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Applications of AI for Disease Detection in Agricultural Crops

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Introduction to Artificial Intelligence (AI)

Artificial Intelligence is the development of computer systems that are able to perform tasks which normally needs human intelligence (Russell and Norvig, 2021), for example learning from experience, reasoning, decision-making, and recognizing patterns. As far as the agriculture sector is concerned, AI technologies like ML (machine learning) and DL (deep learning) comes in handy for tasks such as analysis of large volume of data for monitoring the crops, analyzing the quality of soil and disease detection in the crop. Utilizing the capacity to learn from historical data and images, AI systems make highly accurate predictions. This helps and supports farmers in managing crops more effectively & efficiently at a cheaper cost in multiple dimensions, namely cost, time, labor etc.

Importance of Agricultural Crops

The global economy is heavily dependent on agricultural crops and it is the assurance of food security (Zhang & Kovacs, 2012). They fulfill most crucial needs of human race like food supply, raw materials, and employment to a great extent, serving lion's share of the global population. In several regions worldwide, agriculture is the mainstay of GDP & rural livelihood. Assurance of healthy crops guarantees not only food security but also stability in the continents, international business & trade along with national economies. So, detection & protection of crops from diseases is extremely crucial to sustain productivity and reduce losses which ultimately nursers the human race.

Problems with Disease Detection in Crops

Disease detection in crops is a multi-degree task and requires to cross several hurdles. Challenges are posed from several angles:

a) Economic Factors: Diseases can cause yield losses up to 20–40% of crops globally (Singh et al., 2016). This may cause significant financial damage. Farmers with small-scale farms are likely to have lack of access to modern facilities like diagnostic tools, and heavy dependency on traditional observation. Misdiagnosis or late diagnosis may lead to excessive use of pesticide, rise in costs and labor along with the risk of harming the environmental balance.

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b) Other Factors: One of the most tiring & time-consuming task for farmers is the visual inspection of crops and the process is prone to error, particularly at beginning stages. Some symptoms may be associated with more than one disease, while probably create confusion in identification. It demands expert knowledge and results in late diagnosis or wrong diagnosis. Whereas timely detection is crucial to avoid the spread of diseases across large fields. Hence manual monitoring carries a sygnificant amount of risk & is not suitable for large-scale farming.

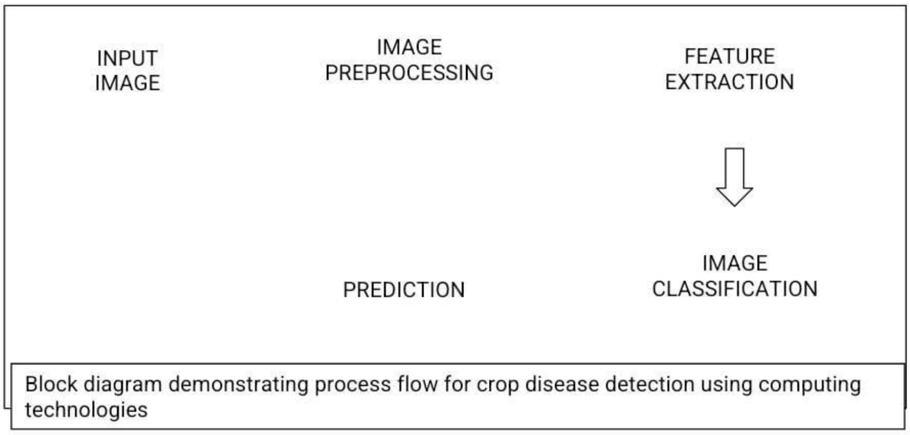
Introduction to Computer Vision

It is a sub-field of Artificial Intelligence that allows machines to interpret and analyze visual data (images or videos) (Goodfellow, Bengio, & Courville, 2016). This phenomenon may be compared to how human beings perceive the surrounding world. One of the most fundamental needs of the society, crucial for global health & economy is agriculture, where computer vision can make significant stride to enable the systems to:

- Capture crop images using modern devices such as smartphones, drones, or sensors.
- Automate the task of recognizing patterns, shapes, and colors associated with the healthy or a plant having disease.
- Detect symptoms (for example leaf spots, discoloration, wilting, or growth of fungus etc.)

Computer Vision automates the process of disease detection, that results in reduced human error and faster as well as more consistent results. Thus, whole the process of farming gets increased effectiveness and efficiency in disease management. A simple computer vision block diagram is presented below:

Role of Image Processing in Disease Detection



Block diagram demonstrating process flow for crop disease detection using computing technologies

One of the most crucial steps is image processing in the procedure of applying AI for disease detection in crops (Kamilaris & Prenafeta-Boldu, 2018). Here we transform raw crop images into meaningful information that is feature. Important steps are:

a. Preprocessing: Noise removal, brightness/contrast adjustment, and quality enhancement.
b. Segmentation: Effected diseased area (such as affected part of a leaf) is isolated.
c. Feature Extraction: This is the final & important activity for research where we Identify important features for example change in shape, color, texture or lesion area extent.

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AI plays a crucial transformative role, primarily using computer vision and image processing, in agricultural disease detection (crops). This will enhance early, accurate, and cost-effective detection & diagnosis of crop diseases. It immensely helps farmers avoid losses, guarantee food security, and sustainability increases in farming sector.

Figure 1: AI Generated Image

Image Processing Algorithms

Some relevant image processing algorithms for disease detection in crops were discussed below:

1. Normalization: The basic purpose of normalization is to bring image pixel values to a common scale or range, improving consistency and reducing sensitivity to lighting or contrast differences. Converts pixel intensities into a normalized range (often 0–1 or 0–255). Normalization will provide uniform brightness and contrast across images. This is a basic preprocessing steps a before proceeding further in agricultural crop disease detection. Some common techniques applied are:

a) Min–Max Normalization: This technique helps us to rescale pixel intensity values (or any numerical data) into a fixed range. Ranges usually used are: [0, 1] or [−1, 1]. This provides a common platform so that all images or features are comparable and consistent for analysis or model training later on.

b) Z-score Normalization: In this technique we subtract mean and divide by standard deviation.

c) Histogram Normalization (Equalization): Employing this technique we can adjust the intensity distribution for better contrast. One of the use cases is in medical images (such as X-rays / MRI etc.) to remove intensity variations due to the effect of differentiation in equipment or exposure settings.

2. Image Enhancement: This process is utilized to improve image visual quality. Also, by highlighting important features for better analysis and interpretation gives us valuable

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insights for proceeding further. Normally enhancement modifies an image to make it clearer for human observation. Furthermore, for subsequent algorithmic processing it serves in achieving better outcome. Common techniques in application are:

a) Spatial Domain Methods: It is used for Contrast Stretching, Histogram Equalization, & Logarithmic and Power-Law Transformations

b) Frequency Domain Methods: This technique is utilized to achieve High-pass filtering (sharpening) & Low-pass filtering (smoothing / noise removal)

c) Noise Reduction: Here Median filtering, Gaussian filtering & Bilateral filtering are done.

Use cases includes enhancement of satellite images to highlight land and water, or boundaries or crop disease regions.

3. Feature Extraction: This is one of the most fundamental and equally crucial adventure in crop any of the research activity. Here the main goal is to extract important and distinguishable characteristics from the image in hand (such as color, texture, shape, or edges etc.). These features are going to be of maximum importance & used for classification or recognition. Mainly we convert image data into a set of quantitative features that represent meaningful information for further processing. Features we consider are:

a. Color Features: RGB, HSV, L*a*b histograms etc. are used to identify discoloration.

b. Texture Features: GLCM (Gray Level Co-occurrence Matrix), LBP (Local Binary Pattern), Gabor filters are applied to detect roughness, smoothness.

c. Shape Features: Contours, area, perimeter, roundness etc. are crucial to describe object boundaries.

d. Edge Features: Sobel, Canny, or Prewitt edge detection techniques are applied for thr purpose of defining transitions in intensity.

4. Segmentation: Idea behind segmentation lies in dividing the image into meaningful regions or objects, such as separating background from the region of interest (ROI). Basically, isolation of specific parts of the image (like lesions, tumors, leaves) for accurate analysis is the sole goal of segmentation. One of the examples is segmenting diseased areas from healthy leaf regions. Similarly identifying tumor boundaries in medical scans is another one. Common techniques are:

a) Thresholding: Global (Otsu’s method), Adaptive (local intensity-based) etc.

b) Edge-based Methods: Sobel, Canny, or Laplacian edge detectors.

c) Region-based Methods: Region growing, Region splitting/merging.

d) Clustering-based: K-means, Fuzzy C-means (FCM)

Role of Machine Learning (ML)

ML gives systems the ability to learn patterns automatically from image data (after feature extraction) and make predictions (Singh et al., 2016; Mohanty, Hughes, & Salathe, 2016). In crop disease detection, machine learning can use features extracted from images to train models that classify crop health status. ML can detect early disease symptoms, even when invisible to the naked eye. It provides automated decision support for farmers (e.g., healthy vs. infected, or type of disease). ML also reduces reliance on expert pathologists and enables scalable solutions for large farms.

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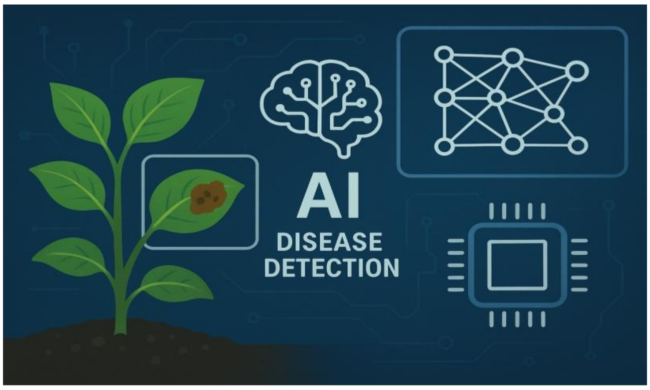

Relevant ML Algorithms

Some widely used ML algorithms in crop disease detection are-
Support Vector Machine (SVM) – effective for binary/multi-class classification using extracted features.
Random Forest (RF) – ensemble method, robust for handling complex crop datasets.
k-Nearest Neighbors (k-NN) – simple distance-based classification (healthy vs diseased).
Naïve Bayes – probabilistic model, often used for initial disease classification.
Decision Trees – interpretable models for identifying disease categories.
ANN- An ANN is a computational model inspired by the biological neurons in the human brain. It learns patterns in data by adjusting connection weights between neurons.

Role of Deep Learning (DL)

Deep Learning goes beyond manual feature extraction by automatically learning disease features directly from raw images (Goodfellow et al., 2016; Too et al., 2019). DL handles large datasets and complex patterns in diseased leaves. These algorithms provide higher accuracy compared to classical ML. They can be used with drones, mobile apps, or IoT devices for real-time disease detection in fields. DL algorithms are able to learns complex and hierarchical features automatically.

Relevant DL Algorithms

Some key DL algorithms that can be used for detecting diseases in crops are as follows:

a. Convolutional Neural Network (CNN): CNNs are a class of DL algorithms that are widely used for image-based tasks (LeCun, Bottou, Bengio, & Haffner, 1998). CNNs consist of convolutional layers that perform convolution operation for feature extraction. They also contain pooling layers for dimension reduction. The final layers in a CNN are the fully connected layers that perform the classification task. Some popular CNN architectures are LeNet (simple), AlexNet, VGG16 / VGG19, ResNet (Residual Networks), Inception (GoogleNet), MobileNet, EfficientNet, DenseNet etc.

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b. Autoencoders: Autoencoders are algorithms that are used for noise removal, anomaly detection, unsupervised learning etc. (Hinton & Salakhutdinov, 2006). These algorithms consist of encoders and decoders. Encoder compresses image into a smaller representation, after which decoder comes into action to reconstruct image from this representation. For disease detection in crops autoencoders can detect unusual crop leaf patterns caused by infections from pests.
c. Generative Adversarial Networks (GANs): GANs are DL algorithms that can generate synthetic images (Goodfellow et al., 2014). GANs consist of a generator and a discriminator network. Generator generates an image and the discriminator distinguishes fake from real images. This task is performed till the discriminator is unable to distinguish between a fake and a real image. GANs can be used to generate synthetic diseased and healthy crop images that can be used to train a DL architecture.

Conclusion

With the growing interest of the researchers and large scale of acceptance among the farmers, latest technology is evolving rapidly and bringing paradigm shift in agriculture. Now, farmers eagerly wait for new developments and blend them for betterment of the community. Such a crucial technological integration is of AI into agriculture, which have emerged as a transformative approach. This will enhance crop health monitoring and disease management. There are several bottlenecks in traditional methods of disease identification & management which rely heavily on manual inspection. It is time-consuming, subjective, and prone to inaccuracy. If we employ AI enabled systems to automate and optimize the detection, diagnosis and prediction of plant diseases, these limitations can be mitigated. This process is entirely based on image analysis and pattern recognition. ML algorithms are mainly utilized for classification tasks, distinguishing between healthy and diseased plants as discussed above. Currently DL algorithms, CNNs in particular, have shown better efficiency in feature learning and classification accuracy. CNNs are capable of autonomously extract hierarchical features from raw images. This reduces the need for manual feature engineering, which ultimately enable us to achieve higher performance in terms of accuracy and scalability.

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