Article ID 240203022

Artificial Intelligence in Plant Phenotyping

Radhika Sharma[1] and Jagmohan Singh[2]
[1]College of Agriculture, CCS Haryana Agricultural University, Hisar, Haryana, India- 125004
[2]Department of Plant Pathology, CCS Haryana Agricultural University, Hisar, Haryana, India- 125004
*Corresponding Author: jsdhillon@hau.ac.in

Since early domestication humans watched and selected plants based on their properties, they did phenotyping. We still study plants but today of course modern technology is used to observe plants in a systematic scientific way by making use of latest non-invasive imaging and centring technologies supported by robotics drones and artificial intelligence. So plant phenotyping help us to understand how plants grow and work. It describes the study of plant structure and function which depends on dynamic interaction between the genetic background and the physical world the environment in which the plant develops. As all civilization depends on vegetation therefore understanding plants is clearly vital especially under conditions of climate change. Using modern planned phenotyping breeders can select plants with best properties in their prevailing environment and farmers will be able to grow healthy plants in a sustainable way.

Plant Phenotyping is the characterization of the plants or the crops. This is required for decision support in agriculture and also plant breeders to select the best genotypes that will be the future cultivars well adapted to different environments. The characterization was mostly achieved with classical scoring by a visual inspection of the plants or by taking measurements which was limited by the throughputs, accuracy and the number of traits for the characteristics that we extract from the plants. Now, it is replaced by new methods, high-throughput methods that are non-destructive, that allow us to get much more accurate and to get different traits. A significant number of plant morphological, physiological, and chemical parameters can be rapidly and conveniently measured using AI. Additionally, the integration of AI and robotics technologies enables real-time monitoring of plants in complex field and controlled environment.

Smart farming helps human beings to have a better degree of control over the nourishment of plants. It is preferred in smart architecture based on efficient and high output farming platforms. Computer vision-based plant phenotyping techniques offer a non-destructive and efficient evaluation of the complex plant traits. Non-destructive methods have the potential to perform large-scale and high-throughput plant phenotyping experiments. Visible spectral imaging, fluorescence imaging, infrared imaging, hyperspectral imaging, three-dimensional imaging, and laser imaging are some of the popular methods used in these experiments. Visible spectral imaging has the advantages of affordability and quick measurement. It can also model a wide range of plant traits. Before the comprehensive assessment of plant traits, computer vision-based recognition of plant species is required. Plant health condition analysis is also an integral part of the phenotypic analysis.

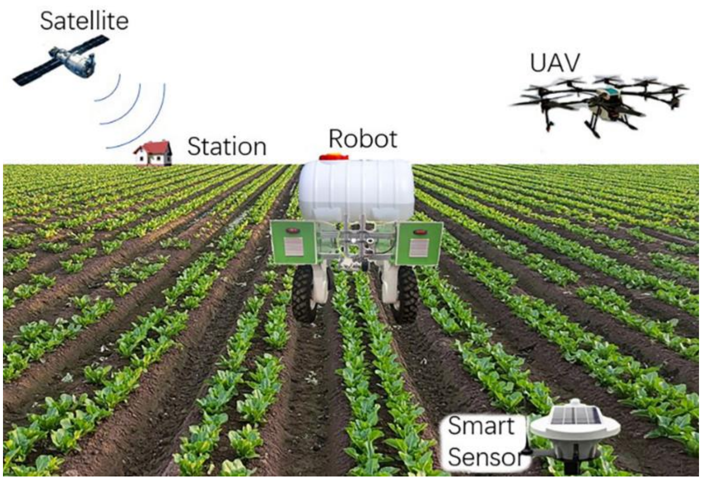


Fig. 1 Dynamic 3-D Plant Phenotyping and Precision Agriculture Framework utilizing AI, Sensors, and Robotics (Source: Editorial article, Volume 14 - 2023)

Recognition and Identification Tasks

Accurate species identification is essential for agriculture. Correct species determination requires a high level of expertise. An identification process using dichotomous keys may take days, even for specialists, especially in locations with high biodiversity, and it is exceedingly difficult for non-scientists (Belhumeur et al., 2008). To overcome that issue, Gaston and O'Neill (2004) proposed to use a computer vision-based search engine to partially assist with plant identification and consequentially speed up the identification process. Since then, we have witnessed an increased research interest in plant species identification using computer vision and machine learning.

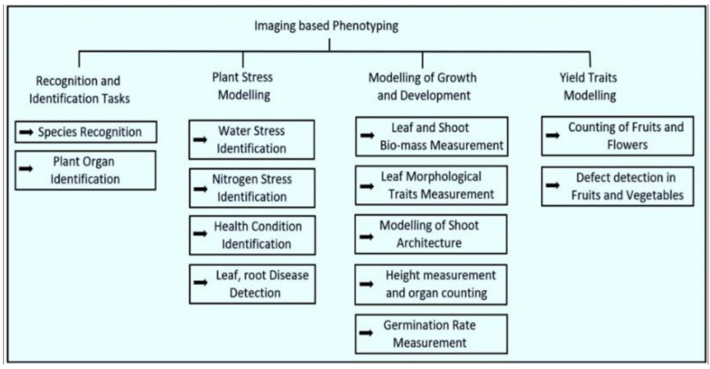


Fig. 2 Role of imaging-based phenotyping

(Source: AI, MDPI 2021, 2(2), 274-289)

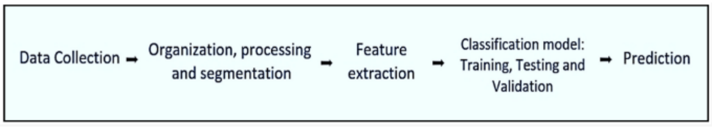


Fig. 3 Process flow of computer vision-based classifications

(Source: AI, MDPI 2021, 2(2), 274-289)

Automatic image-based plant species identification deals with: (i) Different scales: plant species can be observed from various angles and distances. (ii) Intra-class differences: plant organs-leaf, fruit, bark, etc. look very distinct. (iii) Inter-class similarities: the same organ of different species might look very similar. (iv) Background and Clutter: other species are present behind or around the observed sample, and many more.

Plant Stress Modelling

Stress is a defensive state of an organism resulting from deviations of its optimal developmental conditions. Environmental challenges destabilize fundamental biological functions in plants, and this is often perceived as constrained crop growth and development. In agricultural systems, the detrimental effects of plant stress are a significant cause of productivity loss, threatening food security, especially in the current context of climate change. AI tools are helpful to model plant disease and stress, diagnose nutritional deficiencies, and apply agrochemicals in precision agriculture. In particular, Machine Learning (ML) techniques can predict the outcome of various complex biological processes, such as gene function, gene networks, protein interactions, and optimal growing conditions, leading to significant achievements in plant stress research. Detection of plant stress at an early stage is very much essential for improving the crop production. Plant stress when not detected early can lead to severe damage to crops cause of diseases. Vision-based sensor captures the images of the leaves in plants for detecting stress by extracting the features and transmitting it to the cloud platform for further analysis. At the experts end the features are retrieved and will be subjected to classify the disease using machine learning algorithms. Based on the classification solutions are provided to the farmers by experts. Knowing the location of the diseased plants in the field the farmers will be able to apply exact quantity of pesticides, thereby reducing the spread and improving the yield. Image processing take part in evident role in plant disease detection system as pre-processing and segmentation helps in identifying the affected area precisely. From the segmented image the features are extracted as features are important for accurate classification. Jiangyong et al has proposed a system which uses deep convolutional neural network (DCNN) to identify and classify the maize drought stress. The experiment was carried out at optimum moisture, light drought, and moderate drought stress. The images of the maize crop were obtained periodically every two hours throughout the day. The identification accuracy of about 98.14% and classification accuracy of 95.95% respectively was achieved by the system that was observed from the result. Shyamal et al studied that Amalgamating RS data with the Machine Learning Algorithm had paved way for precision agriculture. Enhanced yield prediction, identification obtained with greater precision when compared with the ultimate RS data method. Asheesh Kumar Singh et al. have compared deep learning tools to predict accuracy, requirement of data size, among other existing techniques. Bhange et.al developed a web-based tool for identifying pomegranate diseases by unsheathing the colour and morphology features. K-Means algorithm has been carried out for the process of segmenting and classification through SVM achieving 82% accuracy.

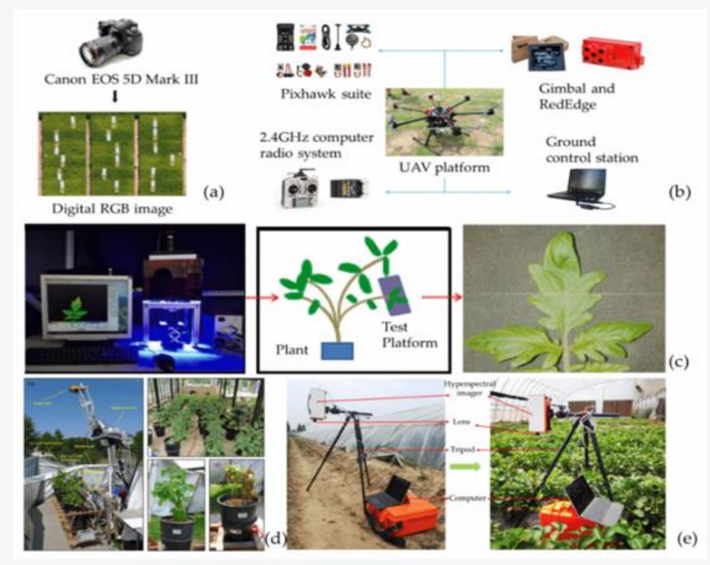


Fig 4. Typical optical sensors used for plant stress detection. (a) Digital sensor for maize heat stress; (b) multispectral imaging sensor for maize water stress; (c) fluorescence imaging sensor for chilling injury of tomato seedlings; (d) thermal imaging sensor for potato water stress, and (e) hyperspectral imaging sensor for apple water stress.

(**Source:** Agri Engineering, MDPI 2020 2 (3), 430-446)

Modelling of Growth and Development

Crop growth models represent the reactions that occur in plants and the interactions between plants and the environment, which can be used to optimise cultivation management. A complete crop growth model not only predicts crop yield but also contains quantitative information about plant growth and development. Plant physiological factors, including transpiration, photosynthesis and respiration, are mostly affected by environmental factors. Several plant growth models have been developed. They can be classified as descriptive models and mechanism models. Plant growth and development are extremely complex and heterogeneous systems. Therefore, descriptive models using statistics or correlation methods, sometimes called empirical models, can provide highly reliable prediction results under normal plant growth conditions. The mechanism model (or explanatory model) represents the quantization process based on complete physical or physiological behaviours. Due to the increase in computing capabilities and resources and experience sharing among plant scientists, mathematicians, and computer scientists, most crop growth models also mix descriptive and mechanism models.

Yield Traits Modelling

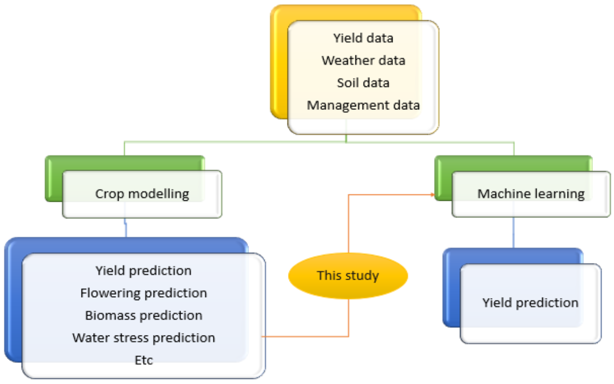
Agricultural experts are improving agricultural and rural statistics and developing methods for more accurate CYP (Crop Yield Prediction) based on agricultural data sets. The main objective of agricultural planning is to increase CP (Crop Production) while conserving limited land resources. Artificial Intelligence (AI), also known as computational intelligence, seeks to create computer programmes that can learn complicated real-world problems just like people do. Complexity and uncertainty arise when challenging problems are solved using conventional programming techniques. The basic idea behind the creation of evolutionary algorithms is to mimic human intelligence in order to resolve reasoning problems. Artificial Neural Network (ANN) techniques can create an automated model that uses computer intelligence to challenge real-world problems. After processing the input data, the algorithm generates an output known as a "model" that aids in forecasting the CY before the harvest.

CYP is an essential agricultural problem. All farmers always try to know how much yield they will get from their prospects. In the past, CYP was designed by analysing a farmer's previous experience with a particular crop. The CY primarily depends on weather conditions, soil nutrients, and temperature. Accurate data about the history of CY is vital for decision-making related to agricultural risk management.

AI mainly focuses on:

- To forecast the CY for different crops by considering temperature, climatic effect, and soil features.
- To use different ML algorithms for CYP.
- To compare the performance of ML algorithms to measure prediction accuracy.
- To improve the accuracy of CYP.

Machine Learning (ML) is a powerful tool for supporting CYP decisions, including decision support on which crops to grow in a specific season. Generally, Artificial Neural Networks (ANN) are usually used to predict the behaviour of complex non-linear models. It determines the correlations between climatic variables, soil nutrients, and CY with the available data.



Conclusion

Plant phenotyping and precision agriculture is becoming a very important topic for future agriculture. The increasing population and climate change push us to take actions to plant crops against pests, diseases, and harsh environments (e.g. lack of nutrients, water, fertilizers or light). The new technologies such as AI, sensors and robotics enables farmers to take a data driven approach to collect and analyse data to monitor the real time status of the plans and crops to improve production yield quality. For precision agriculture, the grand challenges lie in identification of cheap, robust, easy-to-use, rapid and automated phenotyping methods that can feed into Decision Support System. In addition, the field environment will provide challenges in sometimes rapidly varying light conditions, wind and temperature, as well as combinations of multiple stresses. Despite all these challenges, automated and systematic stress detection by field-phenotyping holds great promise to accelerate integrated pest management where on-farm live monitoring of stress and disease are key factors to reduce the reliance on pesticides. In the future, the integration of automated data collection and analysis, AI algorithms, robotics and decision support systems will bring unmanned farming to our lives. Moreover, the ground-level or aerial-level robotic systems will also have a major role in plant phenotyping and precision agriculture, for monitoring, disease control and harvesting. Therefore, AI in plant phenotyping have potential to revolutionize modern agriculture system and have become backbone of agriculture.

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