Frontiers in Bioscience Landmark

Front. Biosci. (Landmark Ed) **2024**; 29(1): 20
https://doi.org/10.31083/j.fbl2901020

Review

Machine and Deep Learning: Artificial Intelligence Application in Biotic and Abiotic Stress Management in Plants

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Academic Editor: Changsoo Kim
Submitted: 29 June 2023 Revised: 16 October 2023 Accepted: 10 November 2023 Published: 17 January 2024

Abstract

Biotic and abiotic stresses significantly affect plant fitness, resulting in a serious loss in food production. Biotic and abiotic stresses predominantly affect metabolite biosynthesis, gene and protein expression, and genome variations. However, light doses of stress result in the production of positive attributes in crops, like tolerance to stress and biosynthesis of metabolites, called hormesis. Advancement in artificial intelligence (AI) has enabled the development of high-throughput gadgets such as high-resolution imagery sensors and robotic aerial vehicles, *i.e.*, satellites and unmanned aerial vehicles (UAV), to overcome biotic and abiotic stresses. These High throughput (HTP) gadgets produce accurate but big amounts of data. Significant datasets such as transportable array for remotely sensed agriculture and phenotyping reference platform (TERRA-REF) have been developed to forecast abiotic stresses and early detection of biotic stresses. For accurately measuring the model plant stress, tools like Deep Learning (DL) and Machine Learning (ML) have enabled early detection of desirable traits in a large population of breeding material and mitigate plant stresses. In this review, advanced applications of ML and DL in plant biotic and abiotic stress management have been summarized.

Keywords: biotic and abiotic stresses; satellite; unmanned aerial vehicle; smart-phones; artificial intelligence; machine learning; deep learning; plant phenotyping

1. Introduction

By 2050, it is expected that the world population will surpass ~10 billion people; hence, crop production must increase by 25–70% [1]. In order to improve crop yield, the selection of biotic and abiotic stress-resistant verities with the deployment of precise and robust tools is needed [2]. High throughput (HTP) tools integrated with AI to collect data, and analyze with ML and DL models have proven very effective (Fig. 1) [3–5]. ML deals with decision theories, visualization, optimization, and probability to analyze various combinations of numerous traits based on guided and unguided instructions (Fig. 1) [6,7]. DL models include generative adversarial networks (GAN), convolutional neural networks (CNN), and multilayer perceptron (MLP) [8] for the interpretation of a large dataset *via* image detection, tracking, classification, and segmentation during plant stress monitoring [9]. In serial manners, ML follows the following four steps: identification, classification, quantification, and prediction to identify biotic stress in plants [10]. To analyze data from both healthy and infected plants, ML uses supervised discriminative models, an unsupervised model for the data of only healthy plants, and a simple deviation detection method for contaminated plants [11]. Unsupervised models are quite useful for quantification and even can be applied to small datasets. ML precisely predicts infection at the earliest stage.

2. Phenotyping Platforms

In phenotyping, low-throughput methods are in practice, which need to be replaced by high-throughput, non-invasive methods [12]. To improve plant phenomics, non-invasive sensors, imaging techniques, analytical tools, and sensors have been invented [13]. The development of a single HTP imaging platform harboring all aforementioned devices and programs has enabled the precise collection of biotic and abiotic stress data (Table 1). For example, GROWSCREEN FLUORO is being used to measure chlorophyll fluorescence and leaf growth to analyze biotic

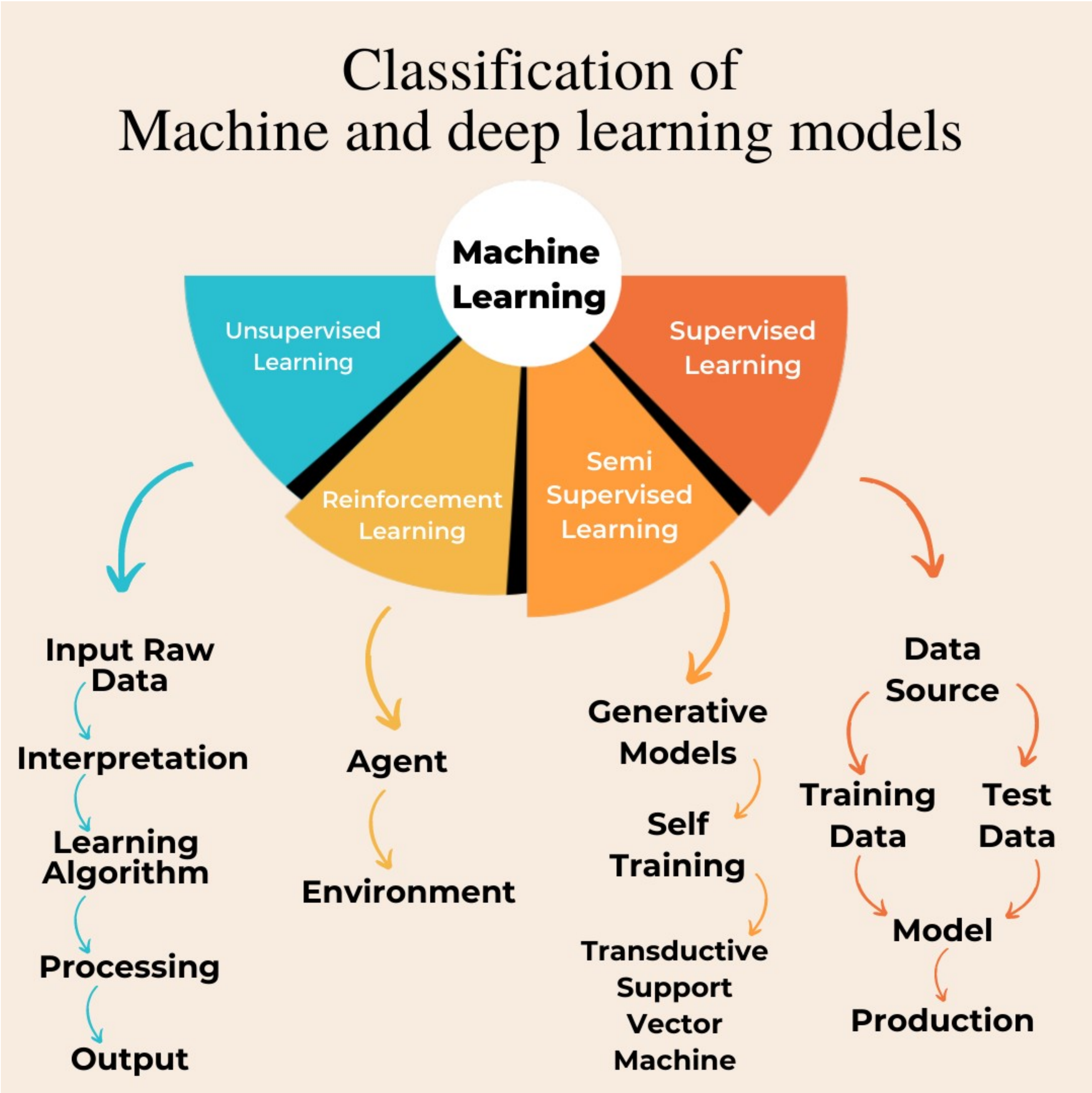

Fig. 1. Classification of machine and deep learning models. Machine learning models are comprised of unsupervised learning, semi-supervised, supervised, and reinforcement learning.

and abiotic stress tolerance [14]. HyperART is being employed in non-destructive quantification of disease severity and chlorophyll contents of various plants like maize, rapeseed, barley, and tomato [15]. Similarly, PHENOVISION and PlantScreen™ Robotic XYZ System are being used to measure drought stress in maize and rice, respectively [16,17]. LemnaTec 3D Scanalyzer system and Phenobox are being employed in the measurement of the effects of salinity stress on rice, maize, and tobacco [18,19]. PhénoField® is very helpful in measuring the effects of numerous stresses on wheat [19]. HTP data about plant height, biomass, radiation use efficiency, leaf, shoot, root, early vigor, and photosynthesis is being recorded automatically (Fig. 2). CropQuant [20], RootReader3D [21], PHENOARCH [22], Zeppe-lin NT aircraft [7], MVS-Pheno [23], Field Scanalyzer [24], and GROWSCREEN-Rhizo [25] are promising HTP platforms for collection of biotic and abiotic stress resistance data of different crops (Table 1).

3. Imaging Techniques

HTP imaging techniques have evolved significantly in recent years. Remote sensing is being employed to detect biotic and abiotic stress in plants *via* satellites (Fig. 2) [26–

Fig. 2. Schematic diagram of high throughput and automated artificial intelligence-based remote phenotyping platform based on satellite, unmanned aerial vehicle (UAV), smart phone, control shed, and ground imagery to record plant height, biomass, radiation use efficiency, leaf traits, herbs and insect identification, early vigor, and photosynthesis.

28]. HTP unmanned aerial vehicles (UAV) are very useful for capturing highly-resolution images with drones and handheld mobile phones (Fig. 2). Additionally, UAVs installed with HTP sensors capture photos of crop fields at once to identify drought stress and insect/pest attack [29]. On the other hand, ground-based imaging platforms can capture pictures of very small areas to analyze miniature changes in plant growth (Fig. 2). Notably, ground-based imaging platforms provide accurate and detailed images at the level of a single plant, branches, and even single leaf in a crop [30]. In addition, ground-based imaging platforms work in an auto-engaged, time-scheduled analysis manner. All these HTP methods of data collection generate terabytes (TB) of data per day, which can only be analyzed with DL and ML algorithms. A brief overview of available imaging techniques to investigate biotic and abiotic stresses is given below.

3.1 Satellite Imagery

Satellites can cover and take images of a big part of ~1000 hectares or even an entire country. These observation satellites are integrated with multiple sensors to collect information from the ground (Fig. 2). These sensors don't work the same way as thermal, time-of-flight, hyperspectral, multispectral, or RGB ones. Instead, gather data from the electromagnetic (EM) spectrum at various wavelengths. These sensors focus on 2–10 of the various bands in the EM spectrum, specifically the Green (G), Red (R), and Blue (B) bands. High-resolution RGB images are then produced using the data gathered from these distinctly necessary bands. In addition to RGB, bands near-infrared or infrared are also employed in satellite imagery [31].

3.2 Mobile Cameras/Imaging

Mobile phones are mostly provided with high-pixel cameras that can capture basic pictures. In order to capture 3D images, the integration of advanced sensors such as LiDAR is very useful [32]. Advanced mobile phones are equipped with high-resolution, influential, and AI computing cameras (Fig. 2). Other portable devices are also equipped with smart phone technology, which is helpful in strengthening and expanding the range of sensors. It provides broad range connectivity and portability as compared to traditional phenotyping equipment.

3.3 Unmanned Aerial Vehicle (UAV) Imaging

UAV imaging is used for large-scale HTP studies [33]. UAV works on an orthomosaic model to capture numerous images of various patches of the field (Fig. 2), which are combined into a large single image [34]. The follow-

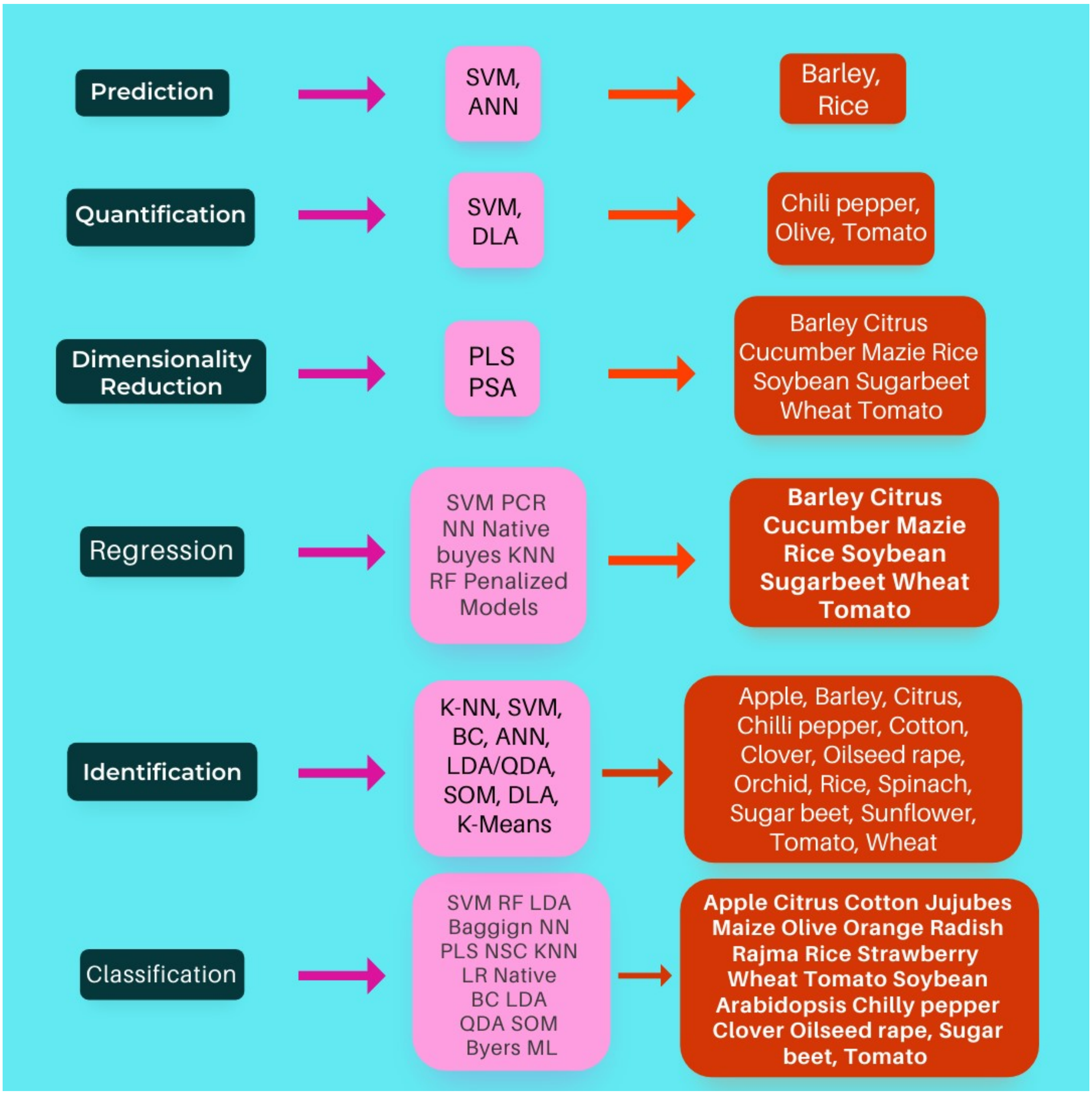

Fig. 3. Application of different machine learning-based algorithms. These algorithms work on identification, classification, prediction, quantification, dimensionality reduction, and regression models. SVM, Support Vector Machine; ANN, Artificial Neural Network; DLA, Deep Learning Application; PCR, Polymerase Chain Reaction; NN, Neural Network; KNN, K-Nearest Neighbour; RF, Random Forest; BC, Bayesian Classifier; LDA, Linear Discriminate Analysis; QDA, Quadratic Discriminate Analysis; SOM, Self-Organizing Map; DLA, Deep learning Application; PLS, Partial Least Square; NSC, Nearest Shrunken Centroids; LR, Linear Regression; ML, Machine Learning.

ing software, Pix4D, QGIS, and Open, are used to capture orthomosaic pictures with the help of UAVs [35]. Images taken from the ground are of high resolution as compared to the images taken from satellites or UAVs. This is an advantage for the hyperspectral sensors because they work on low spatial resolution.

3.4 Ground-Based Imaging Platforms

One of the most advanced imaging techniques is the ground-based imaging platform (Fig. 2). It is very precise to measure biotic and abiotic stress in plants at very close ranges [36]. Its proximate values of phenotyping are very efficient, similar to manually captured pictures [37]. These ground-based platforms use on-board chips to analyze the characteristics of each plant organ in an automatic manner [38].

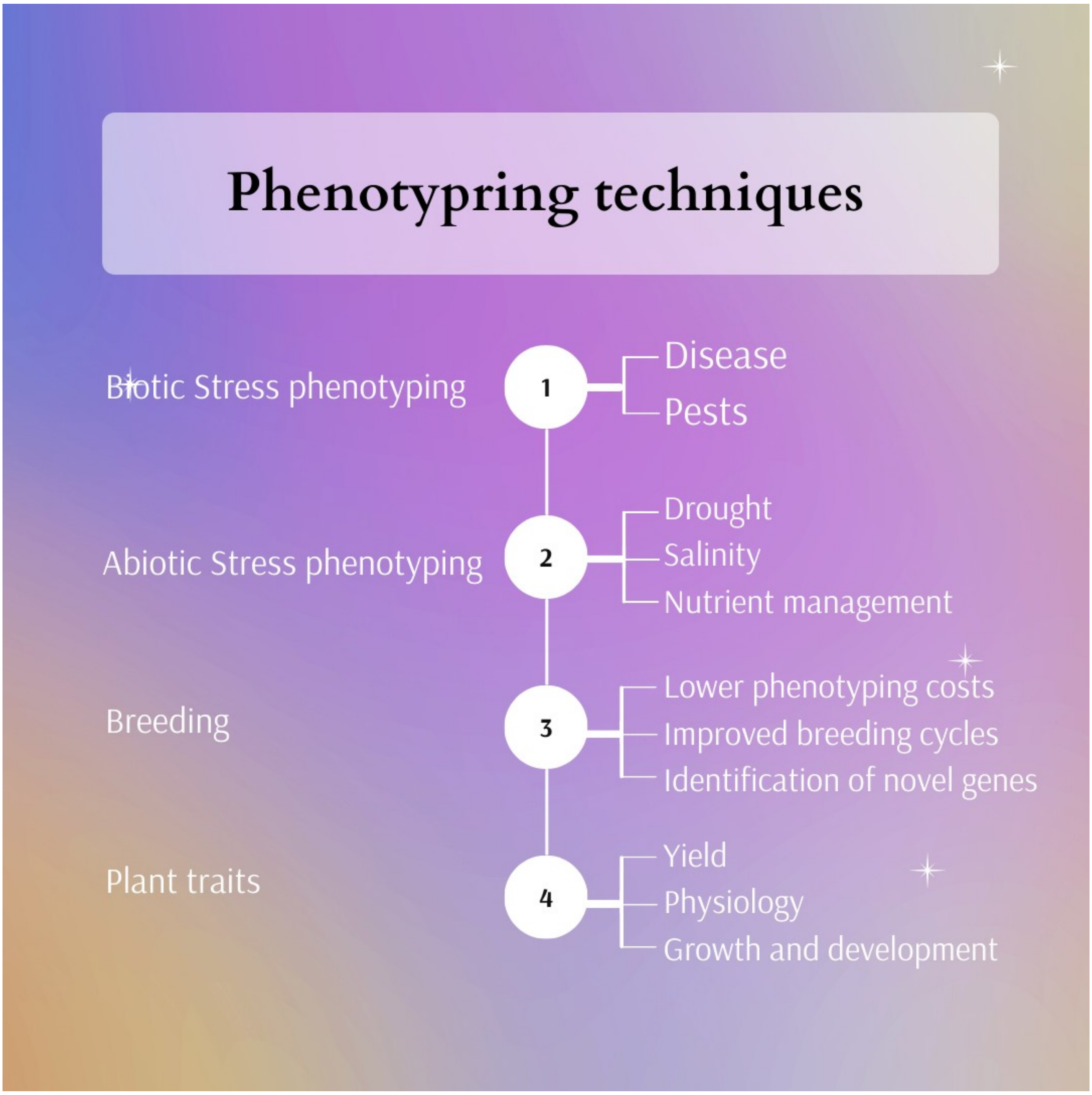

Fig. 4. Plant traits improvement *via* high-throughput phenotyping techniques. These phenotyping techniques are used to instigate the breeding process by lowering breeding cycles, identifying novel genes, and identifying and mitigating biotic and abiotic stress to improve crop yield.

3.5 Wavelength Markers for Phenotyping Plant Stress

Images obtained using the mentioned methods require the use of spectral indices (SIs), such as vegetation indices (VIs) [39], to measure the rate of photosynthesis and canopy structure [40]. It involves the conduction of various operational sets working on different layers of the obtained images. In these operations, a number is assigned to mathematical calculations and wavelengths of spectral references to indicate comparative profusion of a feature of interest [41]. In this study, we have summarized how various VIs are used to deal with different aspects of captured images. Spectral calculations are measured through various spectral bands for measuring information about vegetation and decoding features of the images. VI provides a significant level of information about plant architecture, biomass, phenotype, canopy, rate of photosynthesis, and level of stress [42].

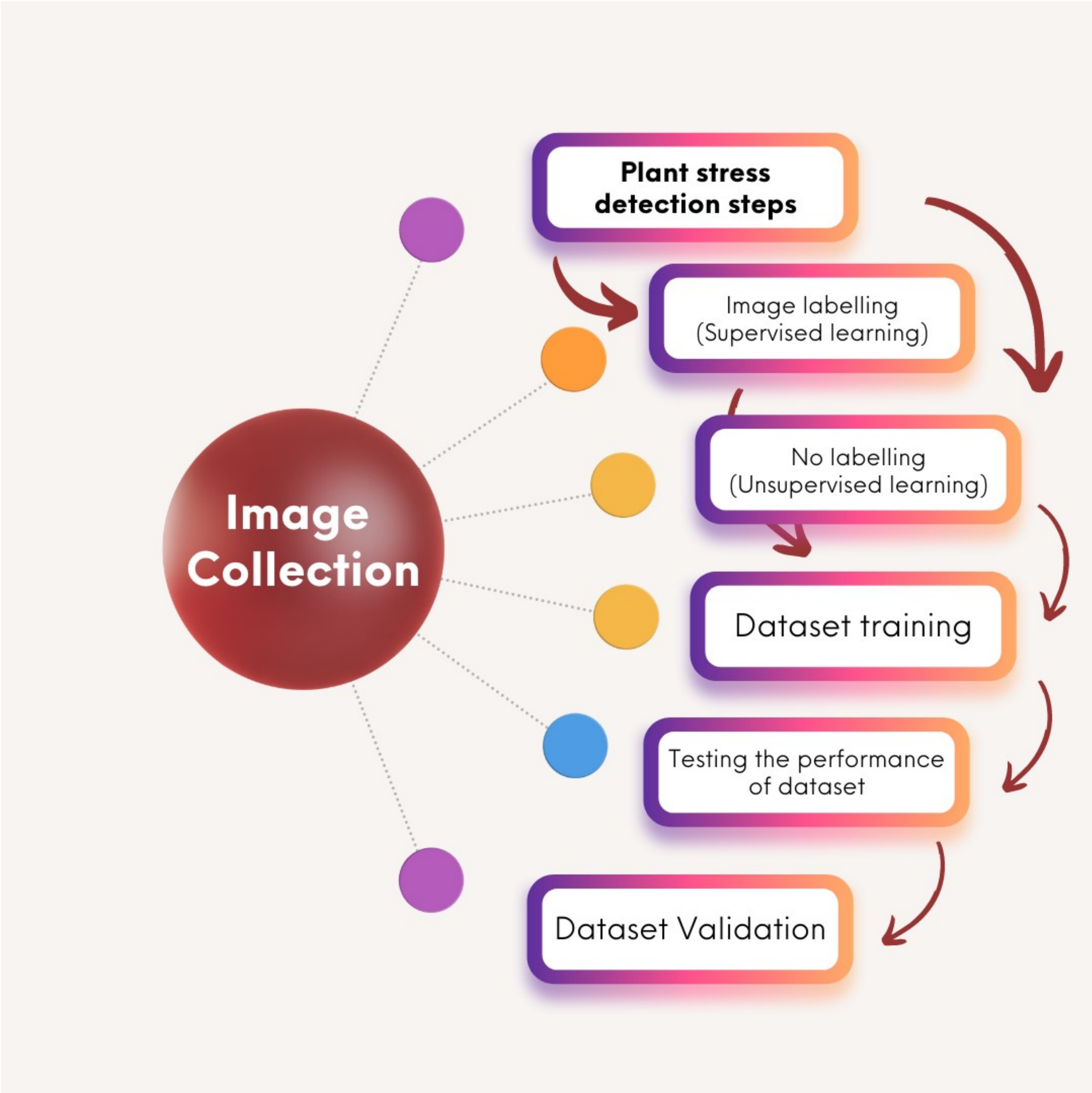

Fig. 5. Image collection and processing by machine and deep learning-based phenotyping tools.

4. Machine Learning

Big data problems are brought on by the increased volume of data obtained by HTP platforms in agricultural practices. In order to invent new and robust technologies, the demand for the capacity to analyze and comprehend data is increasing. Mckinsey industry reveals that there is a 50% increase in data generation every year, a 40-fold increase since 2001 [43]. Pictures are captured and analyzed using DL and ML to detect various amounts and types of challenges (Table 2), such as contents of aflatoxin in maize [44], salinity stress on chickpeas [3], cucumber's powdery mildews [45], and rot on wheat leaves [46]. ML has proven an excellent approach for identifying biotic and abiotic stresses at an early stage and mitigating them in a precise way [2].

4.1 Linear Discriminant Analysis

In order to divide the output into two or more classes, a linear combination of characteristics is used in linear discriminant analysis (LDA). In an experiment, images of citrus orchards were taken through visible near-infrared spectroscopy to identify Huanglongbing *via* different classification algorithms like soft independent modeling of classification algorithm (SIMCA), quadratic discriminant analysis (QDA), and LDA [47]. The accuracy obtained *via* SIMCA and QDA were 92% and 95%, respectively (Table 2).

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Table 1. Machine learning-based studies in plant stress or identification, classification, quantification, and prediction paradigm.

AI Techniques	Algorithms	Application	Datasets	Model plant	Stress
Successive Approximation Model (SAM)	SAM	Identification	Remote sensing	Sugar beet (*Beta vulgaris*)	Pests and disease
Deep Learning	Convolutional Neural Networks (CNN), Alex Net, Google net, Inception V3, Least PLS-DA, LS-VSM	Identification	1200 photos taken by camera under stress and non-stress conditions	Maize, okra, soybean	Water tension
SVM and Gaussian processes classifier (GPC)	SVM and Gaussian processes classifier (GPC)	Identification	Visible and thermal images	Spinach (*Spanicia oleraceae*)	Abiotic stress
Unsupervised Machine Learning	Convolutional Neural Networks (CNN), Alex Net, Google net, PLS-DA, Least squares support vector machine, LS-VSM	Identification	Hyperspectral images of canopy of tobacco plants	Tobacco	Heavy metal stress
Optic Disc (OD) segmentation	OD: 99.61%	Recognizes and removes the blood artery for correct segmentation of the Optic Disc (OD)	Images	Blood artery	
OBIA-based classification	OBIA-based classification	Identification	UAV-based RGB images and multi-spectral image	Sunflower (*Helianthus annus*)	Biotic stress
Deep Learning (Image)	CNN	Identification	1426 images of rice diseases and pests from paddy fields	Rice	Biotic stress
Unsupervised Machine Learning (Video Imaging)	Hidden Markov's model (HMMs)	Identification and Classification	Chlorophyll fluorescence digital profiles from Grow Tech Inc.	*Phaseolus vulgaris*	Stressor level groups (Low, medium, and high stressed) and drought, nutrient, and chemical stress
Deep Learning (Image)	K-nearest neighbors (KNN)	Identification and Classification	1747 smart phone images of arabica coffee leaves	Arabica coffee	Biotic stress, *cercospora* leaf spot
Unsupervised Machine Learning, Partial Least Square Regression, Principal Component Analysis	CNN	Identification and Classification	Spectral signature of leaf samples obtained with a visible, near infra-red spectrometer	Rice	Salt stress
ANN variant	Artificial Neural Networks (ANN) variant	Identification	RGB images	Orchid (Phalaenopsis)	Disease
Supervised Machine Learning	Relief, Support vector machine	Identification and Classification	Images from four wheat lines	Wheat	Salt stress
Deep Learning (Image)		Identification and Classification	1575 images (smart phones, compact cameras, DSLR)	Different plant specimen	Biotic stress
Deep Learning		Identification and Classification	Hyperspectral images	*Bromus inermis*	Drought stress
Supervised Machine Learning		Identification and Classification	RGB leaf images from Kaggle database	Brinjal leaves	Biotic stress

Table 2. Machine learning-based studies in plant stress or identification, classification, quantification, and prediction paradigm.

AI Techniques	Algorithms	Application	Datasets	Model plant	Stressor
Deep Learning (Image)	Deep convolutional neural network (DCNN)	Identification, classification, and quantification	Collection of images of stressed and healthy soybean leaflets in the field	Soybean (*Glycine max* L.)	Bacterial blight (*Pseudomonas savastanoi*), bacterial pustule (*Xanthomonas axonopodis*), sudden death syndrome (*Fusarium virguliforme*), Septoria brown spot (*Septoria glycines*), Frogeye leaf spot, chlorosis due to iron deficiency, potassium deficit, and pesticide damage
KNN, quadratic discriminant analysis (QDA), and linear discriminant analysis (LDA)	KNN, quadratic discriminant analysis (QDA), and linear discriminant analysis (LDA)	Identification	Spectroradiometer	Citrus	Disease
Supervised Machine Learning	Random Forest (RF), Support Vector Machine (SVM), KNN	Classification and prediction	Real-time tetrahertz time-domain spectroscopic data (THz-TDS)	Basil, coriander, parsley baby-leaf, coffee, pea	Water stress
Supervised Machine Learning	RF, Artificial neural network (ANN), and confident multiple-choice learning	Classification	Multispectral images	Maize	Water stress
Supervised Machine Learning	Confident multiple-choice learning	Identification and prediction	Gene expression time series datasets	*Arabidopsis thaliana*	Heat, cold, salt, and drought
Single Ventricle Interactive Model (SViM)	SViM	Identification	Hyperspectral	Tomato	Water stress
Deep Learning (Image)	CNN	Classification	Images of Sorghum plant shoot from the Donald. Danforth plant science center	Sorghum plants	Nitrogen deficiency
Gaussian mixture model	Gaussian mixture model	Identification	RGB images	Wheat (*Triticum aestivum* L.)	Disease
Supervised Machine Learning	Decision tree (DT), SVM, Naive Bayes (NB)	Classification	Metabolite and protein content	*Arabidopsis thaliana*	Metabolic stress
Supervised Machine Learning	SVM	Classification	Biweekly RBG, stereo, and hyperspectral spatio-temporal images	Sugar beet plants	Drought and weed stress, nitrogen deficiency
Linear discriminant analysis (LDA) and K-means	Linear discriminant analysis (LDA) and K-means	Identification and Classification	RGB images	Clover (*Trifolium subterraneum* L.)	Pollution
Supervised Machine Learning	Hierarchical models	Classification	5916 RGB images, plant introduction accessories (PI) in different time points	Soybean (*Glycine max*)	Iron deficiency chlorosis
Supervised Machine Learning	ANN, CNN, Optimum path stress, KNN, and SVM	Classification	Electrical signal under cold, low light, and osmotic stimuli	Soybean plants	Cold, low light, and osmotic stimuli
k-NN and Bayesian classifier	k-NN and Bayesian classifier	Classification	Fusion of RGB and multispectral image	Sugar beet	Disease
Supervised Machine Learning	RF	Classification	Hyperspectral dataset acquired from Indian Agricultural Research Institute (IARI)	Wheat	Water stress

Table 3. Machine learning-based studies in plant stress or identification, classification, quantification, and prediction paradigm.

AI Technique	Algorithms	Application	Datasets	Model plant	Stressor
Deep Learning (Image)	CNN, SVM	Classification	65,184 labeled images from GitHub resource	Soybean	Biotic and abiotic stresses
Supervised Machine Learning	MLP and probabilistic neural network (PNN)	Classification	16 maize and 17 wheat genomic and phenotypic datasets with different trait-environment combinations	Maize and wheat	Drought
Bayesian classifier	Bayesian classifier	Classification	RGB images	Arabidopsis	Disease
Supervised machine Learning	Decision tree (DT) and NB	Prediction	miRNA concentration	*Arabidopsis thaliana*	Drought, salinity, cold, and heat
None Preprocessing via segmentation	None Preprocessing via segmentation	Quantification	RGB Images	Chili pepper	Disease
Supervised Machine Learning	Ridge regression, LASSO, elastic net, RF, reproducing kernel, Hilbert space, Bayes A and Bayes B	Prediction	A set of 29,619 cured single nucleotide polymorphisms. Genotyped across a panel of 240 maize inbred	Maize	Drought stress
Deep Learning	CNN	Prediction	Three maize arid and six wheat datasets	Maize and wheat	Environmental stress
Dirichlet aggregation regression (DAR)	Dirichlet aggregation regression (DAR)	Prediction	Hyperspectral images	Barley	Abiotic stress
SVM, generalized regression neural network (GRNN)	SVM, generalized regression neural network (GRNN)	Prediction	Manual severity rating	Rice	Disease
Supervised machine learning	Genomic random regression	Prediction	Complete genotypes, molecular markers, and phenotypic traits of stressed and control groups	Wheat	Environmental stress

4.2 Support Vector Machine (SVM)

SVM creates hyperplanes *via* maximum separation from the nearest training example [48]. In this hyperplane technique, the maximization of different classes is being performed with the clear separation of different classes [49]. SVM is basically used for the segmentation of images (Table 2). These images can be used to analyze the human pathogen, namely *Salmonella typhimurium*, which also affects Arabidopsis [50]. SVM and LDA techniques use thermal and hyperspectral images to identify verticillium wilt in *Olea europaea* [51].

4.3 Logistic Regression

Logistic regression classifies binary variables using the logistic function. This method uses all the predictors of odd ratios to classify the dependent variables into two different classes. Multinomial logistic regression uses outputs of more than two values. To identify the strategies of crop management and the application of pesticides in orchard plants, hyperspectral imaging was used to detect the apple scab at a very early stage [52]. Classification methods are used in logistic regression to distinguish between infected and healthy plants. This technique uses hyperspectral band classification algorithms (Table 2) [53].

4.4 Random Forest

The ensemble learning technique is the base of random forest (RF) functions (Fig. 3). This divides people into different nodes of the tree using the tree-building method. When compared to tree-based classification, the random forests technique has a number of advantages since it can handle noise, control model overfitting, and a variety of factors. Spectro-diameter is employed in this technique to pick out characteristics of various plant species [54].

4.5 Linear Regression

Most phenomenological research employs linear regression because of its comprehensive data interpretation and user-friendly interface. It deals with the variation of the targeted factors. To measure water stress in maize plants, a regression model was designed between vegetation indices (VI) and crop water stress index (CWSI), which employ regression models and multispectral images to accurately measure drought stress [55]. Another experiment examined the relationships between leaf stomatal conductance (gs), stem water potential (ΨSTEM), linear regression, and Pearson correlations. And thermal indices to calculate water availability status. Thermal and multispectral were used for measurement in a vineyard [56].

The outcome is predicted using numerous explanatory variables using multiple regression, sometimes referred to as multiple linear regression (MLR). MLR simulates the linear relationship between the numerous experimental outcome components. Hyperspectral images are used to measure various diseases like powdery mildews by various data analysis techniques like Fisher linear discriminant analysis (FLDA), MLR, and PLSR. PLSR performs better than the MLR model in various aspects, whereas the highest accuracy is achieved by FLDA [57]. Various spectral images and data analysis techniques are used to measure disease-like bacterial spots in tomato (Table 2). The methods involve data analysis utilizing PLS, SMLR, and correlation coefficient spectrum analysis. For the measurement and investigation of the causes of bacterial spots, different types of predictive models are developed [58].

4.6 Partial Least Square Regression (PLSR)

PLSR can manage collinearity across variables. So, PLSR is a very powerful technique for modeling numerous variables at the same time [59]. The best model is developed by the low values of RMSE and high values of correlation coefficient "r" [60]. The nitrogen concentration in rice is determined using ground-based hyperspectral imaging and the PLSR model (Table 2). The PLSR model was designed to link nitrogen contents and rice plant's phenotype [61].

4.7 Dimensionality Reduction

Dimensionality reduction deals with a few numbers of variables and can explain the whole dataset. It extracts the latent or useful variables from the dataset, which makes it accurate for the measurement. Principal Component Analysis (PCA) is the most common dimensionality lessening procedure. PCA reduces the dimensionality of data and extracts the completely independent variables. Principal Component Score (PCS) uses very few principal components to explain the variance of the dataset. In jujube, insect infestation was identified by stepwise discriminant analysis with the employment of NIR and visible spectroscopy [62].

5. Deep Learning

DL is the best tool to obtain data with maximum accuracy. Evaluation of data obtained through DL is quite easy. DL uses layers and neurons in deep networks to interpret data (Fig. 1) [8]. DL has made outstanding advancements in consumer analytics, automated medical diagnosis, automated financial management, fraud detection, and autonomous vehicles [63]. Multiple DL models, such as GAN, recurrent neural networks (RNN), CNN, and multilayer perceptrons (MLP), are being widely used in phenomics (Table 3). CNN outperforms all other models for image analysis [64]. With the advancement in the model's algorithms, DL is progressing significantly. For the purpose of training models, it helps in the careful estimation of complex hyperparameters [65].

6. Applications of High-Throughput Systems

6.1 Improving Crop Productivity

Field HTP saves time and labor for plant breeders to investigate the potential yield of different cultivars by sowing the field [66]. Cubist regression was used to measure plant maturity, seed size, and yield at early stages in 2551 genotypes of soybean (*Glycine max*) [67]. Similarly, many lines of wheat and barley were examined for desired traits at very early stages [68,69]. In breeding programs, remote sensors are highly useful for the identification of desired traits as well as biotic and abiotic stress (Fig. 4). Various RGB pairings and thermal and multispectral data have been analyzed to forecast crop yield by DL models [70,71]. These models are also used to estimate grain protein contents [72], measure plant height [73], and manage irrigations [74]. Van Klompenburg *et al*. [75] performed a review of the ML model and predicted grain yield. LSTM and CNNs are two examples of the architectures utilized in DL (Table 3).

6.2 Reference Platform

Transportable Array for Remotely sensed Agriculture and Phenotyping Reference Platform (TERRA-REF) has been developed to predict sensor, environmental, genomic, and phenotyping data to expedite the breeding process and farm management [76]. TERRA-REF involves ground-based robotic systems, UAV, satellite remote sensing, and phenotyping trailers to collect real-time data about agronomic traits and image-based phenotyping. TERRA-REF also provides a manuscript management section for researchers to register ongoing studies to avoid overlap and find potential collaborators (https://terraref.org).

6.3 Development of Abiotic Stress Tolerance

To get a high yield, it is quite important to select crops adaptable to abiotic stresses such as climate change [77]. An updated dataset provides accurate information to mitigate the drastic impact of abiotic stressors on the growth and development of plants. For example, the Eschikon dataset deals in spatial pictures of beet under deficiency of nitrogen, weed stress, and numerous independent and combined drought conditions [78]. Eschikon dataset was employed to create a 3D model of the plants that accurately depicted their height, vegetation indices, canopy cover, agronomic attributes, biotic stress, abiotic stress (Fig. 5), and development of precise tools for computer-based stress identification [79]. Infrared thermography is being applied in the detection of crop water use efficiency [80] and enzyme efficiency under salinity and drought stress [81–83]. Infrared thermography revealed that cotton yield, micronaire, and fiber length were decreased at higher canopy temperatures [84]. Stomata conductance is influenced by evapotranspiration and canopy temperature; maps of these stressors were created and utilized to identify phenotypes [85]. Satellites provide thermal data of water resources by mapping ET [86].

6.4 Detection and Management of Pathogens and Pests

Pests and pathogens also migrate to different habitats with the change in environmental conditions [87]. Updated data about plant phenotype, host-pathogen interaction, and ecological conditions can be analyzed to provide recommendations for the management and selection of suitable crops [87]. Numerous datasets, including The Plant Village, RoCoLe, and BRACOL, are available to automatically identify pests and pathogens in cassava, apple, and citrus [30,88,89]. To improve the efficiency of identification of pathogens, ML models supported vector machines, self-attention CNNs, and CNNs-trained have been designed [90,91].

For early disease detection, a variety of models have been developed, including combined HTP images from greenhouses [92], field experiments for quantifying root rot resilience in lentils, and UAV-collected images (Fig. 5) [93,94]. In breeding programs, 12 normalized spectral indices have been developed to correlate the severity and symptoms of diseases. ML and hyperspectral data revealed early (3rd day of infection) detection of charcoal disease in soybean with 90% accuracy [95]. Compared to the broadcast method, image-based intelligent weed detection systems have reduced 60% use of herbicides [96]. Numerous ML and computer vision algorithms-based datasets comprised of multispectral and RGB images (Table 3) have been published to precisely identify different weeds [97]. Further improvement in datasets is required to develop robust tools that can devise the exact quantity of herbicides.

6.5 Root Phenotyping

Root system architecture (RSA) plays a key role in nutrient and water uptake, stress tolerance, and high yield [98]. In crop breeding, the development of intelligent strategies for root phenotyping is of prime importance. To replace soil in order to get rid of pathogens and insects, hydroponic mediums and transparent gels have been developed, which are similar to soil-grown plants [21,99–101]. For root phenotyping, strong sensors, hyperspectral imaging, magnetic resonance imaging, and CT scans were used to collect 2D and 3D images of plants grown in glasshouses [102–106].

6.6 Quantitative Plant Morphology

The yield potential of a plant is influenced by its morphological characteristics, including its canopy cover, seeds, number of leaves, and number of blooms [107]. For measurement of stem segmentation, leaf area estimates, leaf counting, seed counting, and development stage identification, accurate tools based on ML models and NNs (Table 3) have been established [108,109]. DL is being employed to analyze captured photos for various qualitative and quantitative properties, including fruit color, shape, size, and number (Fig. 4). For the development of dataset pipelines to measure quantitative traits from captured pictures, various phenotyping datasets have been released (Fig. 5), *i.e.*, a dataset of hypocotyl of *A. thaliana* seedlings [110]. Image time-series growth of *A. thaliana* was observed for the prediction of presentation, and released dataset for class documentation [111].

7. Conclusions

Machine Learning is a powerful tool to assemble big data in terabytes (TB) and is used in the development of intelligent tools. Progress in HTP has made possible utilization of ML-based tools to perform precision agriculture. This review provides a precise overview of ML- and DL-based tools such as SVM and ANN to perform phenotyping of biotic and abiotic stress. This study also underlined several new avenues of application of ML techniques in agriculture. ML-based tools have replaced manual imaging with real-time automated high-throughput imaging systems and from individual plants to entire populations in a field. The application of ML-based intelligent tools has sped up the breeding process *via* the early detection of desired traits and increased yield *via* the detection of pests and insects at an early stage. ML and DL have successfully integrated seamless data analytics with data collection and curation pipelines. ML has accelerated the breeding process by providing a common platform, namely TERRA-REF, to avoid the repetition of research and connect with experts in the field. ML and DL have resolved fundamental genomics issues and enabled predictive phenomics. The application of ML- and DL-based tools in precision agriculture is a promising technique to feed a growing population.

Author Contributions

Conceptualization, MA, SZ, and ZH; data curation, CG, F, SA and BC; analyzed the data, MA, SZ, F, ZH, NA, NI, HL, JL, AJR and CG; wrote the manuscript, CG, AJR, and MA; revised manuscript, AJR, MA, SA, and SZ; funding acquisition, CG, and JL. All authors reviewed the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

Not applicable.

Acknowledgment

The authors are very grateful to the kind administration of Yibin University, Yibin 644000, China, and Government College University, Faisalabad, Pakistan for providing us such a prestigious and well-equipped platform for research and development. The authors are also grateful to the kind administration of the department of Science and Technology of Sichuan province, P.R. China.

Funding

This work was supported by The Key Research and Development Projects Science and Technology Department of the Sichuan Province (NO. 2021YFS0343).

Conflict of Interest

The authors declare no conflict of interest.

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