International Journal of Current Engineering and Technology
E-ISSN 2277 – 4106, P-ISSN 2347 – 5161

Available at http://inpressco.com/category/ijcet

Research Article

Plant disease and entomology identification using deep learning and computer vision

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Received 10 July 2022, Accepted 01 Aug 2022, Available online 06 Aug 2022, **Vol.12, No.4 (July/Aug 2022)**

Abstract

Identifying plant diseases is the key to preventing losses in yield and quantity of agricultural product. The study of plant diseases means the study of visually observable patterns observed on a plant. Monitoring the health status and detection of plant diseases is very important for sustainable agriculture. It is very difficult to monitor plant diseases manually. It requires a huge amount of work, expertise in plant diseases and also takes too long to process. Image processing is therefore used for plant disease detection. Disease detection includes steps such as image acquisition, image preprocessing, image segmentation, feature extraction, and classification. This article discusses the methods used to detect plant diseases using images of their leaves. This paper also discusses some segmentation and feature extraction algorithms used in plant disease detection.

Keywords: *Automated monitoring | ecology | insects | image-based identification | machine learning*

1. Introduction

Research in agriculture is aimed towards increase of productivity and food quality at reduced expenditure, with increased profit. Agricultural production system is an outcome of a complex interaction of soil, seed, and ago chemicals. Vegetables and fruits are the most important agricultural products. In order to obtain more valuable products, a product quality control is basically mandatory. Many studies show that quality of agricultural products may be reduced due to plant diseases. Diseases are impairment to the normal state of the plant that modifies or interrupts its vital functions such as photosynthesis, transpiration, pollination, fertilization, germination etc. These diseases are caused by pathogens viz., fungi, bacteria and viruses, and due to adverse environmental conditions. Therefore, the early-stage diagnosis of plant disease is an important task. Farmers require continuous monitoring of experts which might be prohibitively expensive and time consuming. Therefore, looking for fast, less expensive and accurate method to automatically detect the diseases from the symptoms that appear on the plant leaf is of great realistic significance. This enables machine vision that is to provide image based automatic inspection, process control and robot guidance. The objective of this paper is to concentrate on the plant leaf disease detection based on the texture of the leaf.

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DOI: https://doi.org/10.14741/ijcet/v.12.4.5

Leaf presents several advantages over flowers and fruits at all seasons worldwide Using the trained data by disease found on pant leaves, our model will be trained to recognize the causes of that diseases and identify species of insects that have caused the respective diseases in the past.

This paper is organized into the following sections. Section 1 gives an introductory part includes importance of leaf disease detection, plant leaves analysis, various types of leaf diseases and its symptoms. Section 2 presents a detailed discussion on recent work carried out in this area. Section 3 includes basic methodology for leaves disease detection which represents a brief review on various image processing techniques. Finally, section 4 concludes this paper along with possible future directions. When trained on these data, deep learning models can provide estimates of insect abundance, biomass, and diversity. Further, deep learning models can quantify variation in phenotypic traits, behavior, and interactions. Here, we connect recent developments in deep learning and computer vision to the urgent demand for more cost-efficient monitoring of insects and other invertebrates. We present examples of sensor-based monitoring of insects. We show how deep learning tools can be applied to exceptionally large datasets to derive ecological information and discuss the challenges that lie ahead for the implementation of such solutions in entomology. We identify four focal areas which will facilitate this transformation:

1) validation of image-based taxonomic identification.
2) generation of sufficient training data
3) development of public, curated reference databases;
4) solutions to integrate deep learning and molecular tools

2. Plant disease and symptoms

The RGB image feature pixel counting techniques is extensively applied to agricultural science. Image analysis can be applied for the following purposes.

1) To detect plant leaf, stem, and fruit diseases.
2) To quantify affected area by disease.
3) To find the boundaries of the affected area.
4) To determine the colour of the affected area
5) To determine size & shape of fruits. Following are some common symptoms of fungal, bacterial and viral plant leaf diseases.

2.1 Bacterial disease symptoms

The disease is characterized by tiny pale green spots which soon come into view as water- soaked. The lesions enlarge and then appear as dry dead spots, e.g., bacterial leaf spot have brown or black water-soaked spots on the foliage, sometimes with a yellow halo, generally identical in size. Under dry conditions the spots have a speckled appearance

2.2 Viral disease symptoms

Among all plant leaf diseases, those caused by viruses are the most difficult to diagnose. Viruses produce no tell-tale signs that can be readily observed and often easily confused with nutrient deficiencies and herbicide injury. Aphids, leafhoppers, whiteflies and cucumber beetles' insects are common carriers of this disease, e.g., Mosaic Virus, look for yellow or green stripes or spots on foliage Leaves might be wrinkled, curled and growth may be stunted.

2.3 Fungal disease symptoms

Among all plant leaf diseases, those caused by fungus some of them are discussed below and shown in figure 2, e.g., Late blight caused by the fungus Phytophthora infesters It first appears on lower, older leaves like water-soaked, Gray-green spots. When fungal disease matures, these spots darken and then white fungal growth forms on the undersides. Early blight is caused by the fungus Alternaria solan. It first appears on the lower, older leaves like small brown spots with concentric rings that form a bull's eye pattern. When disease matures, it spreads outward on the leaf surface causing it to turn yellow. In downy mildew yellow to white patches on the upper surfaces of older leaves occurs. These areas are covered with white to greyish on the undersides.

3. Literature review

A Proliferation of literature is available in plant leaf disease detection. We will highlight some of the key contributions. A methodology for detecting plant diseases early and accurately using diverse image processing techniques has been proposed by Anand H.Kulkarni et al. Where Gabor filter has been used for feature extraction and ANN based classifier has been used for classification with recognition rate up to 91%. F. Argenti, et al. proposed a fast algorithm for calculating parameters of co-occurrence matrix by supervised learning and maximum likelihood method for fast classification. Homogenize techniques like sobel and canny filter has been used to identify the edges by P.Revathi et al. . These extracted edge features have been used in classification to identify the disease spots. The proposed homogeneous pixel counting technique for cotton diseases detection (HPCCDD) algorithm has been used for categorizing the diseases. They claim the accuracy of 98.1% over existing algorithm. Tushar H Jaware et al. proposed a novel and improved k-means clustering technique to solve low-level image segmentation. Spatial gray-level dependence matrices (SGDM) method has been used for extracting statistical texture features by Sanjay B. Dhaygude et al. RGB images have been converted into Hue Saturation Value (HSV) color space representation and showed the H, S and V components. Mokhled S. Al-Tarawneh presented an empirical investigation of olive leaf spot disease using auto-cropping segmentation and fuzzy c-means classification. Rgb to Lab colorspace and median filter used for image enhancement. At end present comparative assessment of fuzzy c-means and k-mean clustering.349 An Overview of the Research on Plant Leaves Disease detection using Image Processing Techniques www.iosrjournals.org 12 | Page The fuzzy feature selection approach namely fuzzy curves (FC) and fuzzy surfaces (FS) have been proposed to select features of cotton leaf disease by Yan-Cheng Zhang, et al. This has been resulted in reduced dimensional feature space. Back-propagation (BP) networks have been used to classify the grape and wheat diseases by Haiguang Wang et al. Also by using principal component analysis (PCA) dimensions of the feature data has been reduced. Texture features based on the local power spectrum of Gabor filters has been proposed by Simona E. Grigorescu et al. where complex moments, Gabor energy and grating cell operator features have been discussed. They concluded that grating cell operator responded only to texture features. Detection of unhealthy region and classification using texture features has been proposed by S. Arivazhagan, et al. Their algorithm has been tested on ten species of plants namely banana, beans, jackfruit, lemon, mango, potato, tomato and sapota. 94.74% accuracy has been achieved by Support vector machine (SVM) classifier. Dheeb Al Bashish, et al. Developed neural network classifier based on statistical classification and could successfully detect and classify the diseases with a precision of around 93%. A Research of maize disease image recognition of corn based on BP networks effectively identified by Song Kai et al. where YCBCR colour space technology is used to

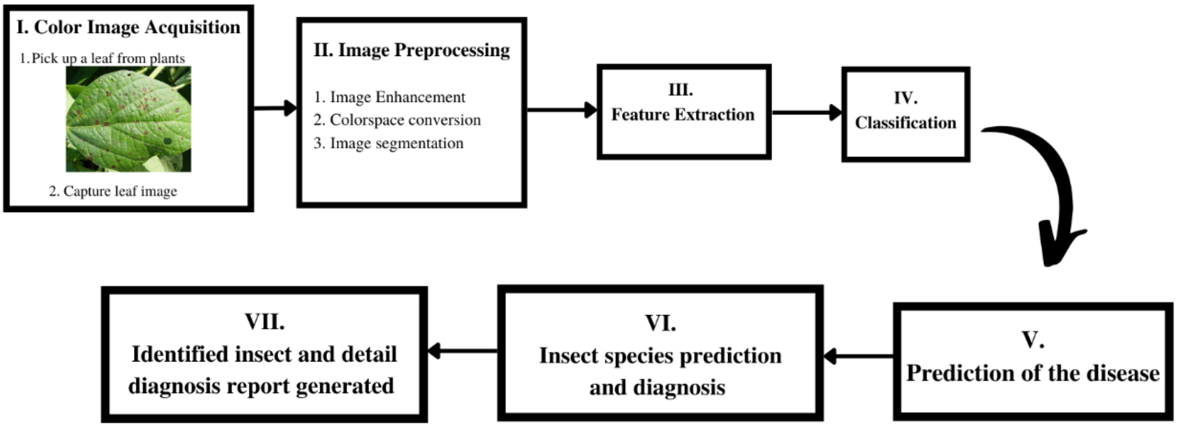

Figure 1: Basic methodology

segment disease spot, Co-occurrence matrix (CCM) spatial gray level layer is used to extract disease spot texture feature, and BP neural network has been used to classify the maize disease. The applications of K-means clustering, BP neural networks had been formulated for clustering and classification of diseases that effect on plant leaves by H. Al-Hiary, et al. They provide adequate support for accurate detection of leaf diseases. The proposed algorithm has been tested on five diseases viz. Early and late scorch, cottony and ashen mold, tiny whiteness. Menukaewjinda et al. Tried another ANN, i.e., back propagation neural network (BPNN) for efficient grape leaf colour extraction with complex background. They also explore modified self-organizing feature map (MSOFM) and genetic algorithm (GA) and found that these techniques provide automatic adjustment in parameters for grape leaf disease colour extraction. Support vector machine (SVM) has been also found to be very promising to achieve efficient classification of leaf diseases. 21 colour, 4 shape and 25 texture features has been extracted by Haiguang Wang et al. [15] and principal component analysis (PCA) has been performed for reducing dimensions in feature data processing, then back-propagation (BP) networks, radial basis function (RBF) neural networks, generalized regression networks (GRNNs) and probabilistic neural networks (PNNs) has been used as the classifiers to identify diseases.

3. Methodology

There are six main steps used for the detection of plant leaf diseases. The processing scheme consists of image acquisition through digital camera or web, image pre-processing includes image enhancement and image segmentation where the affected and useful area are segmented, feature extraction and classification. Then presence of diseases on the plant leaf will be identified, diagnosis will be performed on the concluded information and then cause/ insect prediction process will be started and model will be concluded with diagnosis report with identified insect and cause of the disease

In the initial step, RGB images of leaf samples were picked up. The step-by-step procedure as shown below:

1) Colour image acquisition;
2) convert the input image into colour space;
3) Segment the components;
4) obtain the useful segments;
5) Computing the texture features;
6) Configuring the neural networks for recognition.
7) Prediction of the disease on the affected part
8) Insect species prediction and diagnosis
9) Identified insect and detail diagnosis report generated

3.1. Colour Image acquisition

Firstly, the images of various leaves acquired using a digital camera with required resolution for better quality. The construction of an image database is clearly dependent on the application. The image database itself is responsible for the better efficiency of the classifier which decides the robustness of the algorithm.

3.2. Image pre-processing

In the second step, this image is pre-processed to improve the image data that suppress undesired distortions, enhances some image features important for further processing and analysis task. It includes colour space conversion, image enhancement, and image segmentation. The RGB images of leaves are converted into colour space representation. The purpose of the color space is to facilitate the specification of colours in some standard accepted way. RGB images converted into Hue Saturation Value (HSV) color space representation. Because RGB is for color generation and his for-color descriptor. HSV model is an ideal tool for color perception. Hue is a color attribute that describes pure color as perceived by an observer. Saturation termed as relative purity or the amount of white light added to hue and value means amplitude of light. After the color space transformation process, hue component used for further analysis. Saturation and value are dropped since it does not give extra information. Ycbcr color system is a common color space, which is applied by the most widely used jpeg image. Ycbr and cr, indicates a luminance component and two-color component signals respectively. Different from other color space, Ycbcr color space is orthogonal, which fully takes important factors of composition of RGB from other colors into account. Ycbcr color space model is often used in image compression. A, U, and Cr components from LAB, UVL, and Ycbcr color space used to extract affected leaf color with the purpose of less illumination effects. Image segmentation is process used to simplify the representation of an image into something that is more meaningful and easier to analyze. As the premise of feature extraction and pattern recognition, image segmentation is also the fundamental approaches of digital image processing. There are various techniques for image segmentation discuss below.

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3.3. Region based

In this technique pixels that are related to an object are grouped. The area that is detected for segmentation should be closed. Due to missing edge pixels in this region-based segmentation there won't be any gap. The boundaries are identified for segmentation. In every step at least one pixel is related to the region and is taken into consideration. After identifying the change in the color and texture, the edge flow is converted into a vector. Then these edges are detected for further segmentation.

3.4. Threshold based

It is the easiest way of segmentation. Here segmentation is done through the threshold values obtained from the histogram of those edges of the original image. So, if the edge detections are accurate then the threshold too. Segmentation through thresholding has fewer computations compared to other techniques. The disadvantage of this segmentation technique is not suitable for complex images.

3.5. Feature based

Feature based clustering Segmentation is also done through Clustering. The image is converted into histogram and then clustering is done on it. Pixels of the color image are clustered for segmentation using an unsupervised technique Fuzzy C. This is applied for ordinary images. It results to fragmentation if it is a noisy image. A basic clustering k-means algorithm is used for segmentation in textured images. It clusters the related pixels to segment the image. Segmentation is done through feature clustering and there it will be changed according to the color components. Segmentation is also purely depending on the characteristics of the image. Features are taken into account for segmentation. Difference between the intensity and color values are used for segmentation. Improved k-mean used to solve low-level image segmentation. For segmentation of color image use of fuzzy clustering technique is to iteratively generate color clusters using fuzzy membership function in color space regarding to image space. The technique is successful in identifying the color region. Real time clustering-based segmentation. A Virtual attention region is captured accurately for segmentation. Image is segmented coarsely by multithresholding. It is then refined by fuzzy cmeans clustering. It applied to any multispectral images is a major advantage. Segmentation approach for region growing is k-means clustering. A Clustering technique for image segmentation is done with cylindrical decision elements of the color space. The surface is obtained through histogram and is detected as a cluster by thresholding. By using modified self-organizing feature map (MSOFM), clustering process does not require predefined number of color group. This is also adjustable allowing similarity of each color group. The suitable color group numbers lead to the better color extraction.

3.6. Model based Markov Random Field (MRF) based

Model based Markov Random Field (MRF) based segmentation is known as model-based segmentation. An inbuilt region smoothness constraint is presented in MRF which is used for color segmentation. MRF is combined with edge detection for identifying the edges accurately.

3.7. Feature extraction

After segmentation the area of interest i.e., diseased part extracted. In the next step, significant features are extracted and those features can be used to determine the meaning of a given sample. Actually, image features usually include color, shape and texture features. Currently most of the researchers targeting plant leaf texture as the most important feature in classifying plants. With the help of texture features, plant diseases are classified into different types. There are various methods for feature extraction as discussed below.

3.8 Classifier

A Software routine was written in MATLAB. In which training and testing performed via several neural network classifier. Texture Feature Classification Methods are as follows

3.8.1. K-nearest neighbor

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$$d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

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3.8.2 Radial basis function

A radial basis function (RBF) is a real-valued function whose value depends only on the distance from the origin. The normally used measuring norm is Euclidean distance. RBFs are the networks where the activation of hidden units is based on the distance between the input vector and a prototype vector.

$$h(x) = \sum \overset{\text{Variable}}{\downarrow} w_n \overbrace{exp(-\gamma \underbrace{||x - x_n||}_{\text{Radial}})}^{\text{Basis Function}}$$

3.8.2 Artificial neural networks

ANNs are popular machine learning algorithms that are in a wide use in recent years. Multilayer Perception (MLP) is the basic form of ANN that updates the weights through back propagation during the training. There are other variations in neural networks, which are recently, became popular in texture classification. Probabilistic Neural Network (PNN): It is derived from Radial Basis Function (RBF) network and it has parallel distributed processor that has a natural tendency for storing experiential knowledge. PNN is an implementation of a statistical algorithm called kernel discriminate analysis in which the operations are organized into a multi-layered feed forward network having four layers viz. input layer, pattern layer, summation layer, and output layer. Convolutional neural network: It is a neural network that has convolution input layers acts as a self-learning feature extractor directly from input images. Hence, it can perform both feature extraction and classification under the same architecture. Back propagation network: A typical BP network consists of three parts: input layer, hidden layer and output layer. Three parts in turn connect through the collection weight value between nodes . The largest characteristic of BP network is that network weight value reach expectations through the sum of error squares between the network output and the sample output, and then it continuously adjusted network structure's weight value. It is popular and extensively used for training feed forward networks. Also it has no inherent novelty detection, so it must be trained on known outcomes for training feed forward networks.

3.8.2 Support vector machine

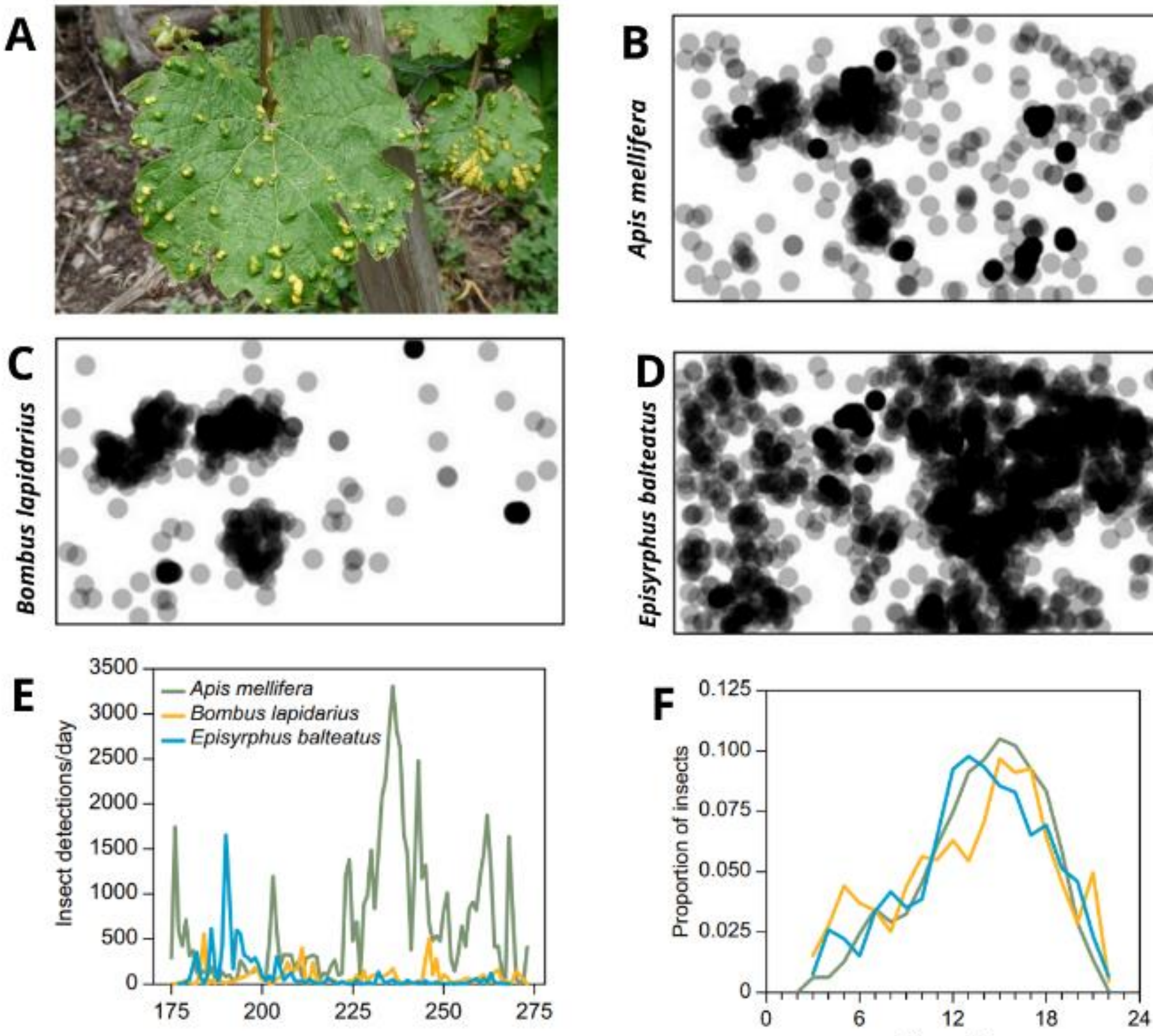
Support vector machine (SVM) is a non-linear classifier, and is a newer trend in machine learning algorithm. SVM is popularly used in many pattern recognition problems including texture classification. SVM is designed to work with only two classes. This is done by maximizing the margin from the hyper plane. The samples closest to the margin that were selected to determine the hyper plane is known as support vectors. Multiclass classification is applicable and basically built up by various two class SVMs to solve the problem, either by using one-versus-all or one.

3.9 Image-Based Solutions for In Situ Monitoring

Some case studies have already used cameras and deep learning methods for detecting single species, such as the pest of the fruits of olive trees Bactrocera oleae or for more generic pest detection. Here, the pest detection is based on images of insects that have been trapped with either a McPhail-type trap or a trap with pheromone lure and adhesive liner. The images are collected by a microcomputer and transmitted to a remote server where they are analyzed. Other solutions have embedded a digital camera and a microprocessor that can count trapped individuals in real time using object detection based on a deep learning model. In both these cases, deep learning networks are trained to recognize and count the number of individuals. However, there are very few examples of invertebrate biodiversity-related field studies applying deep learning models. Early attempts used feature vectors extracted from single perspective images and yielded modest accuracy for 35 species of moths or used mostly coarse taxonomic resolution. We have recently demonstrated that our custom-built time-lapse cameras can record image data from which a deep learning model can accurately estimate local spatial, diurnal, and seasonal dynamics of honeybees and other flower visiting insects . Time-lapse cameras are less likely to create observer bias than direct observation, and data collection can extend across full diurnal and even seasonal timescales. Cameras can be baited just as traditional light and pheromone traps or placed over ephemeral natural resources such as flowers, fruits, dung, fungi, or carrion. Bjerge et al. propose to use an automated light trap to monitor the abundance of moths and other insects attracted to light. As the system is powered by a solar panel, it can be installed in remote locations. Ultimately, true "Internet of Things"-enabled hardware will make it possible to implement classification algorithms directly on the camera units to provide fully autonomous systems in the field to monitor insects and report detection and classification data back to the user or to online portals in real time.

3.9.1 Sensor-Based Insect Monitoring

Sensors are widely used in ecology for gathering peripheral data such as temperature, precipitation, and light intensity. However, solutions for sensor-based monitoring of insects and other invertebrates in their natural environment are only just emerging. The innovation and development are primarily driven by agricultural research to predict occurrence and abundance of beneficial and pest insect species of economic importance, to provide more efficient screening of natural products for invasive insect species, or to monitor disease vectors such as mosquitos. The most commonly used sensors are cameras, radars, and microphones. Such sensor-based monitoring is likely to generate datasets that are orders of magnitude larger than those commonly studied in ecology (i.e., big data), which require efficient solutions for extracting relevant biological information. Deep learning could be a critical tool in this respect. Below, we give examples of image-based approaches to



insect monitoring, which we argue have the greatest potential for integration with deep learning. We also describe approaches using other types of sensors, where the integration with deep learning is less developed but still could be relevant for detecting and classifying entomological information. We further describe the ongoing efforts in the digitization of natural history collections, which could generate valuable reference data for training and validating deep learning models.

Other types of sensor technology are used to automate the recording of insect activity or even body mass, typically without actual consideration of the subsequent processing of the data with deep learning methods. In one of these recent studies, researchers used a sensor ring of photodiodes and infrared light-emitting diodes to detect large- and small-sized arthropods, including pollinators and pests, and achieved a 95% detection accuracy for live microarthropods of three different species in the size range from 0.5 to 1.1 mm. The Edaphology is a low-power monitoring system for detection of soil microarthropods. Probe and sensing are based on detection of change in infrared light intensity, and it counts the organisms falling into the trap and estimates their body size. The probe is connected via radio signals to a logging device that transmits the data to a server for real-time monitoring. Similarly, others have augmented traditional low-cost trapping methods by implementing optoelectronic sensors and wireless communication to allow for real-time monitoring and reporting. Since such sensors do not produce images that are intuitive to validate, it could be challenging to generate sufficient, validated training data for implementing deep learning models, although such models could still prove useful

4. Potential Deep Learning Applications in Entomology

The big data collected by sensor-based insect monitoring as described above require efficient solutions for transforming the data into biologically relevant information. Preliminary results suggest that deep learning offers a valuable tool in this respect and could further inspire the collection of new types of data. Deep learning software (e.g., for ecological applications) is mostly constructed using open-source Python libraries and frameworks such as TensorFlow, Keras, PyTorch, and Scikit-learn, and prototype implementations are typically made publicly available (e.g., on https://github.com/). This, in turn, makes the latest advances in other fields related to object detection and fine-grained classification available also for entomological research. As such, the deep learning toolbox is already available to entomologists, but some tools may need to be adapted for specific entomological applications. In the following, we provide a brief description of the transformative potential of deep learning related to entomological data stored in images structured around four main applications.

5. Taxonomic Identification

Taxonomic identification can be approached as a deep learning classification problem. Deep learning-based classification accuracies for image-based insect identification of specimens are approaching the accuracy of human experts Applications of gradient-weighted class activation mapping can even visualize morphologically important features for CNN classification. Classification accuracy is generally much lower when the insects are recorded live in their natural environments, but when class confidence is low at the species level, it may still be possible to confidently classify insects to a coarser taxonomic resolution. In recent years, impressive results have been obtained by CNNs. They can classify huge image datasets, such as the 1,000-class ImageNet dataset, at high accuracy and speed. Even with images of >10,000 species of plants, classification accuracy of the best CNNs was close to that of botanical experts. Currently, such performance of CNNs can only be achieved with very large amounts of training data, but further improvements are likely, given recent promising results in distributed training of deep neural networks and federated learning. It is common for ecological communities to contain a large fraction of relatively rare species. This often results in highly imbalanced datasets, and the number of specimens representing the rarest species could be insufficient for training neural networks as such, advancing the development of algorithms and approaches for improved identification of rare classes is a key challenge for deep learning-based taxonomic identification. Solutions to this challenge could be inspired by class resampling and cost-sensitive training or by multiset feature learning. Class resampling aims at balancing the classes by under sampling the larger classes and/or oversampling the smaller classes, while cost-sensitive training assigns a higher loss for errors on the smaller classes. In multiset feature learning, the larger classes are split into smaller subsets, which are combined with the smaller classes to form separate training sets. These methods are all used to learn features that can more robustly distinguish the smaller classes. Species identification performance can vary widely, ranging from species that are correctly identified in most cases to species that are generally difficult to identify. Typically, the amount of training data is a key element for successful identification, although recent analyses of images of ~65,000 specimens in the carabid beetle collection at the Natural History Museum London suggest that imbalances in identification performance are not necessarily related to how well represented a species is in the training data. Further work is needed on large datasets to fully understand these challenges. A related challenge is formed by those species that are completely absent from the reference database on which the deep learning models are trained. Detecting such species requires techniques developed for multiple-class novelty/anomaly detection or open set/world recognition. A recent survey introduced various open set recognition methods with the two main approaches being discriminative and generative. Discriminative models are based on traditional machine learning techniques or deep neural networks with some additional mechanism to detect outliers, while the main idea of generative models is to generate either positive or negative samples for training. However, the current methods are typically applied to relatively small datasets and do not scale well with the number of classes (96). Insect datasets typically have a high number of classes and a very fine-grained distribution, where the phenotypic differences between species may be minute while intraspecific variation may be large. Such datasets are especially challenging for open set recognition methods. While it will be extremely difficult to overcome this challenge for all species using only phenotype-based identification, combining image-based deep learning and DNA barcoding techniques may help to solve the problem

Conclusions

The present paper reviews and summarizes image processing techniques for several plant species that have been used for recognizing plant diseases. The major techniques for detection of plant diseases are: BPNN, SVM, K-means clustering, and SGDM. These techniques are used to analyses the healthy and diseased plants leaves. Some of the challenges in these techniques viz. effect of background data in the resulting image, optimization of the technique for a specific plant leaf disease, and automation of the technique for continuous automated monitoring of plant leaf diseases under real world field conditions. The review suggests that this disease detection technique shows a good potential with an ability to detect plant leaf diseases and some limitations. Therefore, there is scope of improvement in the existing research. The present paper reviews and summarizes image processing techniques for several plant species that have been used for recognizing plant diseases. The major techniques for detection of plant diseases are: BPNN, SVM, K-means clustering, and SGDM. These techniques are used to analyses the healthy and diseased plants leaves. Some of the challenges in these techniques viz. effect of background data in the resulting image, optimization of the technique for a specific plant leaf disease, and automation of the technique for continuous automated monitoring of plant leaf diseases under real world field conditions. The review suggests that this disease detection technique shows a good potential with an ability to detect plant leaf diseases and some limitations. Therefore, there is scope of improvement in the existing research.

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