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A Review on Application of Various Deep Learning Techniques and Filtering Approach in Plant Phenotyping

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ABSTRACT:
Plant phenotyping is one of the recent research areas that play an essential role to develop a better understanding of plant traits, genotypes, stresses, and other related features. It is regarded as essential concept as it facilitates development in several fields such as botany, agronomy, and genetics. Plant phenotype helps in acquiring relevant information about plant organs and whole features that allows the farmers to make informed plant cropping decisions. It includes the use of Deep Learning (DL) which is part of a machine learning technique that makes use of several processing layers to provide reliable outcomes from abstraction. DL-based approaches are highly useful in providing a sufficient amount of data related to plant strapping, stresses, and growth indices. Deep learning approaches are highly efficient in analysing plant phenotype and characterizing the phenotyping aspects by classifying the plant stress datasets into open, labelled, and broad-spectrum. In this paper, a review work makes an attempt to explore the efficiency of deep learning and filtering approaches in plant phenotyping. The recent works related to the DL principles have been utilized for digital image–based plant stress phenotyping. Then a comparative assessment of DL tools against other existing techniques, with respect to decision accuracy, data size requirement, and applicability in various scenarios. Therefore, it is strongly recommended in the study to use the imaging data process so that there is the attainment of accurate information from training datasets by using high-throughput systems like UAVs and other autonomous systems.

KEYWORDS: Plant Phenotyping, Deep Learning, Structural Phenotyping, Physiological Phenotyping, Temporal Phenotyping.

1. INTRODUCTION

Agriculture is the main occupation of people in India but due to challenges like poor seeds, lack of fertilizers, inadequate irrigation facilities, absence of mechanization, soil erosion, and others, the yield of the farmers and cultivators remains low. Due to poor farm practices, the overall share of agriculture has decreased from 51.8% in 1951 to 15.8% in 2019. The major factors (seed replacement, crop intensity, irrigation, and others) that reduced the profits of Indian agriculture are shown in the below Figure.

Based on Fig.1, it can be said that poor extension, poor seed quality, and gaps in inputs such as fertilizer and agrochemicals cause under-development of the agriculture sector in India.1 Apart from this, the survey conducted by the Centre for Study of Developing Societies (CSDS), revealed that due to farming challenges, 76% of the farmers do not prefer to continue farming activities. About 70% of the farmers stated that issues such as unseasonal rains, pest attacks, floods, and drought create challenges for them to carry out farm practices.

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Factor	Status
1. Seed replacement rate %	
Wheat	31.6
Gram	21.7
Rapeseed/mustard	63.4
2. Crop intensity	1.42
3. Irrigation coverage %	48.6
4. Irrigated area under micro irrigation %	15.0
5. Gap in NPK use as compared to optimum %	
Nitrogen	3.31
Phosphorous	19.14
Potash	51.09
	Falling in low use states
6. Use of Compost	One third since early 1970s
7. Average size of land holding hectare	1.08

Fig. 1. Factors related to low productivity and high average cost in India.
(https://www.niti.gov.in/sites/default/files/2020-01/Presidential_Address.pdf)

All these challenges adversely impacted the condition of farmers in India reduced farm productivity, and increased food security pressure on land. Under such conditions, plant phenotyping is to be included in agriculture practices to gain a better understanding of crops, plant traits, genotypes, stresses, and other related features and perform adequate crop management activities. It will help agriculturists, farmers, plant breeders, and cultivators to make important crop and farming decisions that support a sustainable farming environment. It provides a wide range of plant information such as biochemical, anatomical, biochemical, and historical features that help in the breeding and selection of plants to increase productivity over time.[2]

2. PHENOTYPING COMMUNITIES

Plant phenotyping is the quantitative evaluation of the complicated features of the plant features. It helps in acquiring relevant crop information and promotes plant research. It helps in acquiring relevant information about plant breeding, quality assessment, and product development.[3] Based on phenotyping communities, plant phenotyping is categorized into three parts which are structural, physiological, and temporal.

2.1. Types of Phenotyping Communities

Focusing on structural phenotype is related to the morphological features of the crop, while physiological phenotypes refer to the peculiarity of the crops. It considers all the conditions and features that are related to the regulation of plant growth processes and metabolism. On the other hand, the temporal phenotype is referred to the identification of growth patterns of the plants which is one of the major forces to differentiate between several plant species. Temporal cues are very beneficial in developing differentiation between plants that have similar features and appearances.[4] While focusing on the structural phenotyping of the plant, it is associated with acquiring detailed information about the plant in terms of physical attributes such as root, stem, leaf, flower, fruit, and seed. Structural phenotyping plays an important role in identifying plant features and carrying out different activities such as gene discovery, yield estimation, and precision agriculture.

On the other hand, based on different plant features, plant phenotyping is classified into two parts which are plant organ phenotyping and whole-plant phenotyping plant organ phenotyping includes the structural, physiological, and temporal classification of plants. Structural plant organ phenotyping describes the morphological features of the plant that are related to shape, area, angle, and others. It also includes other traits such as water content, chlorophyll content that impact the metabolism and growth of the plant.[5] It includes above-ground and below-ground organ phenotyping so that there is the determination of morphological changes and growth aspects of the plant.

Physiological phenotyping is an essential component of the plant research process that provides in-depth insights into plant breeding during climate change. It also helps in testing and monitoring plants and the development of methods through which plant treatments could be improved. The physiological phenotyping of plants includes acquiring information about biotic and abiotic features of the crop/plant in the multifactorial environment. It provides information related to quantitative and qualitative traits of the crop by analyzing their different parts such as organ, tissue, and entire organism level.[6]

While focusing on temporal phenotypes, it is classified into two types which are trajectory-based and event-based. The temporal phenotypes provide information about the genetic variability of the plant such as insights about trajectories of stem angle, plant growth rate, and leaf elongation rate. The determination of temporal features of the plant could be executed with the help of line graphs so that there is the attainment of insights about the length of leaf, mid-leaf curvature, stem angle, integral leaf skeleton, apex curvature, and others. It helps in determining the genetic influence on a plant that brings variations in its growth and characteristics. Apart from this, adaptive hierarchical segmentation and optical flow-based tracking methods are also used to identify plant features and patterns. Based on the above facts, it is said that plant phenotyping is an essential procedure to acquire information about a plant in terms of its characteristics, features, and differentiation from another plant that has similar traits.[7]

2.2. Segmentation Process in Plant Phenotyping

The plant organ segmentation is carried out by using different methods such as Otsu, Adaptive thresholding, Edge detection fuzzy numerical morphology calculation, Canny edge detection, and others so that there is the determination of valuable insights about plant organs such as flower, leaf, stem, fruit, and others.[8] For example, the Otsu method is used to determine the efficiency of plant organs such as flowers and fruit. However, its use is limited owing to pixel grey value and lack of spatial details. On the other hand, canny edge detection is used to accurately position the edge and carry out a fast computing process. However, its use is limited owing to the closure of edges and non-suitable for different kinds of edges.[9]

The whole plant phenotype is associated with 3D phenotyping and identification of plant stress. By using 3D phenotyping, there is the attainment of reliable insights into the complex plant structure and diversity within the species. The 3D plant phenotyping is based on three applications which are 3D image acquisition, 3D image processing, and 3D image analysis. The Figure below provides details of the different 3D phenotyping methods and implications.

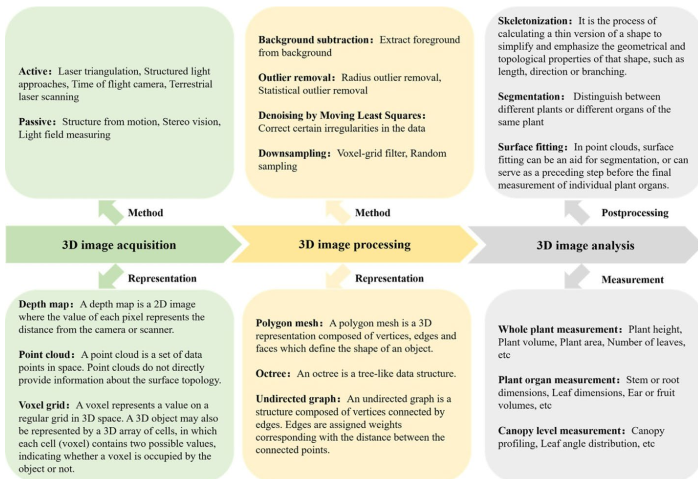

Fig. 2. The pipeline of 3D plant phenotyping.

Additionally, 3D plant phenotyping is carried out with the help of different methods such as Laser triangulation, Terrestrial laser scanning, Time of flight, and others to identify plant features. For example, Laser triangulation provides accurate measurement accuracy and high resolution at a low cost. However, its use gets restricted owing to no colour information, and heavy computing requirements. On the other hand, Terrestrial laser scanning provides a wide measurement range and high resolution with the help of a mature algorithm. However, the use of this technique is restricted owing to the high cost and time-consuming assessment.[10]

Plant stress phenotyping is also included in the study which provides insights into different diseases and pest attacks on plants. It includes biotic stresses and abiotic stresses that impact the growth of plants adversely. Therefore, to bring improvements in the organ and whole plant phenotyping, it is essential to advance technology-based tools such as deep learning techniques and filtering approaches in plant phenotyping so that there is a classification of plant traits and detection of plant stresses.

3. PLANT PHENOTYPING ENVIRONMENTS AND TECHNIQUES

3.1. Controlled environment

i) Imaging sensors:

Different imaging techniques such as RGB imaging, thermal imaging, multispectral imaging, hyperspectral imaging, and others are used to obtain valuable insights about crop features. Considering the RGB method, visible light is used to carry out the morphological study of the plant. It includes studying the plant from the stage of shoot emergence to reach the ground area to form the canopy. For example, 2D and 3D-based RGB imaging are used to carry out greenhouse studies and conduct proximal sensing of the plant. As a result, by using RCB, reliable information is acquired about the plant roots which facilitates further study process. However, the use of RGB imaging is restricted owing to the limited assessment of physiological when using the technology with other systems.[13] The RGB image is captured from the camera by creating syntax with the camera board. In the case of using the mycamera application, the camera is connected to the camera board by using MATLAB software. It helps in taking a photograph and recording video by creating a connection with Raspberry PiTM hardware.

Thermal imaging is another method that helps in acquiring information about the physiological features of a crop. This method is related to studying the surface temperature of the leaf or canopy so that reliable insights are gained about stomatal conductance. It helps in carrying out research related to plant stress when there is the emergence of different climatic conditions such as droughts or famines. However, the conduct of the thermal imaging process is highly challenging as it includes assessing information related to the temperature of the soil, air, wind, and humidity.[14] For example, Near-infrared cameras based sensors are used in the agriculture sector to capture raw data related to whole shoots, leaf tissues, and time series. It is based on pixel-based map resolution of surface temperature that helps in capturing phenotype parameters in the field-controlled environment. As a result, there is the detection of insect infestation and canopy or leaf temperature in crops such as barley, wheat, maize, rice, and grapevine.[15]

In Multispectral imaging near-infrared range of the light, spectrum is used to acquire plant features. It facilitates the process of leaf biochemistry and provides valuable insights into leaf pigment and water content. It also helps in assessing vegetation indices (VIs) so that there is the quantification of nitrogen and biomass. However, this process has certain limitations owing to the provision of discrete spectral information. As a result, it limits the multifaceted study of canopy and leaf biochemistry.[16] The image-based techniques were more useful than the manual separation process, however, their use was restricted owing to the lack of attainment of 3-D information.[17] The recent developments in light detection and ranging (LiDAR) helped in eliminating the 3-D image processing limitations and provided valuable 3-D information about plant/crop from the vegetation.[18]

On the other hand, in Hyperspectral imaging, a continuous spectrum is used to acquire information about plant physiological characteristics. It includes the use of the entire visible and near-infrared region, to carry out complex studies of the crop. As a result, this process helps in acquiring information about biochemical compositions, water composition, vegetation indices, and pigmentation. Hyperspectral imaging also helps in identifying plant diseases in both indoor and outdoor conditions. It helps in analyzing the wind effect on the plant when measuring the optimal signal-to-noise ratio.[19] The hyperspectral camera is based on spectroscopy and advanced digital imaging technology to capture the image. The hyperspectral cameras play an important role in agriculture by detecting bruises on apple trees, inspecting citrus fruits, and sorting potatoes. It also helps in the planting of seeds, ascertaining the freshness of fish, assessing the distribution of sugar in melons, and thereby, ensuring the quality of food and securing food chains. Though the implementation of hyperspectral images is costly, it is increasingly used to monitor crop health. On the other hand, hyperspectral-based imaging spectrometers are used to detect varieties of grapes in Australia. It also provides warning signals against disease outbreaks in the plants.[20]

ii) Computer vision Imaging techniques:

In computer vision imaging technique, a machine is used to recognize, track, and evaluate plants and crops in place of human beings. It includes the use of different types of sensors and methods to determine plant morphology, measure plant growth, and diagnose nitrogen content. For example, the Canon PowerShot SX20 sensor is based on the use of a non-invasive method to ascertain plant morphology. The technique exhibits strong versatility at low cost in a simple manner that helps in monitoring crop health and growth aspects.[21]

Drone type DJI 3 type Phantom senor is used along with Gray level co-occurrence matrix (GLCM) methodology to monitor palm oil plantations. It is a UAV-oriented monitoring technique. The computer vision imaging technique is known to be the most accurate that helps in obtaining accurate information about the crop health, roots, disease, and phenolic parameters quickly.[22]

Apart from this, the Raspberry Pi Camera Module v2 sensor along with Raspberry PI is used to count and identify flying insects over the crops. The technique is easy to use and provides real-time intelligent monitoring facilities with an accuracy of 92.50% levels. The average classification accuracy of the Raspberry Pi Camera Module v2 sensor-based computer vision imaging technique is 90.18% which helps in chemical analysis of the crop and identification of plant stress.[23]

0.9R-G Otsu algorithm Canny operator Hough transform type sensor along with robot vision system identification method is used identify cherries in the natural environment. The technique reduces the difficulty and high cost related to picking and brings improvement in efficiency by recognizing cherries with 96% accuracy. It also supports automatic harvesting of crops because of which there is a significant reduction in human labor costs for harvesting.[24]

Machine learning methods such as deep learning methods are also used in the structural plant phenotyping process so that valuable information is gained about plant features. The deep learning method includes the use of

Convolutional neural networks (CNN to detect, segment, and categorize objects. For example, CNN has been successfully used for the identification of diseases in rice panicles. It helped in acquiring reliable information related to species classification, crop stress, and segmentation.[30] Additionally, advancements have been made in the field of CNN phenotyping because of which 3D information analysis is included in the image-based CNN classification. It includes the use of different methods such as octree, voxel, point cloud, multi-surface, and others so that reliable insights are gained about the structural phenotypic of plants.[25]

Additionally, Deep learning algorithms such as AlexNet, GoogLeNet are used for the classification and identification of biotic crop stresses such as Tomato yellow leaf curl virus, tomato mosaic virus, target spot, spider mites, Septoria spot, leaf mold, late blight, early blight, a bacterial spot in tomato plantation.[26] Deep learning algorithms such as AlexNet are used for the identification, classification, and quantification of biotic and abiotic stresses like Bacterial blight, bacterial pustule, frog eye leaf spot, Septoria brown spot, sudden death syndrome, iron deficiency chlorosis, potassium deficiency, herbicide injury in soybean crop plantation. On the other hand, Deep learning tools such as AlexNet, GoogLeNet, VGGNet-16, ResNet20 are used to identify stresses such as Alternaria leaf spot, mosaic, rust, a brown spot in apple plantations.

3.2. Field Environment

i) Imaging sensors

Imaging of plants is more than just capturing pictures and aims at measuring the phenotype characteristics of the plants quantitatively by analyzing the interaction between light and plants. It includes evaluating the photons against each component cell of the plant so that there is the attainment of information related to absorbing, reflecting, and transmitting qualities of the plant. For example, the visible-light imaging technique is used in a field environment to cover canopy color, canopy, and color information. It includes the use of 3D stereo reconstruction from several viewpoints to capture the images of the canopy structure. It does not require any specific spectral calibration and take measurements automatically. However, its use is limited owing to under or over-sunlight and shadow conditions in the absence of spectral calibration.[27]

Fluorescence imaging techniques in the field conditions such as field tractor and agriculture machinery to determine the photosynthetic status of the plant. It also helps in the indirect assessment of the biotic and abiotic stress experienced by the plant. However, the use of this technique is limited because of the small signal-to-noise ratio. As a result, the soar-induced fluorescence is restricted to be used remotely.[28]

The imaging spectroscopy technique is used in field conditions to acquire information about the biochemical composition of the canopy or leaf. It also helps to acquire information about leaf area index, leaf growth, panicle health status, and coverage density. However, the use of this technique is restricted because of an absence of sensor calibration. Due to a lack of sensor calibration, the technique could not be used to record changes in the light conditions which limits its use for assessing the influence of canopy structure.[29]

LiDar method is another useful imaging technique that is also used to acquire vital plant information in terms of threshold levels and geometry levels. The threshold level provides plant information by analyzing intensity, multiwavelength, and waveform threshold, while the geometry level uses machine-learning-based and point-based techniques to acquire reliable information related to waveform width and intensity.[30] The use of the threshold-based method for plant phenotyping is less as it includes the implementation of full-waveform LiDAR systems. The use of this method also gets limited as it could not identify differences between the features of plants that have similar stems and leaves. On the other hand, the geometry-based method makes use of point –oriented approach to create differentiation between the plant features and record valuable information about them.[31]

ii) Computer vision

Convolutional Neural Networks is a Deep Learning (DL) computer vision technique that is used for the image classification of plants. It includes the use of the AlexNet model for image classification purposes, while the RCNN family model is used for object detection purposes. The other models such as FCN, U-Net are based on Fully convolutional architecture and encoder-decoder architecture to carry out semantic segmentation of the plant. The ground-Based Remote Sensing technique is used to acquire environmental, field, and phenotype information on individual plants. It is based on the use of advanced technologies such as automation and robotic precision so that there is the tracking of plant growth and determination of biomass amount. The information related to plant stem position, leaf area, crop plant count, leaf count, and inter-crop spacing. For example, robots such as BoniRob are used to collect information about real-world conditions. The robot also helps in tracking plant growth which helps the farmers and breeders to make the crop-growing decision.

Artificial Intelligence (AI), a subset Machine Learning (ML) is used to exploit plant feature learning and identify patterns. It is based on neural networks so that high-quality information is acquired about plant phenotype in terms of yield, roots, stress, disease, phenolic features, and chemical analysis. All the information that is acquired from the DL-based tool is stored in different datasets such as CropDeep, Arabidopsis, and others. The use of the DL technique helps in panicle and spike detection that allows the breeders to carry out panicle segmentation process.

4. DEEP LEARNING AND FILTERING TECHNIQUES IN PLANT PHENOTYPING

The concept of deep learning came into form in the year 1960 with the use of multiple layers of non-linear features in polynomial activation functions. The implementation of deep learning in the agriculture sector has simplified the conduct of traditional activities such as assessing plant growth rate, leaf count, crop plant count, biomass amount, and others because of which they are performed seamlessly.[32] It is classified into different categories such as supervised, semi-supervised, and unsupervised. Supervised learning techniques include labeled data, while semi-supervised learning technique includes deep Reinforcement Learning (DRL) or Reinforcement Learning (RL). On the other hand, the unsupervised learning technique is based on labeled data and the representation of important features within the input data.[33]

While focusing on the application of deep learning and filtering techniques in plant phenotyping, it includes three approaches which are ground-based remote sensing, unmanned aircraft vehicles, and satellites. Ground-based remote sensing for plant phenotyping is related to the use of automation and robotic technology in the agriculture sector. The success of the implementation of advanced technology-based tools depends on the availability of information about the environment. It includes the use of available data, computer vision-based deep learning, and robots such as BoniRob to promote autonomous farming practices.[34]

The use of robots for plant-specific treatment can be enhanced by equipping farming robots with a crop identification and classification system. It provides reliable information to the robots and they would perform actuator activity with the desired action in real-time.[35] For instance, Weeds do not have any nutritional or medicinal value, and cannot be used for food purposes. They harm the growth of actual crop plants by taking their nutrients and space. Moreover, the manual conduct of the weeding process consumes a lot of time, and effort, and increases the cost of production. Therefore, extensive research is carried out in this direction to create differences between crop vs. weed identification, crop vs. weed classification, and crop seed classification.[36] It helps in introducing an automated process of weeding so that significant crop losses and increased farming costs are reduced.[37] Technology-based weed control practices promote precision framing by modulating the herbicide spraying process.

In-plant phenotyping, crop detection, and segmentation are some of the most crucial processes to carry out farm management activities. Crop detection and segmentation include different tasks such as monitoring of crop growth, real-time detection of crop disease, yield estimation, and visual crop classification. However, a major limitation with the present deep learning network technology is that it is not suitable to carry out farm-based activities such as spraying pesticides, fertilization, irrigation, and picking. The major reason behind the limited use of deep learning networks is the lack of benchmark datasets that could facilitate agricultural processes. The only reliable database that is available for detection is acquired from CropDeep, while others such as databases such as Rosette plant or Arabidopsis provide information about crop/weed segmentation, Sorghum-Head, Crop/Tassle segmentation, and others. Fig. 3 below shows a few examples that have been extracted from the CropDeep dataset. On the other hand, Fig. 4 signifies the multi-modal annotations that have been acquired from the Rosette Plant Phenotyping dataset.

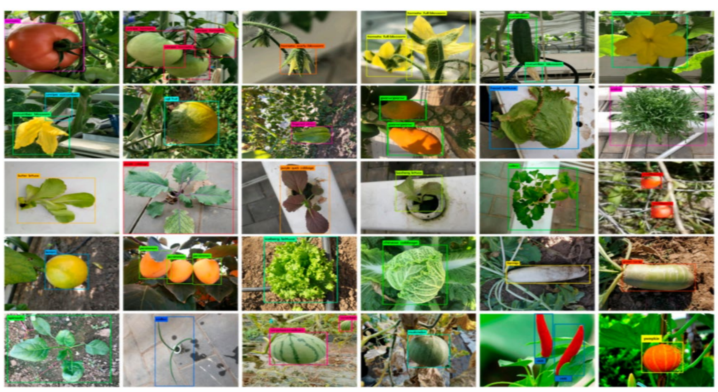

Fig. 3. Some annotation examples from the CropDeep dataset.

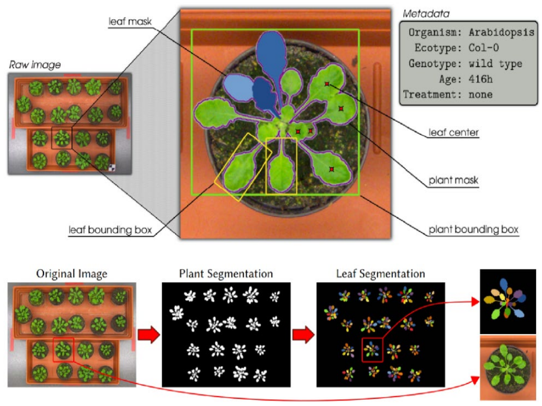

Fig. 4. Visual illustration of all types of annotations available in Rosette Plant Phenotyping dataset.

The adoption of modern technologies has enhanced the capacity of cultivators to produce sufficient food products so that the food needs of more than 7 billion individuals are met. However, the food security achieved by the cultivators is impacted by several factors such as plant diseases, reduction in pollinators, climate change, and reduced capacity to grow.[38] Due to plant diseases, Indian farmers lose 35% of their crop yield, while developing countries lose more than 50% of their produce. It also adversely impacts the earning level of smallholder farmers and increases the risks of pathogen-derived disruptions in the food supply. Therefore, implementing crop disease and pest recognition techniques is necessary to be introduced to bring improvements in agricultural practices.[39]

However, a major issue with real-time disease and pest identification is that there is a lack of sufficient information among the farmers. Under such conditions, the farmers have to rely on the government-aided helpline and fellow cultivators to seek pest control advice. Therefore, to reduce the issues that are faced by the farmers, several researchers researched this segment and developed public datasets such as PlantDoc and PlantVillage.[40] Through these datasets, the farmers could gain relevant information about pests and crop diseases. The datasets also provide valuable insights related to the control of crop disease and pest recognition**.** Figs. 5- 10 below describe the identified crop disease and the expected outcome of the trained disease detection model.

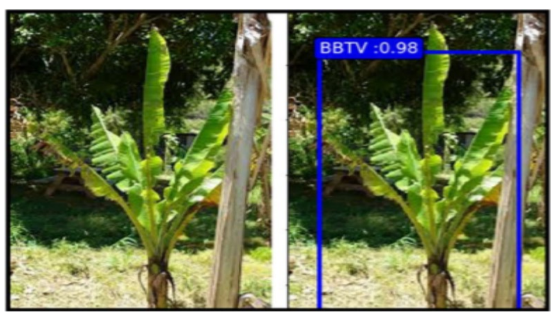

Fig. 5. Entire plant affected by the banana bunchy top virus (BBTV).

Fig. 6. Leaves affected by black Sigatoka (BS).

Fig. 7. Cut pseudostem of Xanthomonas wilt (BXW) affected plant showing yellow bacterial ooze.

Fig. 8. Fruit bunch affected by Xanthomonas wilt (BXW).

Fig. 9. Cut fruit affected by Xanthomonas wilt (BXW).

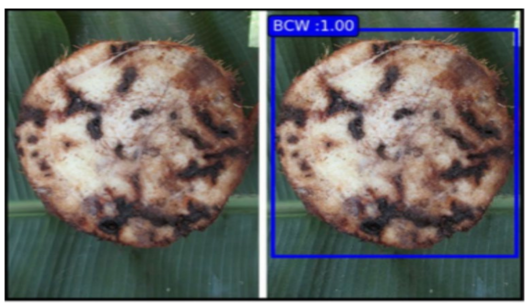

Fig. 10. Corm affected by banana corm weevil (BCW).

Unmanned aircraft vehicles (UAVs) are increasingly used in the civilian sector to carry out remote sensing and photogrammetry activities. As compared to manned aircraft vehicles, UAVs are considered to be more beneficial as they provide flexibility, high spatial resolution, and easy operational facilities. The high efficient and low-cost features of UAVs make them highly useful to carry out remote sensing, inspection, construction inspection, and search & rescue activities. As a result, UAVs can be utilized for performing precision farming, monitoring, and crop management practices.[41] UAVs also help in the identification of weeds, spraying pesticides, recognizing insects, detecting an agricultural pattern, and scheduling irrigation. UAV adoption facilitates farm administration, weed supervision, and pest control processes. The conduct of all these activities by UAVs helps in improving crop yields, increasing the productivity of the farm, and augmenting profitability in agricultural systems.

UAVs are used to carry out monitoring activities and quantify factors associated with irrigation, crop water need, amount of rainfall, availability of soil water, and assessment of the effectiveness of the irrigation system.[42] It is also utilized in the farming process to evaluate the spatial distribution of the surface soil and assess the level of moisture for the crop cultivation process. It also helps in monitoring the temporal and spatial patterns of plant diseases during different phases of plant growth. Due to the use of UAV, there is the detection of the pests in the early phase which helps in reducing crop losses for cultivators.[43] The features of UAV also make it well efficient to capture thermal images and analyzing the texture of soil for crop cultivation. It also helps in evaluating the temperature differences on the land surface by considering the homogenous climatic conditions.

The thermal images that are captured by UAVs provide valuable information about wind and water. It also determines the variability in crop residue that is essential for carrying out tillage practices by developing a protective layer on farmlands. The accuracy of the thermal images of UAVs is such that it can explain more than 95% variability in crop residue cover in comparison to 77% visibility provided by IR images.[44] UAV implementation in the agriculture sector also helps in determining harvest time and monitoring the crop maturity of the crops. As a result, by using UAVs, the farmers acquire accurate information related to the yield of product that helps them to make decisions related to crop insurance, storage arrangements, harvest planning, and budgeting cash flow activities.[45] For example, UAV was utilized in Thailand to evaluate total produce levels and biomass quantity of the rice crop, while it was utilized in Germany to make predictions about corn yields during the crop growth stages.

UAVs feature of the combined aerial and ground-based system is highly helpful in carrying out precision agriculture activities. It has additional features such as relaxed flight regulations, geo-referencing, machine learning algorithms, and mosaicing help to conduct crop and soil monitoring activities.[41] Additionally, satellites are used for carrying out plant phenotyping activities. As the climate change conditions are unpredictable, it becomes difficult for the cultivators to save their yield from environmental uncertainties. Under such conditions, satellite imagery provides crucial information related to weather and soil conditions. Satellite imagery helps in reducing scouting efforts of the cultivators because of which there is optimal utilization of nitrogen and water schedules. It also helps in estimating field efficacy and benchmarking them to analyze levels of soil erosion and risks of drought and mineral exhaustion. India has specifically designed seven satellites to provide benefits to the cultivators.

Satellites and their imagery features are applied in the farming sector to estimate crop yields, soil moisture, types of crops, pH of the soil, and salinity levels in the soil.[57] The implementation of radar and optical sensors in the satellite provides an accurate image of the land that is to be cultivated and differentiates between crop types in terms of health and maturity. Additionally, the optical satellite sensors can detect different rays such as infrared- wavelengths and visible rays on agricultural land. The combination of the different rays helps in determining the condition of the crop and provides early warning related to famine or crop failure.[46]

The satellites for plant phenotyping are used for carrying out efficient precision agriculture practices where satellite images are used to characterize fields in detail. It is used in combination with geographical information systems (GIS) so that there is the facilitation of efficient farming practices. For instance, it recommends different crops for different fields and helps the farmer to make optimum utilization of fertilizer.[47] Moreover, satellite imagery plays an important role in developing trust between several agricultural-oriented parties such as cultivators, governing agencies, and private bodies involved in farming. Satellite imagery encourages the use of different web-based platforms such as Earth Data Search, Geocento, Google Earth Engine, and others that help the farmers to acquire all the past and present information about the crops, fields, and allied practices that must be implemented to increase the efficiency of the produce.[48] Based on the facts, it can be said that deep learning-based plant phenotyping plays an important role in acquiring relevant information about the crop, soil, fertilizer, soil types, fertilizer usage, climate change, and others that help in increasing the productivity of the farm and income of the farmers.

The factors that controlled the features of deep learning in the forecasting model were explored.[49] Initially, plant pathology was studied to determine the factors of plant diseases. While carrying out in-depth analysis, the shortcoming of deep learning was presented. The examination was conducted over the 50, 000 images from the academic views. The factors such as inefficient size, annotated datasets, symptom analysis, shift variable analysis, the background of the images, and the image capturing constraints. This study has explored the scope of CNN architectures in plant disease identification. Improper labeling and capturing conditions have delayed the train and test set ratio in deep learning.

Detecting the plant diseases using visualization of saliency map was explored [50]; under the CNN framework of GoogleNet and AlexNet some deep learning architectures have vented out the qualities of the black boxes prevailing the features. Here, the features were examined using a saliency map which has helped to visualize the data consumption rate, hardware utilization and extraction module. Data augmentation during the training process has incorporated several complexities over the network input layer. The pixel by pixel exploration and mapping toward the input layer have increased the estimation of image gradient scales. This system has obtained 0.9976 accuracy by analyzing the deep and broad approaches.

Mobile technologies have also intervened in the production rate of the wheat crop by intelligently predicting the diseases in an early stage, which is explored by.[51] In the preparation to reduce the loss of crop production, the treatment of the crops was improved by developing an association among the crops using resistivity features. Though it leveraged the automated classification module, forecasting it early is a pending process. Thus, the use of mobile technologies has significantly reduced the forecasting time using an improved image processing algorithm. Just, it drew the statistical inference among the images to discover the affected diseases. The analyzed metrics and receiver Operating Characteristics (ROC) curve have shown the efficacy of mobile technologies.

The qualitative and reliable measures using phenotypic features of an image were studied.[52] It was observed that the least works were done under phenotypic features of the leaves. Here, canopy hyperspectral data was analyzed using normalized difference water index (NDWI) and Partial Least Squares (PLS) regression models. The analysis has stated that the 93% accuracy obtained at kappa=0.60 detected the plant disease named Septoria tritici blotch (STB) disease. Though it has improved detection efficiency, the disease-resistance is higher among breeding of the pants.

The growth of spectral data has been constantly increasing with the growth of technologies which have also improved the detection accuracy. In other aspects, the variations prevail in the Leaf Area Index (LAI).[53] Here, Support Vector Regression (SVR) and Gaussian Vector Regression (GVR) were studied to explore the performance of SVM classifiers. It was operated on the different wavelengths of the leaf region. System has improved the detection accuracy with a reduced error rate of 8.5%. Additionally, it has also predicted the severity score of the diseases. When the dataset size varies, the error rate increases and the accuracy rate tends to decrease.

Wheat disease diagnosis model of the in-field was studied by.[54] The health status of the crops and its monitoring process involves a huge time as well as a significant task. Multiple instance learning models were studied by stating the image-level annotations. Performing localization schemes over the training images has improved the recognition accuracies. Wheat Disease Database 2017 was used for experimental purposes. Compared to the conventional CNN architectures, the designed localization based CNN has maintained a lowered error rate. Bounding box was applied in the image segmentation process that deliberately enhanced the error rate while addressing the network layers.

Some studies make use of disease symptoms for earlier forecasting processes using optimization models.[55] To improve the classification process, the segmentation technique was devised. The survey has stated the scope of the image segmentation process which is devised in this study using genetic algorithms. It performs with the set of solutions known as population. Relied upon the feedback given by the previous population, the objective functions and the new population surfaced. This has helped to increase the probability of converged solutions and also reduced the searching time. The system has reduced the computational steps, however, the logic behind the classification process has fuzzed the environment.

A deep CNN was used for exploring the identifying the rice diseases.[56] The identifying the diseases based on similar patterns has developed an interest among the researchers, specifically CNN architecture was studied. The report states, there are 10 common rice diseases available. Thus, the authors have introduced a 10 fold-cross validation process of the CNNs and obtained 95. 48% accuracy. It has reduced training time but the data augmentation process over the colored channels increases the convoluted filter rate. It is not suitable for large-scale datasets.

Plant disease based on visible ranges images and its challenges were reviewed by (Jayme Garcia, 2016).[58] The study has stated the complex challenges prevailing in the image analysis of different parts of plants and the diseases associated with them. Most studies have stated that due to the complex backgrounds of the images, the accuracy of the segmentation process is observed. Along with this, several boundaries of the diseases have also collapsed the classification process leading to an error rate. The effectiveness of image processing is still in the developmental stage due to the above-mentioned challenges.

The disease identification models for the soybean leaf using UAV images were studied.[59] The image processing analysis over the captured UAV images has to deal with the complex backgrounds. It is studied using deep convolutional neural networks. Black boxes passing on the labeled images were demodulated by adjusting the network weights. The different parameters of the transfer learning modules were fine-tuned under the categories of leaf diseases. SLIC superpixels algorithm was used to segment plant leaves in the images. The segmented images were then observed on the Inception-v3, Resnet-50, VGG-19, and Xception. It has achieved 99.04% classification accuracy, however the image training has anticipated different training models due to the variation prevailing in the background images.

One of the deep NN was combined with the Jaya algorithm was studied to detect the disease class of the paddy leaf.[60] In general, the leaves of the plants are spotted with normal, bacterial blight, brown spot, sheath rot, and blast diseases. These color variations portrayed the stage of the disease. During the background analysis process of RGB into HSV images, the saturation and hue of the images are distorted and bring an effect over the segmentation process. It does not differentiate between normal and diseased parts. Hence, an optimized Jaya algorithm was used to improve the post-processing results. System has achieved an accuracy of above 90% for all color variations. Visual features affect the training module when the color and size gradually increase, which was not focussed by the researchers.

Mobile technologies to enhance the production rate of the wheat crop by intelligently predicting the diseases in an early stage have been introduced.[51] Though it leveraged the automated classification module, forecasting it early is a pending process. Thus, the use of mobile technologies has significantly reduced the forecasting time using an improved image processing algorithm. Just, it drew the statistical inference among the images to discover the affected diseases. The analyzed metrics, Receiver Operating Characteristics (ROC) curve has shown the efficacy of mobile technologies.

Northern-side maize plants and their leaf diseases were analyzed.[61] The detection of leaf blight disease prevailing in the northern side is a complicated task due to its time consuming process. To ensure the reliability of the detection model, CNN was designed to leverage the pipeline related to the computational efforts. The affected regions of the leaf were classified into small and large lesions. Both are analyzed separately and the heat maps were generated to yield the converged solutions. The designed model has achieved 96.7% accuracy which has resolved the disease resistance rate, usage of pest amount, and high-throughput.

The scenario of the leaf rust in the wheat crop is explored in which, Puccinia triticina Erikss (Pt), a fungal disease was detected using genes-based algorithms.[62] Due to the invasion of the Non-Host Resistance (NHR), the production of wheat crops decreases with the highest prevalence of Pt genes. It has been found that the APR genes such as Lr34, Lr46, Lr67, Lr68, and Lr77 were the main reasons to form leaf rust in the wheat crop. While doing the data augmentation process, the similar characteristics of the genes developed a contradiction towards the identification of leaf rust. Triticum aestivum L is one of the fungal diseases that cause leaf rust in the wheat family by altering the genes of the auxins response factor.[63] Auxin Response Factor (ARF) is one of the plant-transcription factors that has affected the wheat plant during its developmental stage. The accumulation of high DNA nuclei has to be localized under image processing techniques which are a complex task.

Due to the accumulation of leaf rust, the economic returns from wheat cultivation are declining dramatically in the southwestern region of Iran.[64] Therefore, the intensity of the diseases was measured under the aspect of economics in a varied region. It has proven that an improper use of fungicides on the crop has introduced new diseases that were not able to be predicted earlier. Prediction systems become complex due to different forms of diseases according to the climatic conditions. The presence of hazardous materials has affected the wheat soil systems[65]; in which Bioavailable arsenic and amorphous iron oxides were not easily predicted. The bioavailable arsenic extracted by NH 4 H 2 PO 4 has altered the humidity of the wheat soil. Risk assessments of the soil capability have reduced the prediction ability. Detection of Fusarium head blight of wheat has been explored using spectral images.[66] Principal Component Analysis was used to reduce the dimension of the hyperspectral images. Finally, the decision tree has improved the optimized feature selection process. Then, the affected part of the leaf was classified using deep neural networks. Some color space of the images was not easily executed on large datasets.

The detection of aphid diseases in wheat leaves using computer vision approaches was explored.[67] Identification of the aphids is a critical task and thus, image processing techniques were applied to it. Maximally stable extremal region descriptors were used to extract the affected regions from the background. Then, histogram analysis was done on the gradient features. Finally, SVM was used to classify the aphid diseases. The results have stated that the 86.81% of detection accuracy with 8.91% of error rates. Though it has decreased the detection time, the segmentation accuracy is not calculated. Detection of wheat diseases based on spectral indices and kernel discriminant analysis was explored.[68] Spectral vegetation indices-based kernel discriminant approach (SVIKDA) for the detection and classification of yellow rust, aphid, and powdery mildew in winter wheat at the leaf and canopy level was designed. By using 5-cross validation models, the disease classes were identified. Then, a gaussian kernel function was also employed to form a nonlinear framework. Disease Indices (DI) were provided with the high coefficients of determination. Since the identification was done at the canopy level, the time taken for the detection process is high.

The use case model for the automatic detection of plant diseases was explored.[51] Hot spot candidate detection models with statistical inference were employed to detect the diseases under three winter areas. With the help of mobile devices, the affected leaves were easily predicted with a reduced error rate 0.1. It does not perform well in some suspected regions. An observation model was designed during the wheat heading stage.[69] Illumination while capturing images created a problem in the image segmentation process. Thus, it was improved by a coarse detection process on the higher-level features. Scale-Invariant Feature Transform (SIFT) and Fish Vector (FV) encoding were used for better representation of images. It has increased the robustness rate of early detection processes. Yet, the classification model of those images is not studied. The water stress detection for the cause of wheat leaf diseases using SVM classifier models was explored.[70] Septoria tritici infection is one of the dangerous diseases that causes stress in water plants. With the help of the Least Square Support Vector Machine (LSVM), the stress rate was investigated. The system fails in the cases of lowered energy during optical fusion.

Color change detection of affected wheat leaves plays a significant contribution in the segmentation process.[71] An improved Chan-Vese model was suggested for segmentation wheat leaf lesion. By developing adaptive weighting models, the three color channels were devised and the segmentation accuracy was improved. The wheat biomass estimation based on the crop height was studied.[72] Based on the plant coverage and the heighting measurements, the growth stages of the wheat using NDVI and NIR image segmentation approaches. With the use of k-means, Partition Around Medoids (PAM), and the fuzzy clustering approaches, the images were clustered. This was very useful for the biomass estimation as well as the leaf growth monitoring. It is observed that the error rate increases as the threshold height value increases.

Genetics-oriented leaf diseases were studied on each species.[73] Bipolaris sorokiniana is a common genetic disease that prevails in the tissues of wheat and barley. By analyzing the tissues using pathogen-specific primers COSA_F/R derived from the melanin biosynthesis pathway Brn1 locus, the disease was detected. However, the risk factors of the affected leaves are not studied. The risk of the Pyrenophora tritici-repentis diseases in the wheat plant using a phototypic process was studied.[74] Initially, the pigments of the wheat leaves were explored. Then, by ANOVA test, the presence of fungus and bacterial pigments were studied. Though it was helpful to reduce the risk of spreading diseases, the classification process is not studied. The pre-symptomatic wheat leaf rust detection was studied.[75] With the help of fluorescence signatures of the healthy and unhealthy leaves, the frequency oscillations between those leaves were investigated. The pre-symptomatic pathogen identification has helped a lot in classifying diseases with low training samples. The classification accuracy was 93%, yet the robustness of the inoculation process is a bit low.

Fusarium species is one of the causes of changing the colors in wheat leaves. Thus, multispectral image analysis was studied to detect the head blight diseases of the wheat plant.[76] The chlorophyll defects of the wheat leaf were segmented using binarization methods. It has increased the flexibility of morphological operations, yet some defects on head blight are not visible due to the maturation of wheat plants. The detection of wheat dwarf virus by using PCR methods was studied.[77] Coat protein of the gene sequence was analyzed using gel-based PCR. This model has detected the sensitivity rate of virus diseases. Though the detection was easier, it could not accommodate the large datasets.

The leaf level detection using continuous wavelet analysis which summarized the correlation between disease severity and the power of wavelets was studied.[78] Here, 22 conventional spectral features were analyzed for disease severity and then the training methods were conducted on the linear regression models. Absorption rates of the systems are not focussed on the verification of the normal areas. The genetic correlation on the transpiration efficiency of the wheat leaves was discovered.[79] The synthesis of wheat leaves was explored and then the contribution of each synthesis was correlated. This combined analysis of stress at high temperatures revealed the level of affected leaves. This has been efficiently detected at the breeding stage of wheat diseases. Moreover, some chemical syntheses have altered over time which poses serious challenges. Real-time weed detection systems on wheat fields were studied.[80] Here, two optical weed sensors and control modules were networked under the controller area network. Classification accuracy was greater than 90% due to the efficiency of training models. The installation cost is too high.

The effects of bixafen in wheat fields were discussed.[81] The presence of fungal diseases has been studied in the applications of fungicides. The temperature of ears and leaves was negatively correlated to grain yield. Lower tissue temperature of fungicide-treated plants was a suitable indicator of tissue vitality and higher photosynthetic activity due to the retardation of ear and leaf senescence. Two optical weed sensors and the control modules were developed and embedded into the real-time network along with the global positioning systems.[82] With the help of controller area networks, the accuracy of weed detection was achieved at 70%. The obtained classification accuracy has improved the positioning of the sensor systems. The stress inducing greenbugs using remote sensing images was discovered.[83] By using SAS PROC MIXED statistical analysis procedure and ratio-indexed based approaches, the bands were analyzed and discovered the stress inducing bands.

The detection of rice leaf diseases such as leaf smut and brown spot diseases using the k-Nearest neighbor algorithm was discussed.[84] It has achieved 97% accuracy than the decision tree and logistic regression. It fails to operate on optimum local strategy. A similar study is extended that explored the disease detection module by improving the image segmentation process.[85] Though it has achieved 99% accuracy, the ROI values of the image edges are distorted which brings practical infeasibility. The classification of all plant diseases was explored using a combination of machine learning and image preprocessing techniques.[86] As a large number of plants suffer from common plant diseases related to brown spots, an improved and intelligent detection of plant diseases was designed. The performance analysis of all ML classifiers has achieved a better accuracy rate. The role of hyperparameters in each classifier is ignored due to time constraints.

The drought stress detection module using ML techniques, so as to improve the cost efficiency is explored.[87] The seasoning of images was collected and preprocessed using time-series scale data. The information acquisition process has affected the stress factor analysis which brings in collinearity issues among the developed data patterns. Weed control in pasture using machine learning techniques was studied by [88]. With the use of local binary patterns, the textures of the plants are extracted. Due to the improper monitoring process, the weeds are stressed. However, the scalability of the ML techniques is not assured. Disease detection in potato leaf was done by (Md. Asif Iqbal, 2020).[89] The segmentation of the potato leaf was improved by extracting the optimal global feature descriptors. Compared to the random forest classifiers, DT and LR outperformed in terms of better segmentation accuracy. Similarly, the disease in tea leaves was studied.[90] Convolutional Neural networks have introduced several pooling layers that resolve the image denoising during the image construction process. This has improved the classifier accuracy, however, it is not suitable for the real-time applications.

A deep learning-based approach that provides an accurate classification for wheat varietal level classification (VLC) was studied.[91] Particularly, the Convolutional Neural network (CNN) was used to classify the wheat grain image into four varieties (Simeto, Vitron, ARZ, and HD). Furthermore, five standard CNN architectures were trained based on Transfer Learning to boost the classification performance. To assess the proposed models' quality, we used a dataset of 31,606 single-grain images collected from different Algeria regions, and their images were captured using different scanners. The results showed that the test accuracy ranged from 85% to 95.68% for varietal-level classification.

5. PERFORMANCE MEASURES AND METRICS- FOR DIFFERENT TYPES

High throughput plant phenotyping is an essential requirement in the current agricultural practices so that there is a reduction in the cost related to breeding trials and crop management. It includes the use of Automated Machine Learning (AutoML) to reduce efforts in manual ML practice. It provides end-to-end ML pipelines that help in data preparation, feature engineering, and model generation purposes. AutoML is based on the use of neural architecture search (NAS) that facilitates the construction of well-performing architectures to carry out the selection and combination of fundamental modules in search spaces that are already defined.[92]

The four sensing modalities of the Multi-Modality Plant Imagery Database (MSU-PID) help in analyzing the morphological and physiological phenotypes. For example, it uses a 730nm to 750nm based chlorophyll fluorescence tool to measure the efficacy of photosynthetic abilities of the plant. It also helps in the assessment of the photosynthetically active compounds present in the chlorophyll-containing leaf area.

Unmanned Aerial Vehicles (UAVs) and thermal imaging sensors are used to promote precision agricultural practices and plant phenotyping activities. The use of UAV thermal cameras such as ICI 8640 P-series, FLIR Vue Pro R 640, and thermoMap are commonly available and can be bought cheaply to carry out plant monitoring activities and identification of vegetation stress. For example, these cameras were flown over the forests of Columbia, Maricopa, and Arizona to analyze forest environments, detect plant stress, and acquire high throughput phenotyping.[93]

The qualitative and reliable measures using phenotypic features of an image were studied.[52] Here, canopy hyperspectral data was analyzed using normalized difference water index (NDWI) and Partial Least Squares (PLS) regression models. Though it has improved detection efficiency, the disease-resistance is higher among breeding of the pants. in other aspects, the variations prevailing in the Leaf Area Index (LAI).[53] Here, Support Vector Regression (SVR) and Gaussian Vector Regression (GVR) were studied to explore the performance of SVM classifiers. It was operated on the different wavelengths of the leaf region which has given detection accuracy with a reduced error rate of 8.5%. When the dataset size varies, the error rate increases and the accuracy rate tends to decrease.

Some studies make use of disease symptoms for earlier forecasting processes using optimization models.[55] To improve the classification process, the segmentation technique was devised. It performs with the set of solutions known as population. Relied upon the feedback given by the previous population, the objective functions and the new population surfaced. This has helped to increase the probability of converged solutions and also reduced the searching time. The identifying the diseases based on similar patterns has developed an interest among the researchers, in specific to, CNN architecture was studied.[56] The report states, there are 10 common rice diseases and achieved 95.48% accuracy. It has reduced training time but the data augmentation process over the colored channels increases the convoluted filter rate. It is not suitable for large-scale datasets.

6. COMPARATIVE STUDY

The comparative study is made to find out the discovered stresses and the review of designed the deep learning architectures.

Table 1. Instances of DL approaches in plant stress image based phenotyping.

DL algorithm	Plant	Stress type	Stress name	Refs
LeNet architecture	Banana	Biotic stress	Early scorch, cottony mold, ashen mold, late scorch, tiny whiteness	Amara, J. et al. (2017)[12]
AlexNet, GoogLeNet, VGGNet-16, ResNet20	Apple	Biotic stress	Alternaria leaf spot, mosaic, rust, brown spot	Liu, B. et al. (2018)[94]
Inception-v3, ImageNet	Cassava	Biotic stress	Cassava brown streak disease, cassava mosaic disease, brown leaf spot, cassava green mite damage, cassava red mite damage	Ramcharan, A. et al. (2017)[95]
AlexNet, ALexNetOWTBn, GoogLeNet, Overfeat, VGG	apple, banana, blueberry, cabbage, cantaloupe, cassava, celery, cherry, corn, cucumber, eggplant, gourd, grape, onion, orange	Biotic stress	Bacterial spot, apple scab, cedar apple rust, black rot, banana sigatoka, banana speckle, brown leaf spot, cassava green spider mite, Cercospora leaf spot, common rust, northern leaf blight,	Ferentinos, K.P. (2018)[96]
AlexNet, GoogLeNet	Apple, blueberry, cherry, corn, grape, peach, bell pepper, potato, raspberry, soybean, squash, strawberry,	Biotic stress	Apple scab, apple black rot, apple cedar rust, cherry powdery mildew, corn gray leaf spot, corn common rust, corn northern leaf blight, grape black rot, grape black measles, grape leaf blight, orange huanglongbing (citrus greening), peach bacterial spot, bell pepper bacterial spot, potato early blight, potato late blight, squash powdery mildew, strawberry leaf scorch,	Mohanty, S.P. et al. (2016)[97]
Modified LeNet	Olive	Biotic stress	Olive quick decline syndrome	Cruz, A.C. et al. (2017)[98]

CNN	Cucumber	Biotic stress	Melon yellow spot virus, zucchini yellow mosaic virus, cucurbit chlorotic yellows virus, cucumber mosaic virus,	Fujita, E., et al. (2016)[99]
CaffeNet, ImageNet	Pear, cherry peach, apple, grapevine	Biotic stress	Porosity (pear, cherry, peach), powdery mildew (peach), peach leaf curl, fire blight (apple, pear), apple scab, powdery mildew (apple), rust (apple, pear), grey leaf spot (pear), wilt (grapevine), mites (grapevine), downy mildew (grapevine), powdery mildew (grapevine)	Sladojevic, S. et al. (2016)[100]
VGG-A, CNN	Radish	Biotic stress	Fusarium wilt	Ha, J.G. et al. (2017)[101]
AlexNet	Soybean	Biotic and abiotic stress	Bacterial blight, bacterial pustule, frogeye leaf spot, Septoria brown spot, sudden death syndrome, iron deficiency chlorosis, potassium deficiency, herbicide injury	Ghosal, S. et al. (2018)[102]

Table 2. Comparative study on recent deep learning techniques.

References	Techniques	Achieved outcomes	Scope of the future work
Ghosal, S. et al. (2018) An explainable deep machine vision framework for plant stress phenotyping. Proc. Natl. Acad. Sci. U. S. A. 115, 4613–4618	A deep learning framework was used to develop a DCNN framework that helped to identify, classify and quantify eight stresses of the soybeans. An unsupervised approach was used in this framework to find out the stress region of the plant leaf and isolate the visual clues. DCNN model uses visual clues for decision-making. Stress is quantified using the unsupervised localization of visual clues. The study helped in identifying plant stress by developing a plant stress quantification scheme. The framework generally avoids the use of expensive stress annotations and uses an image-based phenotyping process to carry out precision	The overall classification accuracy of the model is 94.13%	The major limitation of the study was related to inconsistency that occurred because of different image content and features in convolutional nets and network parameters.

	agricultural practices.		
Zhang, J. et al. (2017) Computer vision and machine learning for robust phenotyping in genome-wide studies. Sci. Rep. 7, 44048	The study specifies the use of a Machine Learning-based approach for the classification of five stress classes of plants. It includes using automated severity classification and hand-crafted feature extraction to quantify the abiotic stress among crops on the scale of 1% to 100%. The study majorly focused on the identification of iron deficiency chlorosis in soybean by making use of a smartphone app-based framework. Additionally, the study included the use of hierarchical classification with multiclass SVM and Deep Learning-based frameworks so that there was automation in the feature extraction and categorization phase.	Accuracy and average per-class accuracy were 99.4% and 95.9%, respectively, using this hierarchical SVM+SVM classifier.	The major limitation of the study was that it required the use of HTTP tools to acquire real-time information about plant phenotyping when using UAV.
Fuentes, A. et al. (2017) A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors (Basel, Switzerland) 17, 2022 Trends in Plant Science, Month Year, Vol. xx, No. yy 15 TRPLSC 1707 No. of Pages 16	The study describes the use of the Deep learning approach for the identification of biotic stresses such as diseases (e gray mold, leaf mold, canker, plague, powdery mildew) and pests (leaf miner and whitefly) on the tomato crops. The study also focused on detecting abiotic stresses that were related to analyzing temperature and estimating nutritional excess in the crops. The study included the use of a non-destructive imaging protocol to detect stresses in field settings. It also helped in capturing images by considering different plant aspects such as background, color, size, and shape of tomato fruit. Apart from this, deep learning tools such as AlexNet, ZFNet, VGG-16, GoogLeNet, ResNet-50, ResNet-101, and ResNetXt-101 were used to capture different crop images. It also includes the use of object detectors such as Faster RCNN, R-FCN, and SSD to detect stresses such as whitefly, leaf mold, leaf miner, and grey mold canker.	The classifier with data augmentation is 83.06%	The study was limited as it did not provide valuable information about stresses in real time.
Deng, J., et al. (2009) ImageNet: a large-scale hierarchical image database. In 2009 IEEE Conference on Computer Vision and Pattern Recognition, pp. 248–255, IEEE	The study was conducted to identify biotic and abiotic stresses in tomato plantations. It included inspecting and imaging viral, bacterial, and fungal diseases that impact the growth of tomato plants. The study captured about 14828 images and found that the sample tomato species taken into consideration was inflicted by 9 stresses. It included viral stress such as yellow leaf curl virus and tomato mosaic virus, fungal stress such as target spot, leaf mold, late blight, and early blight. The bacterial stress includes bacterial spots and the pests such as spider mites were also recognized that impacted the tomato plant. Therefore, the study focused on the implementation of		The study was limited as accuracy levels of GoogLeNet and AlexNet were not compared.

	train deep architectures such as GoogLeNet and AlexNet to identify network weights.		
Amara, J. et al. (2017) A deep learning-based approach for banana leaf diseases classification. In Lecture Notes in Informatics (LNI), pp. 79–88, Gesellschaft für Informatik	The study includes the use of LeNet architecture on image datasets to detect and classify diseases among the crops. The entire data was categorized into three categories such as healthy, black Sigatoka, and black speckle to identify the biotic stresses. The study included the use of open-source data PlantVillage to acquire relevant insights about automating disease identification. Additionally, the study also included the use of a deep learning approach for the classification and detection of challenging conditions with the help of different images. As a result, there was the attainment of insights about resolution size, background, orientation, and the illumination of the crop. Apart from this, the study also included two-class classification in which healthy and diseased conditions of the plant were compared.	Classifier has yielded 92.06% accuracy for 80% training dataset with 10% testing dataset.	The study was limited as there was a small learning rate for the attainment of précised outcomes.
Mohanty, S.P. et al. (2016) Using deep learning for image-based plant disease detection. Front. Plant Sci. 7, 1419 http://dx.doi. org/10.3389/fpls.2016.01419	The study includes 54 306 images that have been captured with the help of DCNN (AlexNet and GoogLeNet) architectures to detect stresses and diseases among different crop species. The study included 14 different crops and focused on identifying 26 diseases from which the plants were infected. To determine the F1 score of the sample, an assessment metric was included and found that GoogLeNet outperformed AlexNet. As per the study analysis, it was recorded that AlexNet showed accuracy levels of 99.35% while GoogleNet showed accuracy levels of 85.5% while considering the PlantVillage dataset.	The trained model achieves an accuracy of 99.35% on a held-out test set, demonstrating the feasibility of this approach.	The major limitation was related to the use of the traditional assessment metric process which consumed a lot of time for assessment and procuring outcomes.
Ferentinos, K.P. (2018) Deep learning models for plant disease detection and diagnosis. Comput. Electron. Agric. 145, 311–318	The study included the use of advanced technologies such as VGG CNN to identify plant stresses. It was found that the tools provided better image processing as there was the detection of plant stress with 99.5% accuracy. The study also included the use of model performance but it did not lay any major impact on the collecting of information and provided better outcomes when used with original images. The study also included the use of preprocessed images but it did not lay any significant impact on the prediction accuracy. Its only contribution was towards reducing computational time.	The final highest successful classification percentage of 99.53% VGG model	The study was limited as the models included in the study did not provide robust outcomes and could not validate facts when comparing images from greenhouse and field settings.
Lu, J. et al. (2017) An in-field automatic wheat disease diagnosis system. CoRR abs/1710.08299	The study includes the use of a deep CNN model to detect plant diseases. By using the trained deep CNN model, there was the attainment of valuable information about	wheat disease identification tasks has yielded the	The study was limited as it majorly focused on

	plant diseases with an accuracy of 91% to 98% resulting in an average accuracy level of 96.3%. The study highlights the use of a new architecture known as deep multiple instances learning (DMIL) to identify plant diseases among wheat crops. The Wheat Disease Database 2017 was included in the study that provided 9230 images of wheat amongst its seven classes. It was analyzed in the study that the VGG-FCN architecture was a better performer as compared to VGG-CNN and provide more accurate information related to plant disease classifications.	95.12% of VGG-FCN-S exceeds 93.27% of VGG-CNN-VD16.	classification and disease identification in the wheat crop that was provided by Wheat Disease Database 2017 (WDD2017) and did not consider other databases.
Ramcharan, A. et al. (2017) Deep learning for image-based cassava disease detection. Front. Plant Sci. 8, 1852	The study included the Inception-v3 model to identify and train five cassava diseases among different crops. As per analysis, it was found that three cassava stresses such as cassava brown streak, cassava mosaic, and brown leaf spot were accurately identified in the study. There was also identification of two mite classes such as red and green mite that damaged the crop fields adversely. By using the Inception-v3 model, there was an identification of 93% accuracy in cassava determination by analyzing the images from the test dataset.	The best model achieved an overall accuracy of 93% for data not used in the training process.	The study was limited as the Inception-v3 model was used to provide only 78.1% accuracy with the ImageNet dataset.
Mohanty, S.P. et al. (2016) Using deep learning for image-based plant disease detection. Front. Plant Sci. 7, 1419 http://dx.doi.org/10.3389/fpls.2016.01419	The study includes the use of a smartphone-based algorithm to identify disease among the crops. It helps in the scouting of disease by making use of the learned model. It is based on the use of a CPU that provides consumes less than a second time to analyze the data and provide information related to queried data.	The trained model achieves an accuracy of 99.35% on a held-out test set, demonstrating the feasibility of this approach.	The study is limited as it mainly uses leaves to establish comparisons between leaf canopies that have been sampled from the datasets. The study needs to focus on including more diverse species for the stress imaging process.
Ha, J.G. et al. (2017) Deep convolutional neural network for classifying Fusarium wilt of radish from unmanned aerial vehicles. J. Appl. Remote Sens. 11, 042621	The study includes the use of Deep learning-based architecture to identify plant disease in radish plantations. It includes the use of unmanned aerial vehicles (UAV) to capture aerial images so that there is the identification of plant stress. As per the analysis, it was found that UAV image assessment provided accurate outcomes and there was identification plant stress such as Fusarium wilt on the sample radish plantation.	CNN obtained an accuracy of 93.3% which is better than standard machine learning algorithm, obtaining 82.9%	The major limitation of the study was that it only focused on the use of the UAV approach and did not establish a comparison with other tools

		accuracy	that can be sued for the detection of plant stress.
Yamamoto, K. et al. (2017) Super-resolution of plant disease images for the acceleration of image-based phenotyping and vigor diagnosis in agriculture. Sensors (Basel) 17, E2557	The study includes the use of the super-resolution convolutional neural network (SRCNN) to detect diseases in tomato crop plantations. SRCNN approach is a combination of two approaches such as conventional imaging and super-resolution imaging that helps in the identification of tomato diseases. The model analyzes the spatial resolution to identify the disease which is more accurate as compared to other conventional disease classification methods.	The resulting classification accuracy was better with super-resolution images than with low-resolution images.	The study is limited as the high-definition SRCNN approach cannot be used with a small image.

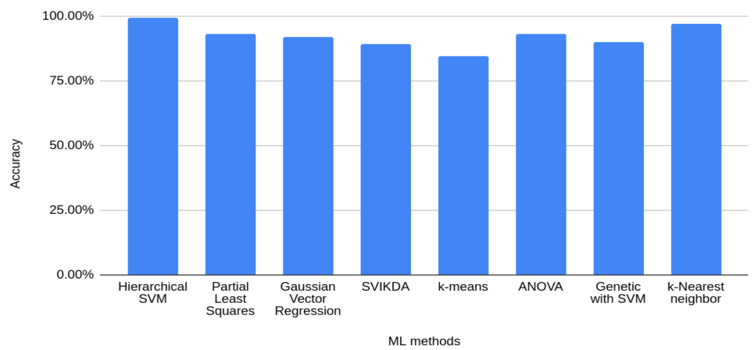

Fig. 11. Accuracy analysis of Machine learning algorithms.

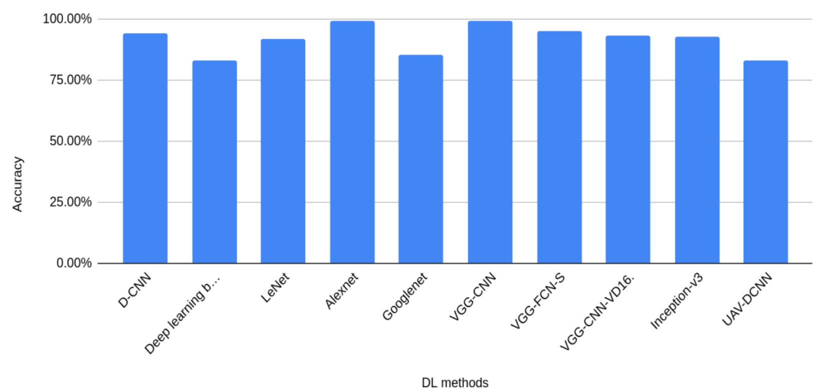

Fig.12. Accuracy analysis of Deep Learning algorithms.

7. LIMITATIONS AND FUTURE SCOPE

The major limitation with phenotyping is that different techniques are required to carry out phenotyping activities such as determination of plant growth rate, leaf count, leaf area, inter-crop spacing, biomass amount, plant stem position, crop plant count, and others. Each technique has its set limitations that restrict the conduct of the plant phenotyping process. For example, Imaging spectroscopy is limited because of lack of sensor calibration, while thermal imaging technique is limited because of changes in the ambient conditions. Under such conditions, it becomes difficult to create differences between soil and plant temperatures that restrict the automation of image processing activity. However, the present study focuses on providing valuable information related to agriculture status in India, phenotyping, and plant phenotyping environments and techniques that help to meet the literature gaps that had existed between previous and current literature. The present study provides in-depth insights about identification, classification, quantification of plant stresses, and promotion of plant growth opportunities that help the cultivators and breeders to carry out crop management activities. It includes providing valuable insights about deep learning approaches that help to bring significant improvement in plant science and the identification of plant phenotyping problems. The use of DL approaches provides an end-to-end solution to the plant phenotyping problem and streamlines the image and spectrum of plant stress phenotyping. By using DL, there will be positioning of the plant phenotypes by focusing on the imaging modalities which help farmers to enhance their product yield. The major research challenges are;

a. Misuse of training classifier: In the perspective of phenotyping stresses, both the detection process differs from its controlled environment. The classification has been trained using deep features.
b. Class imbalance: In the view of deep learning algorithms, class imbalance is one of the research issues of any deep learning techniques. Due to a disproportionate number of samples per class, then the number of benign and malignant classes violates the detection rules during the minority classification process. In some cases, major classes are detected by ignoring the subclasses which leads to lowered accuracy.
c. Public benchmarks datasets: The improper collection of dataset differs in the research community. Henceforth, appropriate labelling procedures have also decreased the accuracy on different datasets.

8. CONCLUSION

Plant phenotyping methods help in carrying out crop monitoring activities and executing crop management processes. Plant phenotype helps in acquiring relevant information about plant organs and whole features that allows the farmers to make informed plant cropping decisions. Deep learning approaches enhance identification, classification, quantification of the plant stresses and provide accurate and reliable outcomes related to plant phenotyping. Deep learning approaches present a great promise to enhance the detection speed, accuracy, reliablity and scalablity of the diseases phenotyping systems. The present focuses on adopting Deep learning-based approaches so that image data helps in acquiring reliable information about plant characteristics. The analysis of deep learning approaches on image based plant phenotyping from identification, classification and quantification. It was analyzed that different DL approaches such as LeNet architecture, Inception-v3, ImageNet, AlexNet, ALexNetOWTBn, GoogLeNet, Over feat, VGG, and others that care extensively used for detecting and categorizing the plant stresses such as Early scorch, cottony mold, ashen mold, late scorch, tiny whiteness, Bacterial spot, apple scab, cedar apple rust, black rot, banana Sigatoka, banana speckle, brown leaf spot, cassava green spider mite, and others. The study identified that DL-based approaches are highly useful in providing a sufficient amount of data related to plant strapping, stresses, and growth indices. It also helps in the exploration of hyperparameters by making use of DL-based architecture such as computational hardware, computation resource, and normalization techniques. As a result, by using different algorithms there is a validation of data at low over lifting value levels. It also helps in checking the robustness of the data by using the model perturbation process. It also includes the intermediate feature visualization aspects so that there is the attainment of accurate outcomes by comparing the plant phenotyping features. Based on the above facts, it can be said that Deep learning approaches are highly efficient in analyzing plant phenotype and characterizing the phenotyping aspects by classifying the plant stress datasets into open, labeled, broad-spectrum. Plant phenotyping using hyperspectral imaging is a particularly promising avenue, where the individual datasets (i.e., each hyperspectral cube) themselves become quite large. Here novel DL approaches, for example 3D CNN architectures, would be promising candidates. Therefore, it is strongly recommended in the study to use the imaging data process so that there is the attainment of accurate information from the training dataset by using high-throughput systems like UAVs and other autonomous systems. As a result, there is it attainment of more robust fine-tuning features throughout the entire network. It includes attaining insights about smaller learning rates, convolutional nets, and network parameters without changing the data dramatically.

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