and Image Processing 2019.

[10] Masum Aliyu Muhammad Abdu, Musa Mohd Mokji, Usman Ullah Sheikh, Kamal Khalil, "Automatic Disease Symptoms Segmentation Optimized for Dissimilarity Feature Extraction in Digital Photographs of Plant Leaves," IEEE 15th International Colloquium on Signal Processing & its Applications 2019.

[11] http://dx.doi.org/10.17 (J & GOPAL, 2019), A. P., & GOPAL, G. (2019), https://data.mendeley.com/datasets/tywbtsjrjv/1.Retrieved, http://dx.doi.org/10.17632/tywbt sjrjv.1.

[12] Suja Radha, "Leaf Disease Detection using Image Processing," Article in Journal of Chemical and Pharmaceutical Sciences, March 2017.

[13] Sneha Patel, U.K Jaliya, Pranay Patel, "A Survey on Plant Leaf Disease Detection," International Journal for Modern Trends in Science and Technology, April 2020.

[14] Priyanka Soni, Rekha Chahar, "A Segmentation Improved Robust PNN Model for Disease Identification in Different Leaf Images," 1st IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES-2016).

[15] S. Arivazhagan, R. Newlin Shebiah S. Ananthi, S. Vishnu Varthini, "Detection of the unhealthy region of plant leaves and classification of plant leaf diseases using texture features," CIGR Journal, March 2013.

[16] Adedamola Adedoja & Pius Adewale Owolawi & Temitope Mapayi, "Deep Learning Based on NAS Net for Plant Disease Recognition Using Leave Images," 2018.

[17] Prajwala TM, Alla Pranathi, Kandiraju Sai Ashritha, Nagaratna B. Chittaragi, Shashidhar G. Koolagudi, "Tomato Leaf Disease Detection using Convolutional Neural Networks," Proceedings of 2018 Eleventh International Conference on Contemporary Computing (IC3), 2018.

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ISSN 2319 - 8354

[18] VGG16 - Convolutional Network for
Classification and Detection, 21 Nov 2018 https://neurohive.io/en/popular-networks/vgg16/

[19] “Python Numpy Tutorial | Learn Numpy Arrays with Examples,” Edureka, Jul. 14, 2017. https://www.edureka.co/blog/python-numpy-tutorial/ (accessed Apr. 21, 2020).

[20] J. Han and C. Moraga, “The Influence of the Sigmoid Function Parameters on the Speed of Backpropagation Learning,” in Proceedings of the International Workshop on Artificial Neural Networks: From Natural to Artificial Neural Computation, Berlin, Heidelberg, Jun. 1995, pp. 195–201, Accessed: Apr. 13, 2020. [Online].