<u>Short communication</u>

An overview on phenomics applications in different agriculture disciplines

Abstract

In the past ten years, ground and aerial platforms with several sensors have been rapidly adopted for phenotyping diverse biotic, abiotic stressors and other characters during the crop plant's growth stages. An increase in yield achieved from traditional breeding programs around worldwide are no longer sufficient to meet the projected demand for all three major cereals like Rice, Wheat and Maize. Also the era of genotyping has now a days become much more forward through the next level sequencing techniques but the phenotyping techniques are lacking at various levels in order to cope up with genotyping techniques and also with increasing production demand. Thus the phenomics which includes high throughput phenotyping (HTP) and Artificial intelligence should be paved the way over traditional phenotyping in order to get such needy demands. Also Artificial intelligence (AI)-based data analysis techniques can increase the reliability of diagnoses and, as a result, be included into instruments for effective treatment. These methods find pertinent data for use in plant breeding and pathology activities by using feature extraction, identification, classification, and prediction criteria as well as for precision breeding. This approach has various applications in various agriculture disciplines. The main steps under such techniques includes: Image acquisition, Preprocessing of images, segmentation of images, Image Representation and Description and Image recognition. The use of these helps to speed up genetic progress and lessen the phenotyping bottleneck in breeding projects now a days in.

Keywords: Phenomics, Artificial intelligence, Physioogical, Soil science, Disease

Introduction:

Annual increase in yield achieved from traditional breeding programs around world wide are no longer sufficient to meet the projected demand for all the crops, majorly Rice, Wheat and Maize (Tester and Lanfridge, 2010) by going through traditional phenotyping methods. Further the era of genotyping has now a days become much more forward through the next level sequencing techniques but the phenotyping techniques are lacking at various levels in order to cope up with genotyping techniques and also with increasing production demand. Thus the era of phenomics should be paved the way over traditional phenotyping in order to get such needy demands. Phenomics generally refers to an understanding phenotypic expression at a systems level \Study of “plant growth, performance and composition in high resolution. Also Artificial intelligence (AI)-based data analysis techniques (Pereira et al 2017) can increase the reliability of diagnoses and, as a result, be included into instruments for effective treatment. These methods find pertinent data for use in plant breeding and pathology activities by using feature extraction, identification, classification, and prediction criteria as well as for precision breeding. The use of these helps to speed up genetic progress and lessen the phenotyping bottleneck in breeding projects now a days in. The various applications of phenomics approach used by researchers are listed in the present study.

AI based phenomics approach in disease identification

Data analysis methods based on artificial intelligence (AI) can improve the accuracy of diagnoses and, as a result, be included into devices for efficient treatment. Even more effective methods for identifying plant diseases include those that integrate AI with photo feature analysis. One technique demonstrates an automated method of agricultural disease diagnosis on a number of leaf samples corresponding to various crop species using Local Binary Patterns (LBPs) for feature extraction and Classification. Depending on the condition of the plant, such as healthy, downy mildew, powdery mildew, and black rot *etc* in various crops. Automation makes it much more challenging. Along with the anatomical traits, the lighting circumstances also contribute to the difficulty. In order to create accurate and effective crop management plans, including models for the administration of medicines and prediction tools, it is essential to assess the severity of plant diseases.

The development of feature extraction approaches has been extensive for the monitoring of various plant conditions. A number of variables, including physical and morphological plant features, are employed for feature extraction. Zhang *et al*. (2017) created a tool for identifying leaf diseases in cucumber plants. The programme employs k-means clustering to separate the damaged portion of the leaf before accurately extracting the colour and shape. Guo *et al*. (2014) reported accuracy rates of 94.0 percent, 86.7 percent, 88.8 percent, and 84.4 percent, respectively, for the identification of downy mildew, anthracnose, powdery, and grey mould infections. Venu *et al*. (2020) developed a neural network-based pattern recognition method to pinpoint the most common tomato late blight disease on a global scale. In the present approach of 20 networks, the best prediction level for pixel classification was 97.99 percent. In the study, Pantazi *et al*. (2019) employed one class classification to pinpoint the presence of four different health issues in a variety of leaf samples, including healthy, downy mildew, powdery mildew, and black rot. By analysing in-place photographs without additional improvement, the computer may detect the existence of a disease even in its early stages.

Employing LBP algorithm and image segmentation for plant disease identification:

Initially, an image of the diseased leaf with visible symptoms should be taken using a smartphone or tablet. Then, using photo segmentation, the area of interest is to be focused by eliminating background. In addition, the segmented picture should undergo a Hue Saturation Value (HSV) change and then algorithm will be built. Following are the protocols and steps:

1) The foreground and background of the images can be indicated by the focus points, whereas the unidentified area of the image can be focused differently. 2) Using the Orchard-Bouman clustering approach, a picture should be segmented by modelling the foreground and background as Gaussian Mixture Models (GMMs). 3) Each pixel in the foreground and background will receive the most reliable Gaussian component belonging to the relevant GMMs for the foreground and backdrop. 4) The established pixel sets support the development of new GMMs by learning how to create them. A graph is to be built and the GrabCut algorithm is utilised to define a new foreground class. 5) The GrabCut technique generates K components of multivariate Gaussian Mixture Models for the background and foreground areas (GMM). The values for the GMM components are computed using the colour statistics of each cluster.

By defining the bounds of proximity between pixels, the local binary pattern, a synergistic texture analysis method, can label pixels and produce a binary output. The LBP operator has the ability to transform a picture into a matrix of integer values that describes the local level fine structure of the image. (Pothen and Pai, 2020)

Image fluorescence for plant disease identification:

The primary technique used for disease diagnosis in leaves is fluorescence imaging. The metabolic activities that take place during nutrient flow derivation and the switch from photosynthesis to respiration are the first ones to be affected by disease infection. Fluorescence imaging is generally used to monitor this process. Since using modulated fluorescence requires substantial power for speedy illumination, fluorescence imaging is typically used in a controlled setting. Fluorescence imaging can estimate photosynthesis to detect early stress responses to abiotic and biotic factors and follow the effects of plant illnesses before a decline in growth is visible. Before a drop in growth can be seen, fluorescence imaging can estimate photosynthesis to detect early stress responses to abiotic and biotic variables and track the impacts of plant diseases. (Gavhale and Gawane, 2014)

For disease diagnosis in leaves, fluorescence imaging is the primary technique used. The transition from photosynthesis to respiration and the activities that take place during nutrient flow derivation are the first metabolic processes to be affected by disease infection. Typically, fluorescence imaging is employed to keep an eye on this process. Fluorescence imaging typically takes place in a controlled setting because modulated fluorescence requires a lot of power for fast illumination. Fluorescence imaging can gauge photosynthesis, identify early stress reactions to abiotic and biotic factors, follow the effects of plant illnesses, and detect growth declines before they become visible. (Kulkarni and Patil, 2012)

These elements may also be assessed in large populations, such as mutant populations and mapping populations, because they can be done rapidly and precisely. This enables the identification of the genes causing variation in each of these distinct tolerance-related components using a genetic method. In order to identify cucumber leaf disease, Khan 2020 created a unique technique based on deep feature selection. The recommended strategy consists of four key steps: A) contrast enhancement; B) segmentation of diseased spots; C) extraction and selection of deep features; D) classification.

Image Acquisition: Data collection is the main step in the process of gathering information in the field. There are a number of picture databases containing names, uses, and descriptions that are accessible worldwide. During the picture collecting procedure, the actual source image must be gathered. An picture must be converted into a number before processing. Digitization is the term used to describe this conversion.

Preprocessing of Images: Image enhancement's major objective is to change a picture for a certain activity so that it may be seen more clearly than the original picture. (Mandalik and Dhaygude 2011)

Segmentation of Images: In the process of segmenting an image, several visual characteristics are taken from the original image. An image is divided up into its individual parts, or objects. This method first computes the histogram of the picture before selecting a threshold (intensity) value to segment the area.

Image Representation and Description: Typically, representation and description come after the outcomes of a segmentation process. The initial decision is whether to present the data as an area or a boundary. While border representation is suitable when the focus is on external shape features, regional representation focuses on interior aspects like texture and skeletal form.

Image Recognition: When anything is recognised, a label is assigned based on the information provided by its descriptors. A typical technique for recognising photos is classification. To distinguish one plant species from other species, classification is necessary based on the data obtained through feature selection. Descriptors from the query image are contrasted with those from the image data stored in the database.

Soil Science:-

The phenomic approach is not limited to only disease identification but also has wide ranges at the other agricultural disciplines also. *i.e* Tracking plant health was first attempted very early on by Hetzroni *et al*.(2008). Their approach aimed to identify iron, zinc, and nitrogen shortages by studying lettuce leaves. The images were captured using an analogue video camera, and only afterwards would they be transformed to digital format. The first step of the recommended procedure is to partition the photographs into backgrounds and leaves. In the sections that follow, various size and colour attributes of the image are obtained from its RGB and HSI representations. These variables are ultimately used to assess the plant status and are then fed into neural networks and statistical classifiers. In order to segment images, artificial neural networks were used.

Horticulture:

Vegetables are becoming a benefit of global commerce. In India, the majority of fruit and vegetable farmers grade the fruit by hand. When fruit is graded manually, which used to be done by professional workers who took into consideration a range of grading characteristics, the fruit may be divided into groups based on physical quality. According to

Patel *et al* 2015, the new AI-based technology can also aid to reduce such sort of conventional concerns since manual labour has grown pricey during peak seasons, impacting operation. Neural networks play a key role in this classification of fruits into several quality categories. Based on colour, the neural network receives and inputs pixels from an image. The fruit is then rated based on its mean colour, variability, the presence of ill pixels, and the percentage of red in the fruit picture, which is obtained from the fruit image.

India is second to China in terms of the production of fruits and vegetables. India lacks an automatic grading system despite having a high level of agricultural commodity production. The majority of fruit grading in India is done manually and is based on size features (Vyas *et al* 2013)The most important factors to consider when evaluating a fruit's quality are its colour and size. Therefore, researchers tried to use and create an algorithm for an automated mango grading system that would be profitable for agriculture. Mango data is gathered during the unripe, semi-ripe, and ripe phases. They are sent to the system as processing input. The mango's colour and size thus can be seen from the image.

Forestry:

A limitation in forestry phenotyping and breeding has been identified as the absence of effective phenotyping capabilities. In order to automatically gather large volumes of phenotypic data that can be used to evaluate different characteristics of trees, modern phenotyping methods use systems outfitted with numerous image sensors. A new Green Revolution might be sparked by effective phenotyping, which would also allow for the collection of growth metrics and the analysis of the genetic underpinnings of quantitative features. Phenotyping systems seek to connect data from various sources to learn about the characteristics of trees. The review covered by Bian *et al* (2022) describes a variety of phenotyping applications for forest trees, such as a survey of actual inter- and intra-specific variation, assessing genotypes and species response to biotic and abiotic challenges, and phenological measures. The effectiveness of characteristics phenotyping in forest tree breeding projects can be accelerated with the aid of cutting-edge phenotyping platforms.

Physiological:

The potential for using narrowband spectral vegetation indices to spatially scale CO2 fluxes beyond the area of a tower footprint is highlighted by recent advances in understanding relationships between spectral reflectance of vegetation canopies and the structural and physiological drivers of canopy-atmosphere carbon dioxide exchange. In investigations of plant productivity and CO2 exchange, the main application of spectral reflectance data is the inclusion of spectrally generated vegetation indices into a model of vegetation productivity. Continually detecting upwelling and downwelling radiation in 10 nm wavebands centred at 532 nm, 568 nm, 676 nm, and 800 nm is the capability of the QuadPod, a straightforward, lightweight, reasonably low-cost sensor. For modelling canopy-atmosphere carbon exchange, spectral reflectance indices, such as the photochemical reflectance index (PRI) and the normalised difference vegetation index (NDVI), can be created using readings from multiple QuadPods (Garrity et al 2010).

Novel Phenotyping technologies:

There are some many phenotyping technologies available now a days which are being used in various studies by various researchers and few of them are listed:

- Non-invasive imaging technologies: It's a mathematical treatment of imaging data in order to extract growth dynamics, morphological characters, and spatially described photosynthetic traits in plants (Wang *et al* , 2012)
- Digital imaging and image analysis: Helps to estimate growth rates from projected leaf area in relatively simple and accurate manner.
- Pulse-modulated chlorophyll fluorescence imaging: New tool for examining photosynthetic responses to drought stress in addition to growth rate response.
- 2-D digital images: To develop morphological descriptors for herbarium identification and plant development.
- 3-D plant models: More appropriate to cereals and larger dicots which simulate plant development with a series of generative rules for plant organs such as floral development
- Phenotyping for abiotic stress tolerance in crop plants *i.e* drought evaluation under rain-out shelter

Instruments for acquiring raw data from field plots

Photodiodes: It's a low-cost sensors at specific bandwidths (Garrity *et al*., 2010), *High intensity light emitting sensors*: Allowing novel options for active sensing. *Infrared imagery:* using commercial digital cameras and accurate infrared thermometers, *Stereo image analysis*: which shows potential for characterizing plant height, leaf shape and leaf angle distribution.

Similarly *Phenonet*: for variables like canopy temperature, soil moisture, soil temperature, incoming solar radiation and micrometeorology. *PlantScan*: PlantScan will help in analyses of plant morphology by combining a range of digital imaging technologies. The *Phenotower*: Here data is used for spatial comparison of canopy temperature, leaf greenness and groundcover between genotypes at a single point in time. *Blimp*: The blimp usually carries both infrared and digital colour cameras operating in a height range of 10-100m above the field that will identify the relative differences in canopy temperature indicating plant water use. *Cropatron*: Will bring controlled environments directly to the field, enabling scientists to examine the impact of climate change on crops. These are the various instruments that can be fitted in the field to survey majority of the plant parameters pertaining to most of the agricultural disciplines and research phenotypically.

Need of Phenomics approach and conventional drawbacks:

- Genome sequence of Rice, Maize, Sorghum, Barley and many other dicots and monocots are already sequenced.
- Resequencing of genomes of various crops to assess allelic variation are more common now a days
- Genomic data or information for agricultural application should be carefully and comprehensively linked to plant characters
- Plant community lacks capacity for analyzing complex phenotype effect of genetic modification
- A clear goal of phenomics to bridge gap between genomics, plant function and agricultural traits
- There is need for a developing searchable phenotypic data base
- Linking gene sequence to plant function, development, composition and performance

Drawbacks of conventional

Coneventional needs conducting replicated trails across multiple environments over many season. Phenotyping tools currently in use require destructive harvest at fixed times or at a particular phenological stage which are slow and costly. Also phenotyping work need to be done very precisely for testing allelic variation. Thus the pheomic era has to be bought further over the conventional method of phenotypic analysis.

Conclusion:-

Phenomics approach not only useful for disease derection but also it has number of applications in various fields. i.e Hetzroni et al. made an extremely early attempt to track plant health by observing lettuce leaves to detect iron, zinc, and nitrogen deficiencies as discusse above. Similarly (Patil and Naik, 2015) equipped method in physical quality assessment. Also it can be used to detect crop biomass, root studies and other physiological and morphological parameters. Thus the phenomics which includes high throughput phenotyping (HTP) and Artificial intelligence should be paved the way over traditional phenotyping in order to get needy demands.

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