REVIEW ARTICLE

Advances in Plant Electrical Signals for Plant Health Monitoring and Smart Agriculture

Xiaohui Zhang[1,*], **Yingkai Fu**[1], **Chi Zhang**[1], **Jian Yang**[1] **and Zeyu Zhai**[1]

[1] College of Electrical Engineering, Henan University of Technology, Zhengzhou 450001, China

Abstract

Plant electrical signals are fast electrophysiological responses to environmental stimuli, physiological regulation and stress. Because they often change before visible symptoms appear, they are attractive indicators for early plant-health monitoring and for sensing in precision agriculture. Research in this area has moved from recording single action potentials to analyzing the plant electrome, and now draws on flexible wearable electrodes, implantable and electrochemical sensors, machine learning, multi-source data fusion and edge-cloud computing. This review follows the technical chain from mechanism to application. We first summarize the physiological basis of the main signal types and how they relate to biotic and abiotic stress. We then compare acquisition technologies, including conventional electrodes, flexible wearable devices, microneedles and electrochemical sensors for biochemical markers. Next, we discuss preprocessing, multi-scale feature extraction, and recognition with conventional machine learning, deep learning and multi-source fusion. Finally, we examine applications in environmental sensing and stress identification and outline the remaining obstacles to field use. Most published results still come from laboratory or greenhouse studies with small datasets and non-standard protocols. Progress toward field deployment will depend on standardized acquisition and reporting, long-term sensor stability, cross-species and cross-site validation, open datasets, interpretable models and low-power edge inference. With these elements in place, plant electrical signals could serve as one component of decision-support systems for early warning and crop management.

Keywords: plant electrical signals, plant electrome, sensors, stress identification, smart agriculture.

1 Introduction

Crop production is exposed to drought, salinity, temperature extremes, pathogens and other stresses, and these pressures are becoming harder to predict under climate variability. Conventional diagnosis relies on visual inspection, laboratory assays or expert judgment. These methods are informative but slow, often destructive, and difficult to scale to whole fields. Smart agriculture needs sensing methods that report plant physiological status continuously, in situ and at low cost. Advances in agricultural sensors, electrical characterization of plant tissues, decision-support tools and edge-cloud computing have made such monitoring more realistic [1–4].

Submitted: 01 June 2026
Revised: 27 August 2026
Accepted: 13 October 2026
Published: 26 October 2026

Vol. 2, **No.** 1, 2026.
10.62762/JPE.2026.825022

***Corresponding author:**
✉ Xiaohui Zhang
zhangxh@haut.edu.cn

Citation
Zhang, X., Fu, Y., Zhang, C., Yang, J., & Zhai, Z. (2026). Advances in Plant Electrical Signals for Plant Health Monitoring and Smart Agriculture. *Journal of Plant Electrobiology*, 2(1), 1–12.

© 2026 ICCK (Institute of Central Computation and Knowledge)

Table 1. Main types of plant electrical signals, their characteristics and monitoring value.

Signal type	Main characteristics	Representative stress or agricultural relevance	Monitoring value	Notes and limitations
Action potential (AP)	Rapid, transient, self-propagating response with a relatively stereotyped waveform once the excitation threshold is reached.	Mechanical stimulation, rapid temperature change, herbivory, wounding and other acute stimuli.	Event-level monitoring of rapid responses to defined stimuli.	Occurrence and waveform depend on species, tissue, stimulus intensity and electrode position.
Variation potential (VP)	Slower response with variable amplitude and duration, often associated with hydraulic, chemical or wound-related signals.	Local injury, burning, cutting, severe mechanical damage and systemic stress responses.	Detection of strong local perturbations and their propagation.	Less stereotyped than APs; interpretation requires contextual information and controlled recording conditions.
Evoked potential (EP)	Response induced by an applied electrical, mechanical, thermal or light stimulus.	Controlled assessment of excitability, stress sensitivity and physiological responsiveness.	Comparison of response thresholds and stimulus-dependent traits.	Field use depends on whether the stimulation protocol is practical outside the laboratory.
System potential (SP)	Long-distance signal associated with systemic changes in membrane potential and ion transport.	Distributed stress signaling, wound response, defense activation and whole-plant coordination.	Evaluation of communication between local stress perception and distant responses.	Reflects distributed signaling rather than a specific stress; physiological or molecular context is usually needed.
Periodic oscillation	Repeated potential fluctuation over short or long time scales, often linked to rhythmic physiological processes.	Photosynthesis-related rhythms, water status, circadian regulation, growth and environmental fluctuation.	Tracking of dynamic physiological state and plant-environment interaction.	Affected by both endogenous rhythms and external conditions; requires long recordings and robust processing.
Long-term surface-potential variation	Slow change in surface potential recorded over hours to days.	Drought, salinity, nutrient imbalance, temperature stress, disease progression and long-term adaptation.	Continuous monitoring, early warning and trend-based assessment.	Sensitive to electrode stability, environmental noise, humidity, growth stage and sensor-plant contact.
Spontaneous activity	Fluctuations that occur without an intentionally applied stimulus.	Baseline physiological state, growth status, stress accumulation and plant-environment interaction.	Passive monitoring and baseline characterization.	Difficult to attribute to a single cause without synchronized environmental and physiological data.

Note: The listed applications are representative examples of agricultural relevance, not evidence of one-to-one stress specificity. The monitoring value of each signal type depends on species, organ, developmental stage, electrode configuration, stimulus type, recording duration, environmental conditions and processing method.

Electrical signals are a natural candidate for early monitoring. Water deficit, salinity, temperature change, mechanical injury, heavy metals and pathogen attack all alter membrane potential, ion fluxes, Ca^{2+} signaling, reactive oxygen species (ROS) and hormone networks, and these changes appear as action potentials, variation potentials, system potentials and slow surface-potential shifts. Such responses are fast and can be recorded continuously, often before tissue damage becomes visible. Several studies illustrate this timing under defined conditions: electrical changes after virus infection were detected before or during early symptom development [5]; in the tomato-*Oidium neolycopersici* system, electrical signaling tracked the host response to powdery mildew [6]; and electrical characteristics of apple trees were used to predict their semi-lethal temperature [7]. These results suggest that electrical signals can provide an early or complementary readout of stress, although their timing and diagnostic value depend on the species and experimental context. Electrical data are also more useful when combined with other sources, such as time-lapse images, environmental and soil records, spectral data and biochemical measurements.

This review does not simply list signal types and algorithms. Instead, it follows the full technical chain: the physiological mechanisms that let electrical signals report stress, the acquisition of stable and continuous recordings, the conversion of raw waveforms into diagnostic information through denoising, feature extraction and recognition, and the integration of the results into agricultural decision support. The paper is organized into six sections. Section 2 covers the physiological basis of plant electrical signals, Section 3 acquisition and sensing technologies, Section 4 signal processing and intelligent recognition, Section 5 applications, challenges and future directions, and Section 6 the conclusions.

2 Physiological Basis and Response Mechanisms of Plant Electrical Signals

2.1 Types of Plant Electrical Signals and Their Physiological Significance

Plant electrical signals are external readouts of changes in membrane potential. The main forms are action potentials (APs), variation potentials (VPs), system potentials (SPs), evoked potentials, periodic oscillations, long-term surface-potential variation and spontaneous activity. APs propagate rapidly, follow an all-or-none threshold, and are typically triggered by mechanical or thermal stimuli. VPs follow severe injury such as wounding or burning, and their shape reflects interacting hydraulic, chemical and electrical components. SPs are associated with long-distance signaling and systemic defense. None of these signals acts alone: they are coupled to ion fluxes, Ca^{2+} signaling, ROS, hormone pathways and changes in gene expression, which together link stress perception to adaptive responses [8]. The main signal types are summarized in Table 1.

The signal types differ in time scale, spatial range and dependence on a stimulus, and this determines what each can be used for. APs and VPs are suited to detecting acute events such as mechanical or thermal shocks. SPs, oscillations and long-term surface-potential variation are more useful for following chronic stress, growth and plant-environment interactions. These categories overlap, and their diagnostic value changes with species, organ, electrode arrangement, stimulus and analysis method. For this reason, the electrome concept has gained attention. Rather than isolating individual potential events, it treats the whole electrical activity of a plant as a multi-scale signal and describes it with statistical, spectral, complexity and machine-learning features. This approach is easier to apply under variable field conditions than analysis of single events [9].

2.2 Electrochemical Fundamentals and Electrophysiological Coupling

The generation of plant electrical signals depends on ion concentration gradients, transmembrane potential, plasma-membrane H^+-ATPase activity, fluxes of Ca^{2+}, K^+ and Cl^-, and ROS signaling. Plant electrochemistry provides a framework for linking potential changes to solute transport, energy metabolism and stress responses [10]. Electrical signals also interact with photosynthesis, water transport, stomatal regulation and metabolic state. For example, a study of tomato seedlings grown under high-voltage electrostatic fields related electrophysiological changes to photosynthesis through ion dynamics, indicating that external fields can alter physiological function by acting on internal ionic processes [11].

Electrical activity can also be used to probe how physical factors affect plants. In common bean exposed to a moderate magnetic field, analysis of how signal features dispersed over time revealed the course of the plant's response [12]. Recent work shows that the scope of plant electrophysiology is widening: electrical signals now serve not only as readouts of acute stress events, but as integrative indicators of systemic defense and environmental perception across biotic and abiotic contexts [13].

2.3 Relationship between Plant Electrical Signals and Stress Responses

Plant electrical signals respond early to many abiotic and biotic stresses. Drought changes water potential, stomatal conductance and ion homeostasis, which shifts the membrane-potential baseline and signal frequency. Salt and heavy metals disturb ion channels, membrane stability and redox balance, producing potential fluctuations and ROS-mediated responses. Acute stimuli such as temperature extremes, strong light, UV radiation and mechanical damage often trigger rapidly propagating signals that activate local or systemic defense. There is, however, no simple one-to-one relationship between a waveform and a stress type. Different stresses can produce similar changes, and the same stress can produce different patterns depending on species, tissue, developmental stage and environment. "Stress-specific electrical signatures" should therefore be treated as hypotheses for pattern recognition that need to be tested with multi-source data and mechanistic experiments. The pathway from stress inputs to electrical signals and monitoring outputs is illustrated in Figure 1.

3 Plant Electrical Signal Acquisition and Sensing Technologies

3.1 Traditional Electrodes and Laboratory Acquisition Systems

Conventional recording uses Ag/AgCl, needle, surface or microelectrodes connected to high-input-impedance amplifiers, shielded cables and data acquisition systems, often inside a Faraday cage. This setup is well understood, gives high-fidelity data and allows precise control, so it remains the basis of mechanistic electrophysiology. It is less suited to the

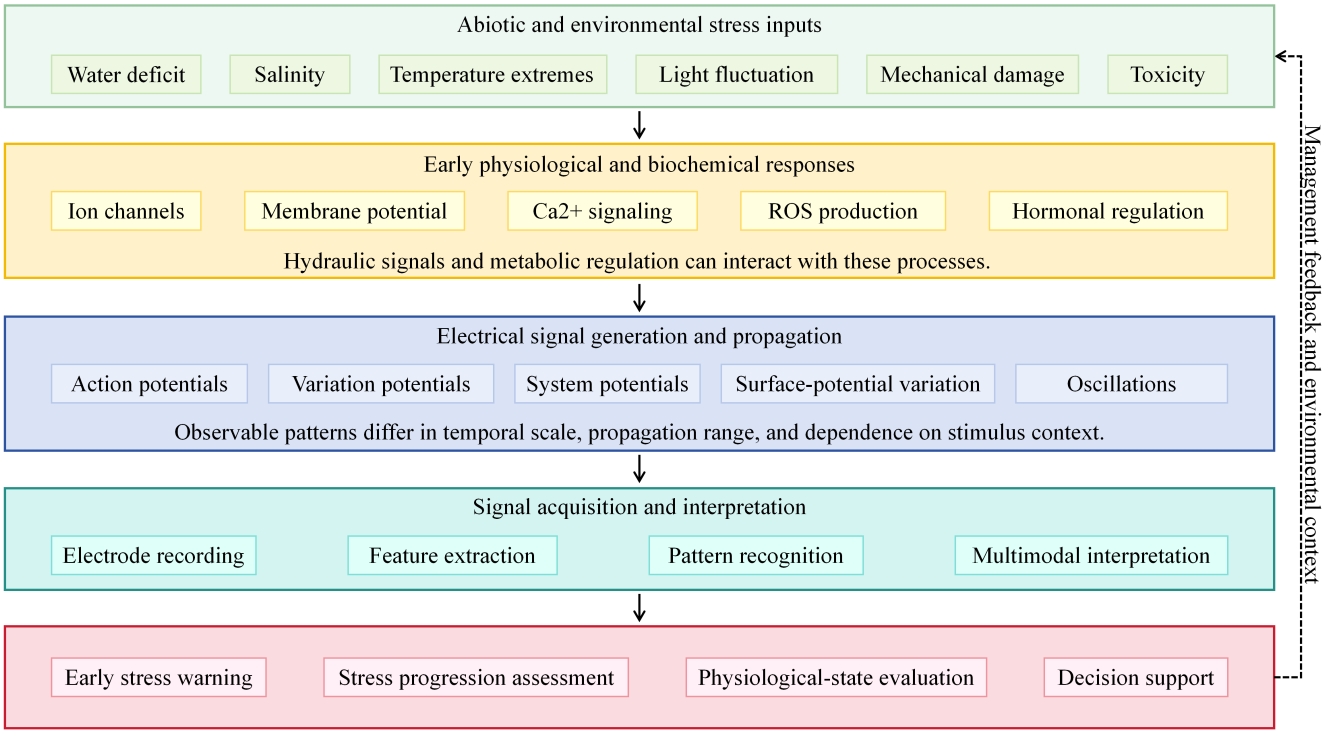

Figure 1. Conceptual pathway from stress inputs to physiological responses, electrical signal generation, signal interpretation and monitoring outputs.

field. Rigid electrodes do not match soft, curved and growing tissues, so contact becomes unstable over time and signals drift, while insertion or clamping can damage tissue locally. Signal quality is also sensitive to electrode placement, reference configuration, sampling frequency, filter settings, recording duration and environmental control. Because these parameters are rarely standardized, datasets from different laboratories are hard to compare and models trained on them generalize poorly. These problems have driven the development of flexible, wearable and implantable sensors that conform to plant organs and keep stable contact during growth and environmental change.

3.2 Flexible, Wearable and Implantable Sensors

Flexible wearable sensors can be attached conformally to plant surfaces and measure physiological and environmental parameters in situ at high resolution, which non-contact methods such as optical imaging and remote sensing cannot always do. Progress in flexible substrates, conductive polymers, carbon nanomaterials and hydrogels has improved mechanical compatibility with plant tissues and reduced problems caused by surface curvature, growth strain and environmental disturbance. Such devices have been used to monitor electrical signals, hormones and water transport, as well as light, humidity, temperature and volatile organic compounds (VOCs) around the plant [14–17].

Implantable and microneedle sensors reach internal tissues and record molecules or electrophysiological activity directly. Recent work points in three directions: microneedle electrodes combined with machine learning for real-time stress monitoring [18]; printed adhesive gel bioelectrodes that improve the electrode-leaf interface for long-term on-leaf recording [19]; and spatial optimization of recording sites, as shown in salt-treated *Clivia miniata* leaves, where electrode position strongly affected which features could be identified [20]. These studies show that sensor sensitivity is no longer the main problem. Interface stability, invasiveness, spatial representativeness and variation between individuals now matter as much.

Each sensor class addresses a different interface problem. Flexible surface sensors make conformal contact with curved, growing organs and suit non-destructive, scalable monitoring. Implantable and microneedle sensors improve local signal fidelity but are more invasive and may induce wound responses. Adhesive and hydrogel electrodes improve ionic coupling and stability during deformation, but they

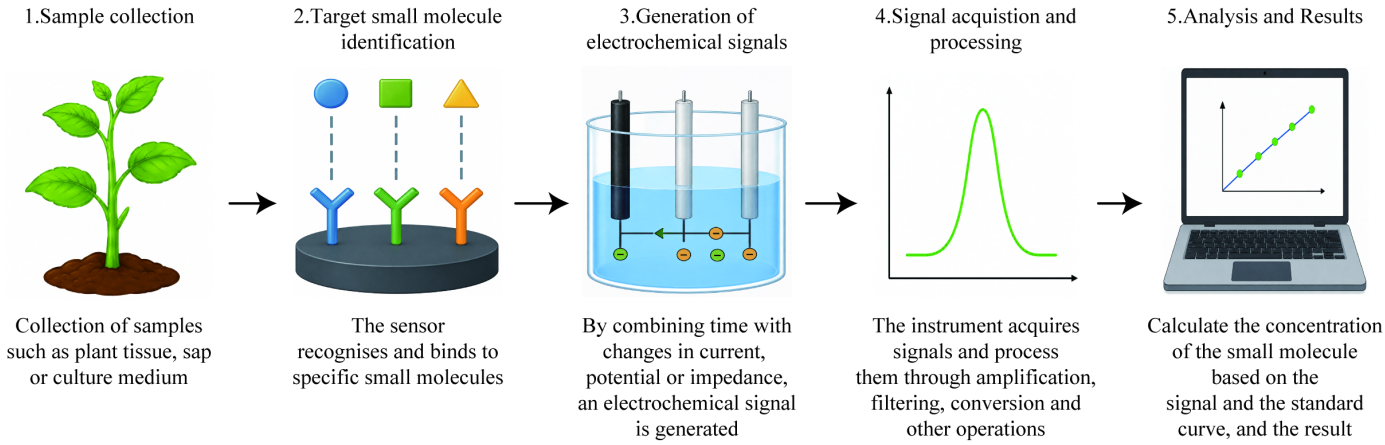

Figure 2. Working principle of electrochemical sensors for detecting small molecules in plants.

can lose performance through dehydration, humidity changes and loss of adhesion. Improving the interface alone does not solve every problem: calibration drift, environmental interference, tissue growth, device-to-device variation and limited comparability between individuals still restrict long-term field use.

3.3 Electrochemical Sensors and Detection of Plant Small Molecules

Electrical signals report fast electrophysiological activity, whereas small molecules, including hormones, ROS, sugars, organic acids, inorganic ions, metabolites and VOCs, provide chemical evidence of physiological regulation and stress. Combining the two gives a multimodal view of plant health. Nanotechnology-based electrochemical sensors and biosensors offer high sensitivity, selectivity and speed at low cost, using direct and ratiometric detection, immunoassays, molecularly imprinted polymers, aptamers and photoelectrochemical schemes. Device formats ranging from microneedles to flexible wearable platforms support measurements in vitro, in vivo and continuously in situ [21–24].

Electrochemical data make electrical signals easier to interpret. An abnormal potential may indicate stress in general, but simultaneous changes in H_2O_2, salicylic acid, glucose, nitrate, pH or VOCs can point to specific processes such as oxidative stress, immune responses, nutrient status or metabolic regulation. Most electrochemical sensors, however, have only been validated in buffer solutions or in short-term controlled experiments. Large-scale field use is limited by interference from the plant matrix, insufficient sensitivity for trace analytes, calibration drift, biofouling, tissue damage from invasive probes and poor robustness under changing conditions. The working principle of these sensors is shown in Figure 2.

4 Signal Processing, Feature Extraction and Intelligent Recognition

4.1 Signal Preprocessing and Quality Control

Plant electrical signals have low amplitude and low frequency, are non-stationary and are easily contaminated. Electrode polarization, changes in contact resistance, soil-potential shifts, temperature and humidity changes, electromagnetic interference and mechanical disturbance from wind or handling all add artifacts, so careful preprocessing is required. In *Aloe vera* var. *chinensis*, time-domain statistics, the fast Fourier transform (FFT), the short-time Fourier transform (STFT), wavelet transforms and autoregressive models captured complementary information on low-frequency energy, transient dynamics and predictability [25]. Decomposition-based methods are effective for weak, non-stationary recordings because they separate components with different oscillatory modes; examples include variational mode decomposition combined with the empirical wavelet transform (VMD-EWT) [26] and complete ensemble empirical mode decomposition with adaptive noise combined with wavelet soft thresholding (CEEMDAN-WST) [27]. The choice of method should follow the temporal and spectral properties of the signal, the sampling parameters, the noise structure and the downstream task, rather than the popularity of an algorithm.

4.2 Feature Extraction and Electrome Parameters

Features of plant electrical signals fall into four groups (Table 2). Time-domain features, such as mean, variance, peak amplitude, duration, skewness and kurtosis, describe amplitude and waveform shape. Frequency-domain features, including power

Table 2. Feature categories, representative parameters and stress-related uses of plant electrical signals.

Feature category	Specific features/parameters	Function and description	Representative application or stress-related use
Time-domain features	Mean, variance, standard deviation, peak value, peak-to-peak value, duration, rise time, fall time, skewness, kurtosis	Describe signal amplitude, waveform morphology, event duration and temporal response.	Waveform or event characterization, such as AP detection, stimulus-response analysis and rapid injury or temperature-response monitoring.
Frequency-domain features	Power spectral density, dominant frequency, band energy, spectral centroid, low-frequency energy ratio	Describe the global frequency composition and energy distribution.	Detection of stress-related shifts in energy distribution, such as changes in low-frequency activity under drought, salinity or long-term disturbance.
Time-frequency features	STFT, wavelet transform, wavelet packet decomposition, EMD	Capture time-varying spectral components and multi-scale changes in non-stationary signals.	Analysis of transient or non-stationary responses, including short electrical bursts, mixed-scale responses and changes during stress progression.
Nonlinear features	Approximate entropy, sample entropy, multiscale entropy, permutation entropy, fractal dimension, complexity measures	Characterize the complexity, irregularity and nonlinear behavior of electrical activity.	Evaluation of complexity changes associated with stress adaptation, physiological state transitions and long-term health monitoring.

Note: The listed applications are representative uses, not universal diagnostic rules. Feature selection should match the signal type, recording duration, sampling rate, noise structure and downstream task, such as event detection, stress classification, physiological-state assessment or early-warning prediction.

spectral density, dominant frequency and band energy, describe how energy is distributed across frequencies. Time-frequency methods such as the STFT, wavelet transform and empirical mode decomposition (EMD) track how this distribution changes over time in non-stationary recordings. Nonlinear features, including approximate, sample, multiscale and permutation entropy and fractal dimension, describe the complexity and irregularity of the signal.

Feature extraction cannot be separated from the acquisition protocol and the purpose of the analysis. For AP detection, event-based measures such as onset, peak amplitude, rising slope and propagation velocity are most informative. Long-term stress monitoring relies more on window-level statistics, band energy, low-frequency drift, complexity and global electrome parameters. When models must generalize across individuals or environments, features should be chosen for robustness to electrode placement, biological variation and batch effects. Feature engineering is therefore moving away from the search for a single best feature toward task-specific, multi-scale and interpretable feature sets.

4.3 Machine Learning, Deep Learning and Edge Intelligence

Conventional machine learning for plant stress identification uses hand-crafted features with classifiers such as support vector machines (SVMs), random forests, k-nearest neighbors (k-NN) and AdaBoost. These methods work well but depend on expert knowledge for feature design. Deep learning (DL) can learn directly from raw waveforms, time-frequency images or multi-channel recordings. Examples include a ResNet-18 with squeeze-and-excitation modules (ResNet-18SE) for recognizing surface APs on maize leaves [28], and a hybrid one-dimensional convolutional neural network and gated recurrent unit (1D-CNN-GRU) implemented on a field-programmable gate array (FPGA) for real-time classification at the edge [29]. Transformer architectures, which rely on self-attention [30], can model long-range temporal dependencies and are therefore attractive for long bioelectrical recordings. Domain adaptation has been used to reduce errors caused by differences between individual *Clivia* plants [31].

Whether conventional machine learning or DL is more appropriate depends on the data and the application. Conventional methods are preferable when datasets are small, features can be defined from physiological or signal-processing principles, computing resources are limited and interpretability is important. DL is advantageous when large, diverse and well-labeled datasets are available and the patterns of interest are hard to engineer by hand. Model selection should not rest on accuracy from a single controlled experiment; it

should also consider validation design, generalization across environments, interpretability, energy use, inference latency and deployment constraints.

DL does not remove the basic difficulties of plant electrophysiology. Samples are usually small, labels are hard to obtain and experimental variability is high, so models can learn electrode placement, environmental noise or batch effects instead of physiological patterns. Rigorous validation, including independent data splits and cross-batch testing, and open datasets are needed before high accuracies can be generalized. Interpretability matters for decision support because users need to know which signal features, physiological indicators or environmental conditions drive a prediction, and how uncertain it is. For field deployment, accuracy must also be balanced against model complexity, energy consumption, latency and hardware cost.

5 Current Status, Challenges and Future Prospects

5.1 Environmental Sensing and Long-Term Monitoring

Plant electrical signals have been used to classify environmental conditions and ozone exposure, to support long-term ecological monitoring, and to infer plant health. Earlier work demonstrated machine-learning assessment of plant physiological status from electrophysiological recordings acquired outside controlled conditions [32], and more recent studies have extended this to classification of environmental conditions in horticultural crops [33], confirming that electrophysiological activity is sensitive to external conditions. Automated phytosensing has distinguished ozone exposure levels [34], and an upgraded PhytoNode platform has improved energy efficiency for long-term environmental monitoring [35]. Machine learning applied to electrophysiological recordings has also been used to identify general stress states in commercial greenhouse crops, demonstrating that electrical signals can serve as practical indicators of plant health under production conditions [36].

In these studies the plant acts as a living sensor that converts environmental change into measurable electrical data. Environmental classification is, however, confounded by interacting factors: light, temperature, humidity, soil moisture, pathogens, nutrients and human activity can all affect the signal at the same time, which makes causal attribution difficult. Future work should move from single-variable classification to separating multiple factors and explaining their effects, using multi-point recording, multimodal sensing and long-term field datasets.

Among these applications, long-term environmental monitoring and automated detection on low-power phytosensing platforms are closest to practical use, because their outputs, such as changes in physiological state, stress onset or anomalous patterns, can feed directly into autonomous early-warning systems. Weather inference, multi-factor classification and mechanistic attribution remain experimental and need extensive field validation and cross-site calibration. Even the more mature applications have not yet demonstrated reliability at field scale.

5.2 Identification of Stress, Disease and Physiological States

Electrical signals have been applied to early disease detection, heavy-metal monitoring, separation of water and nutrient stress, prediction of temperature tolerance and nutrient assessment in greenhouses. For biotic stress, changes in electrical patterns after virus infection [5] and after fungal inoculation of tomato [37] allowed early detection, and electrical signaling in the tomato-powdery mildew system was also informative for diagnosis [6]. For abiotic stress, bioelectrical signals of *Aloe vera* analyzed with wavelet transforms and explainable machine learning detected lead contamination [38], and a parallel machine-learning framework using leaf electrophysiology and impedance separated water and nitrogen stress in wheat [39]. Common bean under different water availability showed classifiable, stimulus-specific electrome signatures [40]. Other studies extended the approach to nutrient deficiencies in greenhouse crops [41], light responses of hydroponic strawberries [42], plant gravimetric dynamics predicted from electrical impedance spectroscopy [43] and the semi-lethal temperature of apple trees [7].

These studies show that electrical signals can be statistically linked to health status, stress type and physiological parameters through machine learning. Reliability, however, varies widely across scenarios. Single-factor abiotic stresses such as drought, salinity or temperature, and well-defined disease models, give consistent results under controlled conditions. Performance falls when stresses are combined, weak or changing over time, or when models are tested on

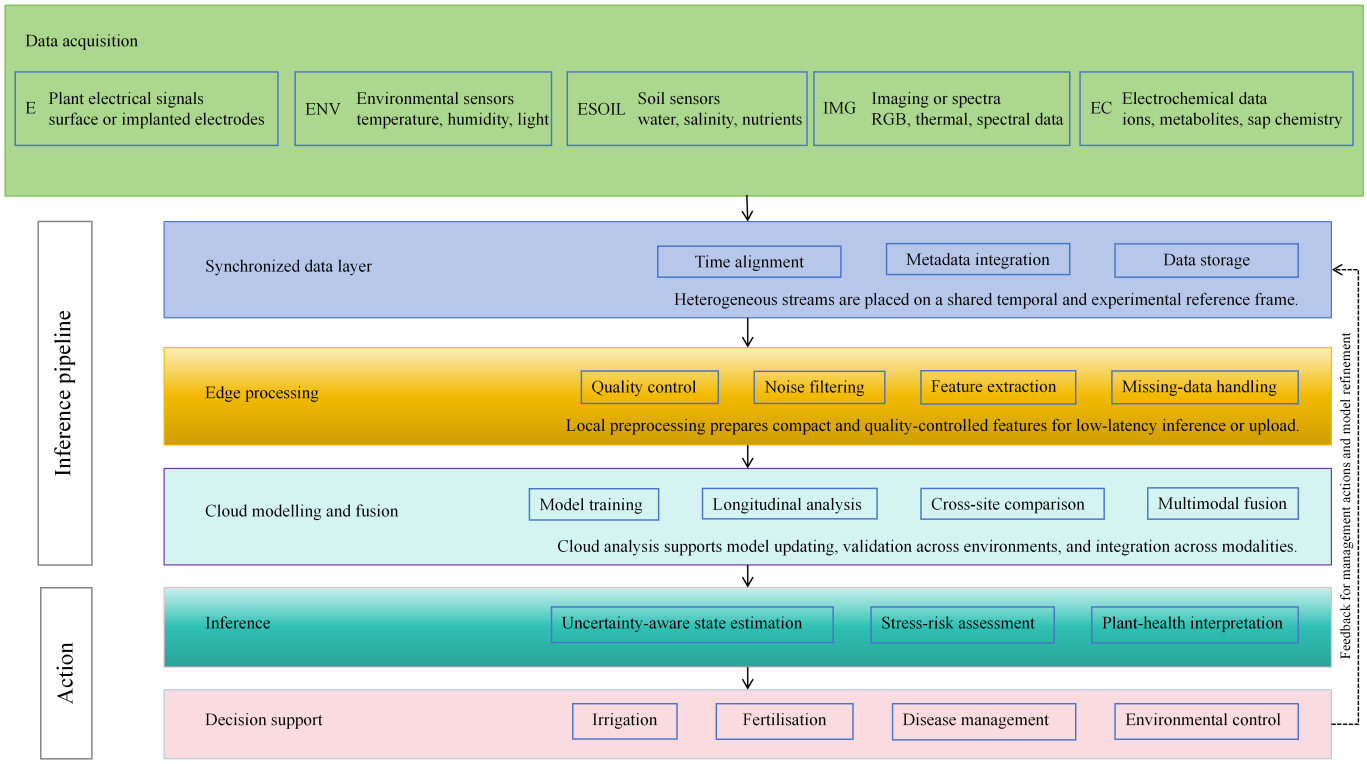

Figure 3. Conceptual workflow for multi-source fusion and decision support in plant electrical-signal monitoring.

Table 3. Key challenges and emerging directions for plant electrical-signal sensing in agricultural applications.

Key challenge	Specific manifestations	Future directions and emerging technologies
Inadequate standardization of data collection	Large variation in electrode type, electrode position, sampling frequency, plant condition, growth stage and environment.	Standardized acquisition protocols, metadata specifications, calibration procedures and reporting standards across species, devices and environments.
Lack of long-term stability	Electrode drift, adhesion failure, changes in contact resistance, environmental noise and disturbance from tissue growth or organ movement.	Flexible, minimally invasive, adaptive and self-calibrating sensing interfaces with better contact stability and environmental robustness.
Insufficient mechanistic interpretation	AI-based recognition and electrome analysis may produce black-box outputs with unclear physiological meaning.	Integration of electrical signals with ion flux, Ca^{2+} signaling, ROS, hormones, transpiration and mechanistic models.
Limited data scale and generalizability	Small datasets, limited species coverage, inconsistent labels and insufficient cross-environment or cross-device validation.	Open long-term datasets, cross-site and cross-device validation, transfer learning, domain adaptation and uncertainty-aware modeling.
Inadequate system integration	Single sensors and isolated models are insufficient for practical management and decision support.	Interoperable sensing platforms combining electrical, environmental, soil, imaging and electrochemical data with IoT, cloud computing and decision-support systems.
Limited real-time and field deployment capacity	Continuous monitoring requires low-power operation, on-device processing, robust communication and timely warnings.	Low-power edge computing, embedded inference, lightweight DL models and edge-cloud collaboration for real-time monitoring and autonomous warning.

Note: The listed technologies are enabling directions, not validated agricultural outcomes. Their practical value depends on long-term field validation, cross-environment robustness, device interoperability and the ability to link model outputs to crop-management decisions. IoT, Internet of Things.

other species and conditions. The main reason is that electrical responses are not specific: different stresses can produce similar patterns, and the same stress can produce different patterns in different contexts. High reported accuracy should therefore be read as a property of a given dataset and validation design, not as an intrinsic diagnostic specificity. Most of the studies above were also carried out in laboratories,

greenhouses or other controlled environments, with very different sample sizes, species, equipment and stress protocols. In the future, studies should use standardized metrics, external validation sets, testing across cultivars and growth stages, and comparison with conventional physiological and biochemical indicators. Only results that hold across environments and devices can support early warning in agricultural production.

5.3 Multi-Source Fusion and Smart Agricultural Systems

A practical way to bring electrical sensing into precision agriculture is to fuse it with other data instead of using it as a standalone diagnostic tool. In the framework shown in Figure 3, flexible electrodes, microneedle sensors and environmental sensors are installed on or in the plant, and their data are synchronized with soil sensors, imaging or spectral systems and electrochemical measurements. An edge layer aligns the data streams in time and performs quality control, noise filtering, missing-data handling, feature extraction and preliminary state identification. The cloud layer supports long-term storage, model training, longitudinal analysis, cross-site comparison and updating of decision rules. Uncertainty-aware state estimation then turns multimodal inputs into plant-health assessments, which in turn support irrigation, fertilization, disease management and environmental control. Separating acquisition, inference and action in this way clarifies what electrical signals contribute within a wider monitoring system.

Because electrical signals from a single plant cannot explain complex stress mechanisms on their own, fusion with other data is needed for reliable monitoring. Combining electrophysiological recordings with time-lapse video allows internal electrical activity and external movement or growth to be followed together [44]. Experience from image-based phenotyping is also relevant: reviews of plant stress detection show that fusing multiple imaging modalities improves accuracy, early detection and robustness compared with any single modality alone [45]. End-to-end deep learning offers a further route for overcoming the limitations of hand-crafted features; for example, applying deep learning architectures directly to plant electrophysiological time series has enabled detection of nitrogen-deficit stress without relying on manually engineered signal features [46]. Such data-driven models may help overcome the limits of single-source and single-modality data. Progress therefore requires joint work on physiological mechanisms, sensing hardware, algorithms and agricultural management.

5.4 Current Challenges

Four barriers currently limit the use of plant electrical signals in smart agriculture.

Data standardization and reproducibility. There are no common acquisition protocols. Signals vary with electrode type, insertion depth, sampling frequency and environmental conditions, and reporting practices are inconsistent, so results are hard to reproduce or compare [1, 9]. Minimum reporting guidelines covering electrode materials, experimental setup and data formats are needed.

Field robustness and sensor stability. Flexible and implantable sensors allow in situ monitoring, but their long-term stability in the field has not been demonstrated. Weather, tissue growth and electrode aging introduce noise and drift. Sensors should be minimally invasive, resistant to interference and self-calibrating, and should be tested in different agricultural settings over complete growth cycles.

Physiological interpretability. Deep learning and similar models can improve classification but often hide the causal links between electrical signals and processes such as Ca^{2+} waves, ROS and hormone signaling. Electrome analysis should be combined with physiological experiments and mathematical modeling so that recognition is based on biological mechanisms and not only on statistical correlation.

Data generalization and integration. Most datasets are small, species-specific and collected under controlled conditions. High accuracy in a single experiment does not guarantee reliability in the field. Open, multi-source benchmark datasets covering several species, stresses and environments are needed [9, 40], and electrical data should be integrated with image, spectral, soil and weather data through edge-cloud architectures.

Of these barriers, the lack of standardized evidence that generalizes under long-term field conditions is the most fundamental, because it amplifies acquisition variability, sensor drift and data fragmentation. Standardized protocols, shared metadata and external validation across sites should therefore be the first priority; without them, better sensors or algorithms cannot be translated reliably into farm decisions.

5.5 Future Directions

The challenges above and the corresponding research directions are summarized in Table 3. Several emerging technologies could speed the move from laboratory studies to agricultural monitoring. Low-power edge inference can reduce data transmission and enable real-time alerts. Adaptive, self-calibrating sensor interfaces can improve long-term stability as tissues grow and conditions change. Interoperable platforms can combine electrical signals with environmental, soil, imaging and electrochemical data in one decision-support framework. These technologies are enablers rather than proof of mature field deployment. Their value for agriculture still has to be shown through long-term validation, cross-site calibration, device interoperability and clear links between sensor outputs and management actions.

6 Conclusions

Plant electrical signals respond quickly to environmental and physiological change, which makes them useful for early health monitoring in precision agriculture. The field has moved from the analysis of isolated electrical events to the characterization of the plant electrome, supported by flexible and implantable sensors, machine learning, multi-source data fusion and edge-cloud architectures. Electrical signals have shown promise for detecting drought, salinity, toxicity and disease, but practical use is still limited by inconsistent acquisition standards, sensor drift in the field, poor transfer across species and incomplete mechanistic understanding.

Electrical sensing is unlikely to replace established diagnostic methods; its value lies in adding continuous, real-time physiological information to multimodal monitoring systems. Realizing this requires stable interfaces and interpretable models, but also validation across environments and standardized reporting. The aim is to connect signal detection with farm management so that electrical alerts lead to concrete decisions on irrigation, fertilization and pest control.

Data Availability Statement

Not applicable.

Funding

This work was supported by the Natural Science Foundation of Henan Province under Grant 202300410117 and Grant 242102240129, and the Science Foundation of Henan University of Technology under Grant 31401252.

Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable. This review did not involve human participants or animal experiments.

References

[1] Wang, R. (2024). Agricultural sensor: Research progress, challenges and perspectives. *Smart Agriculture, 6*(1), 1-17. [CrossRef]

[2] Sun, J., Tan, X., Li, X., Chen, J., Cai, S., Fan, Y., ... & Sun, S. (2026). A Review of On-Site Detection Methods for Plant Health Based on Electrical Characteristics. *Journal of Sensors, 2026*(1), 7479434. [CrossRef]

[3] Steeneken, P. G., Kaiser, E., Verbiest, G. J., & ten Veldhuis, M. C. (2023). Sensors in agriculture: towards an Internet of Plants. *Nature Reviews Methods Primers, 3*(1), 60. [CrossRef]

[4] Yu, P., Teng, F., Zhu, W., Shen, C., Chen, Z., & Song, J. (2025). Cloud-edge-device collaborative computing in smart agriculture: Architectures, applications, and future perspectives. *Frontiers in Plant Science, 16*, 1668545. [CrossRef]

[5] Ghasemi, E., Ebrahimie, E., & Niazi, A. (2024). Machine learning for early detection of plant viruses: Analyzing post-infection electrical signal patterns. *Smart Agricultural Technology, 9*, 100668. [CrossRef]

[6] Matić, S., Masoero, G., Egidi, A., Francese, C., Capra, P. P., & Sosso, A. (2025). Electrical signalling in tomato-*Oidium neolycopersici* pathosystem for detection of powdery mildew. *Computers and Electronics in Agriculture, 237*, 110585. [CrossRef]

[7] Sun, B., Wu, S., Nie, X., Jia, L., Zhang, X., & Qian, J. (2025). Development of a Predictive Model Linking Electrical Characteristics to Semi-Lethal Temperature in Potted Apple Trees with Validation on Mature Specimens. *Agronomy, 15*(6), 1458. [CrossRef]

[8] Javed, Q., & Azeem, A. (2026). Electrobiological Signatures as Early Indicators of Plant Stress and Adaptation. *Journal of Plant Electrobiology, 1*(1), 58-73. [CrossRef]

[9] Kozlova, E., Yudina, L., Sukhova, E., & Sukhov, V. (2025). Analysis of electrome as a tool for plant

monitoring: progress and perspectives. *Plants, 14*(10), 1500. [CrossRef]

[10] Doménech-Carbó, A. (2025). *Plant Electrochemistry: Physiology and Applications*. Boca Raton, FL: CRC Press. ISBN 978-1-032-69781-9. [CrossRef]

[11] Xie, R., Song, Y., Shi, X., Jia, L., & Liu, Z. (2026). Coupling mechanisms of electrophysiology and photosynthesis mediated by ion dynamics in high-voltage electrostatic field-regulated tomato seedling growth. *Frontiers of Agricultural Science and Engineering, 13*(4), 26668. [CrossRef]

[12] de Carvalho Oliveira, T. F., Costa, Á. V. L., Posso, D. A., Reissig, G. N., & Souza, G. M. (2025). Time dispersion analysis of features as a tool for investigating plant electrophysiology: A case study using moderate magnetic field in bean plants. *Journal of Biological Physics, 51*(1), 28. [CrossRef]

[13] Terral, O., Melikov, R., Lim, D. U., Dar, A. M., & Stavrinidou, E. (2026). Plant electrical signals: From scattered observations to functional understanding. *Current opinion in plant biology, 93*, 102954. [CrossRef]

[14] Yan, X., Pang, Y., Niu, K., Hu, B., Zhu, Z., Tan, Z., & Lei, H. (2025). Wearable sensors for plants: status and prospects. *Biosensors, 15*(1), 53. [CrossRef]

[15] Lee, G., Wei, Q., & Zhu, Y. (2021). Emerging wearable sensors for plant health monitoring. *Advanced Functional Materials, 31*(52), 2106475. [CrossRef]

[16] Yan, B., Zhang, F., Wang, M., Zhang, Y., & Fu, S. (2024). Flexible wearable sensors for crop monitoring: a review. *Frontiers in Plant Science, 15*, 1406074. [CrossRef]

[17] Yuan, J., Wang, H., Wang, S., He, X., Xing, J., Cui, S., ... & Li, W. (2026). Wearable and flexible sensor technologies for monitoring plant physiology and environmental conditions. *Sensor Review*, 1-16. [CrossRef]

[18] Zhou, J., Fan, P., Zhou, S., Pan, Y., & Ping, J. (2025). Machine learning-assisted implantable plant electrophysiology microneedle sensor for plant stress monitoring. *Biosensors and Bioelectronics, 271*, 117062. [CrossRef]

[19] Crichton, C. A., Sharpe, T., López-Pozo, M., Kabutz, H., Strand, E. J., Bruno, N., ... & Whiting, G. L. (2026). Long-term on-leaf monitoring of plant electrophysiology with printed adhesive gel bioelectrodes. *Communications Engineering, 5*(1), 86. [CrossRef]

[20] Qi, J., Yang, Y., Wang, Y., Wang, H., Wang, Q., Shi, Y., ... & Men, H. (2026). Spatial Optimization of Electrophysiological Signal Acquisition in Clivia Leaves Under a Controlled Leaf-Surface Salt-Treatment Model. *Plants, 15*(9), 1363. [CrossRef]

[21] Hosu, I. S., Fierăscu, R. C., & Fierăscu, I. (2026). Electrochemical (Bio) Sensors Based on Nanotechnologies for the Detection of Important Biomolecules in Plants and Plant-Related Samples: The Future of Smart and Precision Agriculture. *Biosensors, 16*(2), 107. [CrossRef]

[22] Coatsworth, P., Gonzalez-Macia, L., Collins, A. S. P., Bozkurt, T., & Güder, F. (2023). Continuous monitoring of chemical signals in plants under stress. *Nature Reviews Chemistry, 7*(1), 7-25. [CrossRef]

[23] Seddaoui, N., & Arduini, F. (2025). Recent advances in wearable and implantable electrochemical (bio) sensors for plant health monitoring. *TrAC Trends in Analytical Chemistry, 191*, 118336. [CrossRef]

[24] Zhou, S., Zhou, J., Pan, Y., Wu, Q., & Ping, J. (2024). Wearable electrochemical sensors for plant small-molecule detection. *Trends in Plant Science, 29*(2), 219-231. [CrossRef]

[25] Torre, M. Z. D. L., Sifuentes-Gallardo, C., González-Ramírez, E., Cruz-Dominguez, O., Ortega-Sigala, J., Díaz-Flórez, G., ... & Durán-Muñoz, H. (2025). Electrical Signal Characterization of *Aloe vera* Var. Chinensis Using Non-Parametric and Parametric Signal Analysis. *Applied Sciences, 15*(4), 1708. [CrossRef]

[26] Gu, J., Tian, F., Shi, J., & Tan, F. (2024). Noise reduction and analysis of leaf electrical signals of strap-leaved plants based on VMD-EWT. *Computers and Electronics in Agriculture, 226*, 109441. [CrossRef]

[27] Liu, Z., Tian, F., & Tan, F. (2025). Analysis of electrical signals in plant physiological responses: A multi-scale adaptive denoising method based on CEEMDAN-WST. *Agriculture, 15*(21), 2269. [CrossRef]

[28] Ren, Z., Tian, F., Wang, S., & Chen, S. (2025). Research on maize leaves surface action potential recognition method based on ResNet-18SE. *Smart Agricultural Technology, 10*, 100819. [CrossRef]

[29] Zhou, Z., Zhang, X., Zhang, C., & Shen, H. (2025). A 1DCNN-GRU Hybrid System on FPGA for Plant Electrical Signal Feature Classification. *Applied Sciences, 15*(21), 11446. [CrossRef]

[30] Wahid, A. M. A., Baihaqi, W. M., & Nambo, H. (2026). Transformer Adaptation for Plant Bioelectric Potential Classification: A Scoping Review and Analogical Transfer Framework. *Smart Agricultural Technology*, 102484. [CrossRef]

[31] Liu, C., Qi, J., Xia, X., Wang, Y., Wang, Q., Sun, L., & Men, H. (2025). Cross-individual electrophysiological signal recognition in Clivia biosensors via domain adaptation. *Applied Soft Computing, 178*, 113323. [CrossRef]

[32] Tran, D., Dutoit, F., Najdenovska, E., Wallbridge, N., Plummer, C., Mazza, M., ... & Camps, C. (2019). Electrophysiological assessment of plant status outside a Faraday cage using supervised machine learning. *Scientific reports, 9*(1), 17073. [CrossRef]

[33] Yeom, M. S., Lee, Y., Oh, H., Lee, E., & Oh, M. M. (2025). Applying machine learning for the classification of environmental conditions using plant electrical signals. *Horticulture, Environment, and*

Biotechnology, 66(6), 1481-1490. [CrossRef]

[34] Aust, T., Buss, E., Mohr, F., & Hamann, H. (2025, March). Automated phytosensing: Ozone exposure classification based on plant electrical signals. In *2025 IEEE Symposia on Computational Intelligence for Energy, Transport and Environmental Sustainability (CIETES)* (pp. 1-7). IEEE. [CrossRef]

[35] Buss, E., Aust, T., Hamburger, O., Karl Heck, C., & Hamann, H. (2025, March). Phytonode upgraded: Energy-efficient long-term environmental monitoring using phytosensing. In *Future of Information and Communication Conference* (pp. 119-138). Cham: Springer Nature Switzerland. [CrossRef]

[36] Najdenovska, E., Dutoit, F., Tran, D., Rochat, A., Vu, B., Mazza, M., ... & Raileanu, L. E. (2021). Identifying general stress in commercial tomatoes based on machine learning applied to plant electrophysiology. *Applied Sciences, 11*(12), 5640. [CrossRef]

[37] Simmi, F. Z., Dallagnol, L. J., Ferreira, A. S., Pereira, D. R., & Souza, G. M. (2020). Electrome alterations in a plant-pathogen system: Toward early diagnosis. *Bioelectrochemistry, 133*, 107493. [CrossRef]

[38] Zambrano-de la Torre, M., Olvera-Gonzalez, E., Záyago-Lau, E., Alaniz-Lumbreras, D., González-Ramírez, E., Sifuentes-Gallardo, C., ... & De la Rosa-Vargas, J. I. (2025). Detection of Lead Contamination Using Bioelectrical Signals of *Aloe vera var. Chinensis*: A Wavelet-Based and Explainable Machine Learning Approach. *Applied Sciences, 15*(17), 9319. [CrossRef]

[39] Zhang, S., Du, X., Zhang, B., Wu, Y., Yang, X., Hu, X., & Wu, C. (2025). Impedance-driven decoupling water–nitrogen stress in wheat: a parallel machine learning framework leveraging leaf electrophysiology. *Agronomy, 15*(7), 1612. [CrossRef]

[40] de Toledo, G. R., Reissig, G. N., Senko, L. G., Pereira, D. R., da Silva, A. F., & Souza, G. M. (2024). Common bean under different water availability reveals classifiable stimuli-specific signatures in plant electrome. *Plant Signaling & Behavior, 19*(1), 2333144. [CrossRef]

[41] Tran, D., Najdenovska, E., Dutoit, F., Plummer, C., Wallbridge, N., Mazza, M., ... & Raileanu, L. E. (2024). Advanced assessment of nutrient deficiencies in greenhouse with electrophysiological signals. *Horticulture, Environment, and Biotechnology, 65*(4), 567-580. [CrossRef]

[42] Garcia-Menchaca, L., Guerra-Sánchez, C., Tarchoun, N., Lebbihi, R., Cruz-Dominguez, O., Sifuentes-Gallardo, C., ... & Durán-Muñoz, H. (2025). Early-stage research to characterize the electrical signal of optically stimulated hydroponic strawberries using machine learning techniques. *Engineering Proceedings, 87*(1), 44. [CrossRef]

[43] Singh, H., Garg, D., Bar-On, L., Avni, A., & Shacham-Diamand, Y. (2026). Machine learning-based analysis of electrical impedance spectroscopy for predicting plant gravimetric dynamics. *Computers and Electronics in Agriculture, 246*, 111620. [CrossRef]

[44] Stolarz, M. (2025). Integration of plant electrophysiology and time-lapse video analysis via artificial intelligence for the advancement of precision agriculture. *Sustainability, 17*(12), 5614. [CrossRef]

[45] Shoaib, M., Khan, S. U., AbdelHameed, H., & Qahmash, A. (2025). Plant stress detection using multimodal imaging and machine learning: From leaf spectra to smartphone applications. *Frontiers in Plant Science, 16*, 1670593. [CrossRef]

[46] González I Juclà, D., Najdenovska, E., Dutoit, F., & Raileanu, L. E. (2023). Detecting stress caused by nitrogen deficit using deep learning techniques applied on plant electrophysiological data. *Scientific Reports, 13*(1), 9633. [CrossRef]

Xiaohui Zhang received the Ph.D. degree and is currently an Associate Professor with the College of Electrical Engineering, Henan University of Technology, Zhengzhou 450001, China. (Email: zhangxh@haut.edu.cn)

Yingkai Fu is with the College of Electrical Engineering, Henan University of Technology, Zhengzhou 450001, China. (Email: 221080200318@stu.haut.edu.cn)

Chi Zhang is with the College of Electrical Engineering, Henan University of Technology, Zhengzhou 450001, China. (Email: chizhang@haut.edu.cn)

Jian Yang is with the College of Electrical Engineering, Henan University of Technology, Zhengzhou 450001, China. (Email: yjian@stu.haut.edu.cn)

Zeyu Zhai is with the College of Electrical Engineering, Henan University of Technology, Zhengzhou 450001, China. (Email: 2025930554@stu.haut.edu.cn)