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| **Paper** | **Idea** | **Method** | **Dataset** |
| [1] | This research paper provides a novel technique to detect crop diseases with the help of convolutional encoder networks using crop leaf images.  The idea is to build a set of self-learned features that makes the proposed network unaffected by any variations such as shadows, illumination and skewed images | hybrid approach:  *combination of convolutional neural networks and autoencoders* | PlantVillage |
| [2] | The aim of this work is to detect the unhealthy leaf of ladies finger plant by diagnosing the leaf image.  Noise is added in order to capture the limitations of real time images (To consider the external factors like temperature and  atmospheric environmental constraints, noises are added in the image), and PCA is used for reduction of feature set that expects fast computation and less hardware requirement. | Added Noises:  *1. Gaussian noise*  *2. Poisson noise*  Segmentation:  *1. k-means*  *2. fuzzy c-means*  Feature extraction:  *GLCM*  Feature reduction:  *PCA*  Classification:  *1. SVM*  *2. LSVM*  *3. ANN*  *4. RF* |  |
| [3] | The present study is based on the image processing techniques to identify and classify fungal rust disease of Pea.  The goal of this paper is to detect, to identify the early symptoms of rust disease at the microscopic level. | SVM (Support Vector Machine) classifier | The leaves samples were collected from the field and prepared for dataset.  For image data, leaves of affected plant were collected from Hill Agricultural Research and Extension Centre, Dhaulakuan, Himachal Pardesh, India. |
| [4] | In this work, the focus was on fine-tuning and evaluation of state-of-the-art **deep convolutional neural network** for image-based plant disease classification. | The architectures evaluated include **VGG 16**, **Inception V4**, **ResNet** with 50, 101 and 152 layers and **DenseNets** with 121 layers. | The data used for the experiment is 38 different classes including diseased and healthy images of leafs of 14 plants from **plantVillage**. |
| [5] | For the purpose of improving the extraction of tea plant leaf disease saliency map under complex backgrounds, a new algorithm combining **SLIC** (Simple Linear Iterative Cluster) with **SVM** (Support Vector Machine) is proposed in this paper. | Firstly, super-pixel block is obtained ***by SLIC algorithm***, significant point is detected ***by Harris algorithm***, and fuzzy salient region contour is extracted ***by employing convex hull method***.  Secondly, the four-dimensional texture features of super-pixel blocks in salient regions and background areas are extracted, and then the classification map is obtained by classifying the super-pixel blocks with the help of SVM classifier. Lastly, ***the morphological and algebraic operations*** are implemented for repairing classified super-pixel blocks. As a result, one accurate saliency map of tea plant leaf disease image is obtained. | Tea plant leaf disease images were collected in multiple directions under the tea plantation environment. |
| [6] | Plant Disease Diagnosis with Color Normalization.  A plant disease diagnosis method based on color histogram invariant features, is evaluated on pear diseases. | The employed **fuzzy-like** classification method is tested with five different normalization methods applied on **Red-Green-Blue (RGB)**, **Hue-Saturation-Lightness (HSL)**, **Hue-Saturation- Value (HSV)** and **L\*a\*b format**. | N/A |
| [7] | Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers.  The presented approach demonstrates an automated way of crop disease identification on various leaf sample images corresponding to different crop species employing Local Binary Patterns (LBPs) for feature extraction and One Class Classification for classification. | Feature extraction:  *Local Binary Patterns (****LBP****)*  Classification:  *One Class support vector Machines (****OCSVMs****)* | Inside of the article file, in scan form. |
| [8] | Tea diseases detection based on fast infrared thermal image processing technology.  The overall goal of this study is to develop an effective, simple, apt computer vision algorithm to detect tea disease area using infrared thermal image processing techniques and to estimate tea disease. | Detection algorithms based on **infrared thermography**.  tea disease rapid detection algorithm based on infrared thermal imaging technology. | Tea plant images were taken from Jiangsu Tea Expo Park, China, at noon and camera shooting height was 2 m. |
| [9] | A novel segmentation method of plant disease leaf image is proposed based on a hybrid clustering.  Plant disease leaf image segmentation based on superpixel clustering and EM algorithm. | 1. Superpixel clustering  2. EM algorithm | In order to examine and verify the performance of superpixels + EM, a number of experiments are conducted on a cucumber disease leaf image database, in a mixture platform of MATLAB 7.0 and under Windows XP and 120 G hard disk.  All color disease cucumber leaves in the database were collected with digital camera in the agricultural demonstration zone of Northwest Agriculture and Forestry University in China. |
| [10] | Machine Intelligence for the Detection of Plant Diseases Using Image Processing.  In this work, various machine intelligence techniques include SVM, Back Propagation network, Naïve Bayesian are analyzed and observed and concur Gray Level Co-occurrence Matrix (GLCM) based neural network performs better and gives high accuracy. | Preprocessing methods:  1. *Image clipping & resizing*  2. *Color conversion*  3. *Noise removal*  Enhancement methods:  1. *Histogram equalization*  2. *Green Channel Extraction*  Segmentation methods:  1. *K-Means algorithm*  2. *Fast robust fuzzy C-Means algorithm*  3. *Otsu thresholding algorithm*  Feature extraction methods:  1. *Canny edge detection*  2. *Gray-Level-co-occurrence matrix*  Classification methods:  1. *Support Vector Machine*  2. *Naïve Bayesian Classifier*  3. *Back Propagation Neural Network*  4. *Genetic algorithm* | In this work,  **plant village** dataset repository has been used |
| [11] | Visual Tea Leaf Disease Recognition Using a Convolutional Neural Network Model.  The aim of the present study was to develop a deep CNNs to identify tea plant disease types from leaf images. | CNN model:  ***LeafNet***  Feature extractor:  *dense scale-invariant feature transform (****DSIFT****)-based bag of visual words (****BOVW****) model*  Classifiers:  *support vector machine (****SVM****)*  *multi-layer perceptron (****MLP****)* | Images showing tea leaf diseases were all captured using a Cannon PowerShot G12 camera in  the natural environments of Chibi and Yichang within the Hubei province of China. |
| [12] | Tomato Plant Leaves Disease Classification Using KNN and PNN.  In this article, the authors proposed two methods for identification and classification of healthy and unhealthy tomato leaves. In the first stage, the tomato leaf is classified as healthy or unhealthy using the KNN approach. Later, in the second stage, they classify the unhealthy tomato leaf using PNN and the KNN approach. | Feature extractor:  ***GLCM*** *(Gray level Cooccurrence Matrix)*  Classifiers:  ***KNN***  ***PNN*** | In this work created an own database with 600 data-sets of different tomato leaves images were collected in a farmland using the digital camera of 1080×1920 pixels. |
| [13] | Using Deep Learning for Image-Based Potato Tuber Disease Detection. | ***CNN-F***  ***VGG*** | Photos of 400 diseased potato tubers with smooth skin but different cultivars, shapes, sizes  and colors were taken under normal uncontrolled illumination conditions. |
| [14] | Identification of plant leaf diseases using a nine-layer deep convolutional neural network. | Six types of data augmentation methods were used:  *1. image flipping*,  *2. gamma correction*,  *3. noise injection*,  *4. principal component analysis (PCA) colour augmentation*,  *5. rotation*,  *6. scaling*. | The diseased and healthy plant leaf images were downloaded from the **plantvillage** dataset. |
| [15] | Artificial bee colony optimization (ABC) for grape leaves disease detection.  This paper deals with the identification and classification of diseases in grape leaves by using **artificial bee colony (ABC) based feature selection**.  ABC based attribute selection is used **to find the optimal feature set**. | Feature selection:  *Artificial bee colony optimization (****ABC****)*  Classification:  ***SVM*** | **Plantvillage**  And  Own collected grape leaf dataset. |
| [16] | BRBFNN for Identification and Classification of Plant Leaf Diseases.  **Survey**  This system was created to specify the quality of specific product.  The system is focus on the quality of food which has impact on our health. | Bacterial foraging optimization based Radial Basis Function Neural Network (**BRBFNN**).  Algorithm 1:  *Bacterial Foraging Optimization (****BFO****)*  Algorithm 2:  *Support Vector Machine (****SVM****)*  Algorithm 3:  *Radial Basis Function Neural Network (****RBFNN****)* | N/A |
| [17] | Identification of Plant Disease using Image Processing Techniques in Matlab.  The aim of this project is to develop a software system answer that Mechanically find and classify disease. | Image Segmentation:  ***K-means*** *clustering technique*  Classification:  *Random Forest (****RF****)* | In our work, using camera we tend to  captured healthy and diseased pictures of leaf & fruit. |
| [18] | Non-Destructive Techniques of Detecting Plant Diseases: **A Review** | image processing:  1. *Fluorescence imaging*  2. *Hyperspectral imaging*  3. *K-means segmentation*  Feature extraction:  1. *Colour Co-occurrence method (CCM)*  Classification:  1. *SVM*  2. *ANN*  Spectroscopy-based  1. *Visible and Infrared*  2. *Fluorescence*  3. *Electric impedance*  Remote sensing methods  1. *Hyperspectral*  2. *Multispectral* | N/A |
| [19] | Applying of Advanced Spectroscopic techniques for confirmatory plant disease diagnostics. **A Review** | Spectroscopic methods:  1. *reflectance*  2. *infrared*  3. *Raman*  4. *Surface-enhanced Raman* | 1. qPCR assay  2. Raman spectrum |
| [20] | Performing of plant disease detection and diagnosis using simple leaves images of healthy and diseased plants through CNN models. | CNN models:  1. *AlexNet*  2. *AlexNetOWTBn*  3. *GoogLeNet*  4. *Overfeat*  5. *VGG* | Hughes, D.P., Salathé, M. 2015. An open access repository of images on plant health to enable the development of mobile disease diagnostics. **arXiv:1511.08060** |
| [21] | A Mobile-Based Deep Learning Model for Cassava Disease Diagnosis | 1. ***Smartphone CNN object detection model*** to identify foliar symptoms of three diseases, two types of pest damage, and nutrient deficiency in cassava.  2. ***Single Shot Multibox (SSD) model with MobileNet detector and classifier*** pre-trained on the COCO dataset | COCO (Common Objects in Context) |
| [22] | Depthwise separable convolution architectures for plant disease classification/detection based on images of leaves | 1. ***Depthwise separable convolution***  2. ***Reduced MobileNet***  3. ***Modified MobileNet*** | PlantVillage |
| [23] | An IoT-based cognitive monitoring system for early plant disease forecast.  An IoT-based monitoring system for precision agriculture applications such as epidemic disease control.  We develop artificial intelligence and prediction algorithms to realize an expert system that allows the system to emulate the decision-making ability of a human expert regarding the diseases and issue warning messages to the users before the outbreak of the disease. |  |  |
| [24] | Plant disease identification from individual lesions and spots using deep learning.  This paper explores the use of individual lesions and spots for the task, rather than considering the entire leaf. | GoogleNet CNN | The images in the database were captured using several different sensors (smartphones, compact cameras, DSLR cameras), and their resolutions range from 1 to 24 MPixels. |
| [25] | PD2SE-Net: Computer-assisted plant disease diagnosis and severity estimation network | PD2SE-Net50 -> ResNet50  Shuffle-Net-v2 | The proposed model for multi-function diagnosis system with a  synthetic dataset that was retrieved from AI Challenger Global AI Contest (www.challenger.ai) and the synthetic dataset released by Hughes and Salathe (2014, 2015). |
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