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AI-Based Prediction of Crop Stress Using High-Throughput Phenotyping and Sensor Data: Multimodal Data Fusion, Machine Learning, Digital Biomarkers and Precision Stress Management

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Abstract

Crop stress is increasingly dynamic, spatially heterogeneous and multidimensional because plants are simultaneously exposed to drought, heat, salinity, nutrient imbalance, toxic elements, pathogens, soil degradation and other environmental constraints. Conventional stress diagnosis based on visual symptoms and destructive measurements is often too slow to support timely intervention. High-throughput phenotyping (HTP), proximal and remote sensing, unmanned aerial vehicles, Internet of Things platforms and artificial intelligence (AI) provide a new framework for continuously converting crop structural, spectral, thermal, physiological and environmental information into predictive indicators of plant stress. This review synthesizes advances in AI-based crop-stress prediction using RGB, multispectral, hyperspectral, thermal, fluorescence, LiDAR, soil, weather and physiological sensor data. Particular emphasis is placed on the progression from conventional vegetation indices and statistical analysis to machine learning, deep convolutional neural networks, recurrent architectures, transformers, multimodal learning and explainable AI. High-throughput phenotyping provides the large, temporally resolved datasets required to characterize genotype-specific stress trajectories, while sensor fusion allows models to distinguish visually similar stresses by integrating plant responses with soil and atmospheric conditions. Drought and heat can be detected through changes in canopy temperature, spectral reflectance, stomatal behaviour and growth dynamics; nutrient and toxic-element stress alter pigment, structural and metabolic signatures; and biotic stresses generate spatial and spectral patterns that may be detected before severe visible symptoms develop. The reviewed evidence also demonstrates that genetic diversity, rhizosphere microorganisms, phytohormonal regulation and management practices substantially modify phenotypic expression and therefore represent important contextual variables for AI models. Major challenges include limited labelled datasets, sensor calibration, genotype × environment interactions, domain shift, class imbalance, interpretability, computational requirements and poor transferability from controlled environments to heterogeneous farmers' fields. Future crop-stress prediction should move from single-image classification toward longitudinal digital phenotyping, multimodal foundation models, physics-informed AI, edge computing, microbiome-aware prediction and decision-support systems that estimate not only whether stress is present but its cause, severity, future trajectory and probable yield consequence. Integration of AI with high-throughput phenotyping can ultimately transform crop-stress management from reactive diagnosis to anticipatory and site-specific intervention.

Keywords: artificial intelligence; crop stress; high-throughput phenotyping; machine learning; deep learning; hyperspectral imaging; multispectral sensing; thermal imaging; sensor fusion

Highlights

- AI combined with high-throughput phenotyping can transform crop-stress assessment from subjective visual scoring into quantitative and repeatable prediction [1–6].
- RGB, multispectral, hyperspectral, thermal, fluorescence and LiDAR sensors capture complementary structural, biochemical and physiological dimensions of crop stress [7–18].
- Machine-learning approaches such as SVM and Random Forest remain valuable for structured phenotypic datasets, whereas CNNs, transfer learning and transformer architectures increasingly support automated feature extraction and scalable stress classification [10–16, 21]. The attached multispectral/ML review specifically identifies SVM, Random Forest, CNNs, UAV monitoring and Vision Transformers as useful approaches for crop disease detection.
- Genotype, crop developmental stage, environment and management strongly influence sensor-derived stress signatures [22, 23, 32, 33, 39].
- Rhizosphere microorganisms and phytohormonal regulation can modify observable stress phenotypes, adding a biological-context layer to AI prediction [30, 35, 38, 40].
- Future AI systems should predict stress identity, severity, trajectory, yield consequence and management need rather than merely classifying plants as stressed or healthy [5, 6, 19, 20].

1. Introduction

Crop plants are continuously exposed to environmental fluctuations, but climate variability, soil degradation and intensive production systems are increasing the frequency and complexity of drought, heat, salinity, nutrient deficiency, toxic-element exposure and pathogen attack [17–20]. These stresses may occur individually or simultaneously and can substantially reduce crop growth, reproductive success, yield and quality [17–20].

The phenotypic consequences of stress are multidimensional. Drought alters stomatal conductance, canopy temperature, plant growth, leaf orientation and spectral reflectance [17–20]. Heat modifies membrane stability, reproductive development and canopy energy balance [17, 18]. Salinity changes osmotic status, ion balance and pigment concentration, whereas diseases alter tissue structure, pigments and metabolism [13–16].

A central difficulty is that many physiological changes begin before visual symptoms become obvious. Conventional crop scouting can therefore identify stress only after a substantial proportion of damage has already occurred [1, 7, 11].

High-throughput phenotyping provides a different approach by repeatedly collecting digital measurements from large numbers of plants or plots. These measurements can then be analysed using machine learning and artificial intelligence to identify deviations from healthy crop trajectories [2–6].

The importance of environmental context is illustrated by field research in tomato, where temperature, rainfall and humidity strongly influenced fruit setting, disease development and crop productivity [22]. Such evidence demonstrates that AI models based only on images may fail to distinguish environmental effects from pathological stress if weather variables are ignored.

Genotype is equally important. Jackfruit studies have demonstrated substantial variation among germplasm in morphological, foliage, yield and biochemical attributes [23, 39]. A PCA-based evaluation similarly showed strong multivariate divergence among jackfruit genotypes, identifying accessions with contrasting combinations of economically important traits [39].

Therefore, crop-stress prediction should increasingly be treated as a genotype × environment × management × stress problem rather than a simple image-classification exercise.

2. From Conventional Phenotyping to High-Throughput Digital Phenotyping

Conventional phenotyping includes measurements such as plant height, leaf area, biomass, chlorophyll concentration, disease severity, yield components and final yield. Although biologically valuable, these measurements are usually labour intensive, destructive or limited to a small number of observations [2–5].

High-throughput phenotyping increases the scale, temporal frequency and dimensionality of crop measurements [2–6]. Thousands of plants can be screened repeatedly, providing trajectories rather than isolated measurements.

This is particularly relevant to germplasm evaluation. The attached biofortified sweet-potato study evaluated six varieties for yield, quality characteristics and pest–disease tolerance under Eastern Himalayan conditions [24].

Similarly, characterization of Citrus genetic resources documented morphological diversity and identified

wild species and accessions with potentially valuable traits for crop improvement and stress resistance [33].

AI-enabled HTP can extend such conventional evaluations by providing continuous digital phenotypes such as canopy expansion rate, spectral response, thermal behaviour and stress-recovery dynamics.

3. Major Sources of Phenotyping and Sensor Data

3.1 RGB Imaging

RGB cameras provide information on canopy cover, colour, plant architecture, leaf area, senescence and disease lesions [7, 10–12]. Their low cost makes them particularly useful for field-scale AI applications.

CNNs can automatically extract spatial features from RGB images, reducing the need to manually define visual descriptors [10–12].

However, RGB imagery may detect stress only after visible symptoms have appeared.

3.2 Multispectral Imaging

Multispectral sensors measure selected regions of visible, red-edge and near-infrared reflectance [7, 13–16].

They can detect changes in vegetation indices, canopy vigour, chlorophyll status and some disease symptoms.

The attached machine-learning review describes multispectral imaging as rapid and field applicable, although it has lower spectral resolution than hyperspectral sensing [21].

3.3 Hyperspectral Imaging

Hyperspectral systems collect information across many narrow wavelength bands and can reveal subtle biochemical and structural changes before obvious symptoms emerge [7, 13–16].

They are particularly useful for early detection of:

- pathogen infection;
- nutrient stress;
- water deficit;
- pigment degradation;
- biochemical change.

The major challenges are computational complexity, redundant wavelengths and high equipment cost.

3.4 Thermal Imaging

Thermal imaging measures canopy temperature and provides an indirect measure of transpiration and stomatal behaviour [17, 18].

Water-stressed plants commonly become warmer as stomatal closure reduces evaporative cooling.

However, canopy temperature is affected by radiation, VPD, wind, canopy architecture and time of day, so thermal data should be interpreted with atmospheric information.

3.5 Chlorophyll Fluorescence

Fluorescence measurements provide information on photosystem performance and can reveal physiological stress before structural damage occurs [3, 5].

3.6 LiDAR and Three-Dimensional Phenotyping

LiDAR provides measurements of plant architecture, canopy volume, height and structural development [5, 8].

When combined with spectral sensing, it allows AI models to separate structural and biochemical stress responses.

3.7 Soil and Weather Sensors

Image-based AI alone may identify that a plant is abnormal but may not identify why.

Soil sensors measuring water content, matric potential, temperature, EC and pH provide root-zone information, whereas weather data provide temperature, rainfall, humidity, radiation, wind and VPD [19, 20].

These data substantially improve causal interpretation.

4. AI Workflow for Crop-Stress Prediction

A complete AI-based crop-stress prediction framework can be expressed as:

Data acquisition → calibration → preprocessing → feature extraction → multimodal fusion → AI model → stress probability/severity → temporal forecast → management decision.

Sensor-data preprocessing may include radiometric calibration, geometric correction, normalization, background removal and missing-data treatment [5–8].

High-quality ground truth is crucial. If sensor data are poorly calibrated or stress labels are inaccurate, the model may learn irrelevant differences such as illumination, background or camera settings.

5. Machine-Learning Algorithms

5.1 Support Vector Machines

SVMs remain useful for high-dimensional spectral datasets, particularly where labelled samples are limited [13–16, 21].

The attached review cites the use of hyperspectral imaging combined with SVM for rice-blast detection [21].

5.2 Random Forest

Random Forest models can handle nonlinear relationships, noisy predictors and mixed environmental and phenotypic variables.

They are particularly valuable because variable-importance analysis can identify which wavelengths or environmental parameters contribute most to stress classification.

5.3 Artificial Neural Networks

ANNs learn complex nonlinear relationships between sensor inputs and crop responses and can be useful when physiological stress results from multiple interacting environmental factors.

6. Deep Learning and Automated Feature Extraction

6.1 Convolutional Neural Networks

CNNs automatically identify spatial patterns in images [10–12]. They have become especially important in disease classification because they remove the need for manual feature engineering. The attached multispectral review identifies automatic feature extraction and strong predictive performance as major CNN advantages, while also noting their dependence on large training datasets [21].

6.2 Transfer Learning

Transfer learning allows pretrained models to be adapted to crop-stress datasets, reducing the requirement for very large agricultural training sets [10–12,21]. Its main limitation is domain shift between the original training data and crop field environments.

6.3 Vision Transformers

Vision Transformers use attention mechanisms to model spatially distant relationships in images. They may be useful where crop stress produces canopy-scale patterns rather than isolated symptoms. Transformer approaches are specifically identified as an emerging direction in the attached ML review [21].

7. Temporal AI and Stress Forecasting

Stress prediction is more valuable than stress confirmation. A single image reveals crop condition at one moment, whereas repeated sensor measurements can identify the trajectory:

healthy → physiological deviation → early stress → visible symptoms → severe injury → yield reduction.

Time-series models such as LSTM, temporal CNN and transformer architectures can integrate previous crop and environmental conditions [5, 6]. For drought, a predictive model could combine soil moisture, canopy temperature, VPD, spectral indices, growth rate and weather forecast. The output might estimate the probability of damaging stress several days before visible wilting occurs.

8. AI Prediction of Drought Stress

Drought produces measurable changes in canopy temperature, spectral water indices, growth, leaf orientation, stomatal behaviour and photosynthetic performance [17–20]. However, drought signatures are genotype dependent. Climate-resilient horticultural research shows that drought modifies root architecture, stomatal behaviour, osmolyte accumulation, photosynthesis and antioxidant systems [34].

Microbial interactions can further alter drought expression. The attached walnut experiment showed that *Serendipita indica* colonization improved aboveground and root growth under drought and modified betaine and oxidative-stress responses [35]. AI systems should therefore recognize that identical soil-water levels may produce different phenotypic stress states.

9. AI Prediction of Heat and Combined Stress

High temperatures influence canopy temperature, photosynthetic function, membrane integrity and reproductive development [17, 18]. Heat and drought can produce overlapping thermal symptoms, making single-sensor diagnosis unreliable.

A multimodal model using soil moisture, thermal imagery, VPD and spectral data can better distinguish drought from heat. The attached climate-resilience review notes that crops frequently experience drought, heat, salinity and combined stresses and that these stresses can produce stronger effects together than independently [34]. Future AI models should therefore support multi-label prediction.

10. Disease Prediction and Early Detection

Crop diseases produce local and systemic changes in pigments, tissue structure, temperature and canopy growth [13–16]. The attached ginger soft-rot study describes initial leaf-tip yellowing followed by rapid disease progression under favourable environmental conditions [26]. Early AI-based detection could therefore combine visual and spectral symptoms with weather variables associated with disease development.

The attached ML review cites deep-learning, UAV-based multispectral and hyperspectral methods for detecting several crop diseases [21].

11. Toxicity and Environmental Stress

Crop stress may also originate from toxic elements and environmental contaminants. The attached arsenic review emphasizes that arsenic movement in rice depends strongly on the soil–water–plant continuum and on water-dependent changes in arsenic speciation [31]. An AI model predicting arsenic toxicity could therefore integrate soil chemistry, irrigation conditions, genotype and spectral phenotype.

The attached microplastic phytotoxicity study evaluated a PGPR–biochar–UV remediation treatment and crop growth response in spinach [25]. Such controlled experiments can provide valuable labelled data for future phytotoxicity-prediction models.

12. Nutrient and Management Stress

Nutrient deficiencies affect chlorophyll, canopy colour, growth rate and spectral response.

However, management treatments can also alter these same phenotypes.

The attached late-sown wheat study evaluated different combinations of seed priming, organic liquid manure and nitrogen application [32]. Thus, AI training datasets should include management metadata to avoid confusing treatment effects with stress.

13. Genotype as a Context Variable

One of the largest challenges in crop-stress AI is natural phenotypic diversity.

Jackfruit germplasm differed significantly in leaf dimensions and other morphological traits [23]. PCA analysis of jackfruit germplasm also showed wide multivariate divergence across tree, fruit and biochemical traits [39]. Citrus genetic-resource characterization similarly documented extensive morphological and adaptive diversity [33].

Therefore:

Observed phenotype = genotype + environment + management + stress + interactions.

Models that ignore genotype may classify natural diversity as stress.

14. High-Throughput Phenotyping for Breeding

HTP provides powerful opportunities for screening large breeding populations.

Digital traits can include:

- canopy-temperature depression;
- growth rate;
- spectral water indices;
- stay-green duration;
- recovery rate;
- stress-onset timing;
- senescence progression.

The attached sweet-potato study provides an example of conventional varietal evaluation based on yield, quality and pest–disease tolerance [24]. AI-enabled phenotyping can substantially expand the scale and temporal resolution of such evaluations.

15. Microbiome-Aware AI Phenotyping

The plant phenotype is influenced by both the crop genome and its associated microorganisms.

Beneficial microbes can alter root development, phytohormones, nutrient acquisition, osmolyte concentration and antioxidant systems [30, 35, 38, 40]. The attached functional-profiling review identifies PGPR, mycorrhizal fungi and endophytes as important contributors to plant tolerance against drought, salinity, temperature extremes and pathogens [40]. The *Bacillus rugosus* study detected phosphate and zinc solubilization together with indole compounds, cytokinins and gibberellins [30].

The newly attached rhizosphere-engineering review describes the rhizosphere as a dynamic interface controlling nutrient cycling, plant health and stress adaptation and discusses microbiome engineering, precision agriculture and systems biology [38].

This supports development of future **microbiome-aware crop-stress prediction models**.

16. Multimodal Sensor Fusion

A single sensor cannot represent the complete plant stress state.

RGB records visible phenotype.

Hyperspectral sensing captures biochemical changes.

Thermal sensing reflects transpiration and energy balance.

LiDAR quantifies plant structure.

Soil sensors describe root-zone conditions.

Weather sensors provide atmospheric forcing.

Multimodal fusion combines these complementary signals.

The attached machine-learning review specifically identifies future integration of multispectral, thermal, fluorescence, LiDAR and genomic information as a route to more comprehensive crop-health assessment [21].

17. AI Models and Their Applications

18. Advanced Materials and Sensor Development

Some attached studies are not direct crop-phenotyping experiments but provide relevant context for future sensor development. Plant-derived metal-oxide nanoparticle research used techniques including TEM, FTIR and XRD to characterize optical and structural material properties [27]. The g-C_3N_4/N-doped CeO_2 study demonstrated changes in optical energy gaps and photocatalytic behaviour associated with nanocomposite composition [28]. Ag_2CrO_4/Fe_2O_3/CeO_2 nanocomposites were likewise characterized using XRD, SEM/TEM and optical-absorption measurements [29]. Photosensitive cellulose microfibers were characterized using UV spectroscopy, FTIR, SEM and XRD [36].

These papers should be interpreted as indirect evidence related to advanced materials and optical sensing, not as direct crop-stress prediction studies.

19. Computational Biology Beyond Image AI

Computational crop-health prediction is broader than image classification. The attached *Agrobacterium tumefaciens* study used molecular docking, molecular dynamics and protein–protein interaction analysis to identify quorum-sensing inhibitor candidates [37]. This illustrates the possibility of integrating sensor-based phenotypes with molecular-level computational predictions. Future crop-health platforms may connect:

phenotypic anomaly → predicted biological cause → molecular pathway → management recommendation.

20. Explainable AI

Agricultural AI systems should explain their decisions. If a crop is predicted to be drought stressed, the system should ideally indicate whether the prediction resulted primarily from:

- high canopy temperature;
- low soil moisture;
- reduced red-edge reflectance;
- slowed growth;
- high VPD.

Explainable AI tools include SHAP values, feature importance, saliency maps, Grad-CAM and attention maps. Explainability becomes particularly important when stresses generate similar visible symptoms.

21. UAV-Based High-Throughput Phenotyping

UAVs can carry RGB, multispectral, hyperspectral, thermal and LiDAR sensors. They can produce spatial maps showing where crop stress begins and how rapidly it spreads. The attached ML review highlights the value of UAV-based monitoring for large-scale field coverage while also recognizing its dependence on weather conditions [21].

22. Ground Truth and Model Validation

AI does not eliminate the need for physiological measurement.

Reliable ground truth may include:

- leaf water potential;
- stomatal conductance;
- chlorophyll concentration;
- electrolyte leakage;
- proline;
- nutrient concentration;
- pathogen confirmation;
- disease score;
- biomass;
- yield.

The attached spinach, walnut, wheat and microbial studies provide examples of experimentally defined crop responses that could be combined with sensor information in future model development [25, 30, 32, 35].

23. From Stress Prediction to Yield Prediction

Detecting stress is only the first stage. The agronomically useful pathway is:

sensor deviation → physiological stress → growth effect → reproductive effect → yield loss.

A mild stress may cause measurable thermal or spectral changes without substantially reducing yield. Conversely, moderate stress at flowering may produce large yield losses. Thus, crop-stress AI should increasingly predict yield consequences rather than stress labels alone.

24. Proposed Multilayer AI Framework

A next-generation crop-stress system should contain:

Table 1. Major AI approaches for crop-stress prediction

AI approach	Suitable data	Strength	Limitation	Main application	References
PCA	Morphological/spectral data	Dimensionality reduction	Not inherently predictive	Trait structure and germplasm differentiation	[5, 20, 39]
PLS regression	Spectral data	Interpretability	Limited non-linearity	Quantitative stress severity prediction	[7, 8, 13]
SVM	Hyperspectral/small datasets	Works well in high dimensions	Parameter tuning	Disease and stress detection	[6, 14, 15, 21]
Random Forest	Mixed sensor/environmental data	Robust and interpretable	Large ensembles	Multiple-stress classification	[6, 20, 21]
ANN	Structured sensor datasets	Handles non-linearity	Training requirement	Physiological and environmental stress	[6, 10, 14]
CNN	RGB, multispectral and hyperspectral images	Automatic feature learning	Requires labelled datasets	Disease and stress classification	[9–12, 16, 21]
LSTM	Time-series sensor and weather data	Temporal prediction	Complex optimization	Drought, heat and stress forecasting	[6, 21]
Vision Transformer	Images/time series	Long-range relationships	Computational demand	Complex and spatially heterogeneous stress patterns	[21]
Autoencoder	Unlabelled sensor data	Anomaly detection	Low interpretability	Early and unknown stress detection	[6, 20]
Multimodal networks	Image + soil + weather + physiological data	Better stress discrimination	Data synchronization	Combined and interacting stresses	[5, 6, 21]

Layer 1 – Environmental data: soil moisture, EC, temperature, rainfall and VPD.

Layer 2 – Plant phenotyping: RGB, multispectral, hyperspectral, thermal, fluorescence and LiDAR.

Layer 3 – Biological context: genotype, crop stage, nutrition, management and microbiome.

Layer 4 – AI models: CNN/ViT for imaging, LSTM/transformers for temporal data, and tree-based models for structured data.

Layer 5 – Stress prediction: type, probability, severity and trajectory.

Layer 6 – Decision support: irrigation, nutrition, disease intervention or continued monitoring.

25. Challenges

Major limitations include:

- limited labelled datasets;
- domain shift;
- sensor calibration;
- genotype differences;
- mixed stress;
- temporal variability;
- class imbalance;
- computational cost;
- model interpretability;
- farmer-field transferability.

Natural phenotypic diversity is particularly important. Jackfruit and Citrus studies clearly demonstrate that genetic variation alone can generate substantial differences in morphology [23, 33, 39].

26. Future Research Priorities

First, AI should shift from stress detection to stress forecasting. Second, repeated time-series phenotyping should replace isolated image collection. Third, multimodal sensor fusion should become standard. Fourth, genotype-aware models are needed because germplasm differs substantially in baseline morphology [23, 33, 39]. Fifth, combined-stress datasets should be created because field crops rarely experience only one stress. Sixth, microbiome variables should be incorporated where feasible. Rhizosphere engineering is increasingly linked with precision agriculture and systems biology [38]. Seventh, explainable AI should become mandatory for biologically meaningful interpretation.

Eighth, self-supervised and foundation models may reduce dependence on manually labelled crop datasets. Ninth, federated learning can enable multi-institutional model development without centralizing raw data. The attached ML review identifies federated

learning and self-supervised learning as important future approaches [21]. Tenth, edge AI should enable real-time predictions on mobile devices, UAVs and field controllers. Eleventh, advanced nanomaterial and optical sensing technologies should be explored for detection of biochemical stress markers [27–29, 36]. Finally, future AI systems should predict yield loss and management response, not simply classify stress.

27. Conclusion

Artificial intelligence and high-throughput phenotyping are transforming crop-stress assessment from subjective visual diagnosis to continuous digital prediction. RGB, multispectral, hyperspectral, thermal, fluorescence and LiDAR sensors provide complementary information on crop structure, physiology and biochemical status [7–18]. Soil and weather sensors add environmental context, while UAVs enable field-scale spatial monitoring. Machine-learning approaches such as SVM and Random Forest remain useful for structured sensor datasets, whereas CNNs, temporal deep-learning models and transformers support increasingly complex image and time-series analysis [10–16, 21].

The attached studies demonstrate why crop-stress prediction cannot be treated simply as image recognition. Germplasm studies reveal large genotype-dependent differences [23, 33, 39]; drought and microbial studies demonstrate biological modification of stress expression [30, 35, 38, 40–42]; and disease, arsenic and phytotoxicity studies illustrate multiple physiologically distinct stress pathways [25, 26, 31].

The future should therefore move from:

image → stress label

toward:

genotype + environment + management + microbiome + temporal phenotype → AI → stress identity + severity + trajectory + yield risk + intervention.

Such an integrated framework can shift crop-stress management from reactive diagnosis toward anticipatory, site-specific and biologically informed decision-making.

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