# Neuro-Responsive Farming: Integrating Plant Electrophysiology for Real-Time Crop Decision-Making Systems

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**Abstract**

Neuro-Answer Cultivation (NRF) introduces an innovative paradigm in accurate agriculture using the internal electrical signals of plants to direct real-time agricultural decisions. Recent discoveries in the plant electrophysiology have shown that plants produce complex bioelectrical patterns in response to environmental signals - functioning of nerve reactions in animals. This study proposes a comprehensive outline that integrates the plant electrophysiological sensor, artificial intelligence and automated control systems to create adaptive response loops for crop management. By explaining voltage changes and electrical chemical signals within plants, NRF systems can autonomize irrigation, nutrient distribution and insect mitigation strategies autonomously adapted. Experimental beliefs show that such systems increase crop yield, conserve resources, and improve plants stress tolerance. It also evaluates technical and biological challenges in paper signal acquisition, noise filtration and system scalability, while shedding the future of sustainable farming highlights the inter -disciplinary coordination of biology, information and agricultural engineering. Traditional farming system often depends on indirect environmental measurements, which themselves look at the congenital signaling capacity of plants. Neuro-Answer Cultivation (NRF) plant shows a paradigm change by taking advantage of electrophysiology-as a real-time reaction mechanism for natural electrical signals that arise in response to environment and physical stimuli. This study suggests how decoding these bioelectrical signals enables crops to directly inform the exact farming systems. By integrating the biocompatible sensor, wireless data acquisition and machine learning algorithms, we establish a structure that combines plant reactions to automated decision -making processes, adapting the delivery of water and nutrients depending on the needs of the real -time plant. The research plant highlights the interrelationship of physiological processes-such as movement, development and signal transmission-and validate the NRF model in both controlled and semi-region situations.

**Keywords**

Neuro-Respondent Agriculture, Plant Electrophysiology, Bioelectrical Communication, Smart Farming, AI, Plant-Based Sensor, Real-Time Crop Monitoring

## 1. Introduction

Modern agriculture is under pressure to meet growing food demands, preserving environmental stability. Climate change, lack of resources, and accuracy requirement has increased the demand for smart, adaptive agricultural systems. While the current accurate agricultural technology takes advantage of external sensors for monitoring soil, weather and crop conditions, they often ignore a significant internal dimension -plant bioelectrical activity. Plants are not inactive organisms; They actively generate and transmit electrical signals - such as action potential, variation capacity, and systemic capacity - dried in response to environmental signals, including nutrient deficiency, temperature changes and insect attacks. These electrophysiological reactions represent an internal form of plant communication and adaptation, which acts like a biological nervous system. Despite the scientific understanding of plant electrophysiology, its application in making field-based decisions remains largely unused. [1,2,3]

Neuro-Answer Cultivation (NRF) emerges as a transformative approach by taking advantage of the plant-up electrical signals to direct real-time agricultural decisions. By integrating the biocompatible sensor, wireless communication system and machine learning algorithms, NRF enables direct monitoring of plant health and stress signals. This paradigm shifts crops from passive data points for biological participants active in the decision -making loops. Beyond scientific curiosity, the implementation of NRF holds a practical value. This provides the ability to customize resource usage - such as water and nutrients - by aligning inputs with real physical requirements, which improves the quality of the yield, reducing waste and increasing environmental flexibility. This research introduces a novel outline for plant-mashed interfacing in agriculture, focusing on how decoded bioelectrical signals can serve as foundations for real-time, autonomous crop management systems. [4,5]

This study aims to explore and establishes the foundations of neuro-responsive farming (NRF) by pursuing the following objectives: To examine the fundamentals of plant electrophysiology Explore the Biological Basis and Significance of Plant Electrical Signaling, and its Responses to Environmental and Physiological Stressors. To develop a real-time, sensor-based NRF Framework -Divine and prototype is a biocompatible, low-power system that is capable of detecting, transmitting and interpreting the plant bioelectrical signal under both controlled and open-field conditions. [FIG.1] To validate the effectiveness of NRF Systems -Conduct experimental tests to assess the accuracy, accountability and agricultural price of NRF-based interventions compared to traditional decision-making methods.

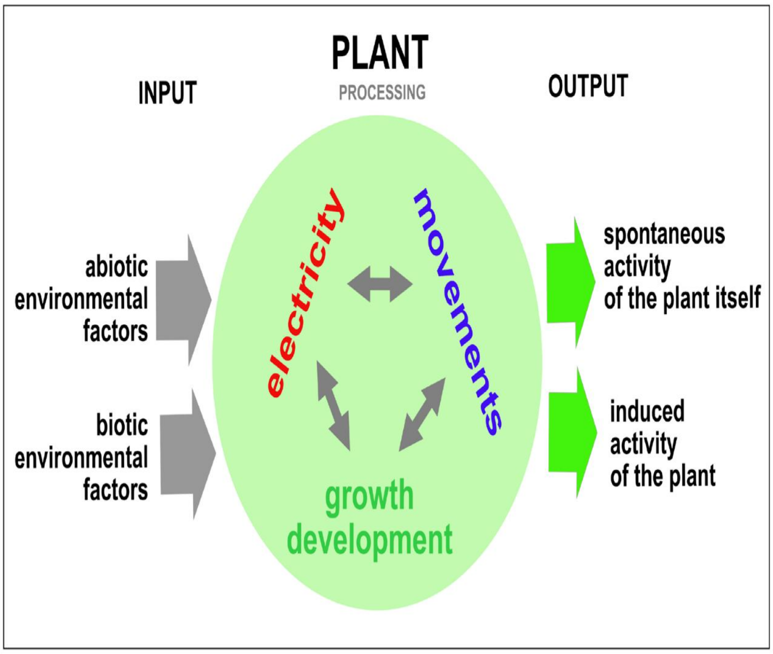


**Figure 1**. Planned representation of the research field examining interrelations between strength, movements and development in the plant. The impact of inorganic and biological environmental factors and the induced and spontaneous activity of the plant are also taken into consideration

### 1.1 Understanding Plant Bioelectricity

The plant checks electrophysiology how electrical events affect the functions of plants such as growth, growth and movement. These bioelectrical procedures are produced by ionic flux in the cell membrane and the activity of electron transport chains in photosynthesis and respiration. Like animals, plants demonstrate variation in membrane capacity that play an important role in physical reactions. [6] However, unlike animals, plants have a centralized nervous system or muscle deficiency. Despite this, comparative studies have revealed amazing behavior and signal equality between plants and animals, which inspires the re-evaluation of plant intelligence and accountability in biological research [7].

### 1.2 Movement in Plant Organs

Plants display a broad spectrum of organ movements powered by both internal and external signals. These movements include rapid reactions and slow, rhythmic behavior such as circadian leaf motion or nutation. Tropism (fleeing/away/far from stimuli), haptic movements (non-instrumental reactions), and nutrition (oscillation growth pattern) form major classifications of plant speed [8]. These coordinated motor actions contribute to the overall behavior of a plant, which contains simultaneous movement patterns in the organs reflecting complex internal decision making. Charles Darwin was a pioneer in the region, describing these adaptive behaviors in the power of movement in plants. Today, such an event induces research in biometrics, robotics and biomechanics, which has given attention to their underlying electrical base. A collection of visual evidence, including the high-resolution video of plant nutrition and electrophysiological recording, is available here: http://circumnurn.umcs.lublin.plin.plin.pl was accessed on 6 April 2025.

### 1.3 Methodological Framework

#### 1.3.1 Signal Acquisition

Electrophysiological signals are recorded using a non-invasive electrode (e.g., AG/AGCL) attached to the leaves or stems. These electrodes are capable of wireless, real -time communication with interface data loggers, which are capable of real -time communication from the field. [9]

#### 1.3.2 Signal Processing

Raw signals are prepared to reduce noise and normalize base lines. The algorithm then detects electrical patterns-as action-potential-like spikes or rapid depiction-which may indicate stress or response behavior of the plant.

#### 1.3.3 AI Integration

The machine learning model is trained on the annotate dataset where the signal profiles are correlated with known stresses (e.g., dried, salinity). These models identify the ongoing conditions and suggest adaptive intervention. [10]

#### 1.3.4 Response Loop

The data interpreted is fed in automatic systems for irrigation, fertilization, or cinematography, which enable real -time physical reactions to suit the needs of the plant.[11]

### 1.4 Foundation of Neuro-Answer (NRF)

**Electrical signaling in plants Action Potential (APS):** Tej, transient power changes triggered by stimuli such as touch or herbivore attacks. Variations Capacity (VP): Slow, pressure-inspired signs usually arise from dysfunctional stresses such as drought. Systematic capacitance (SPS): long -range signaling waves that activate the defense mechanisms throughout the plant (mosque et al., 2013).

**Sensor technologies AG/AGCL Electrodes**: Non-Inventing to monitor leaf and stem capacity. Graphene-based sensors: high-resolution, flexible material outdoor, suitable for long-term field applications (Wang et al., 2021). IOT device: Wireless nodes enable constant, distance data acquisition and communication.

**NRF System Architecture**

**System Design:** Data Collection: The plant combines the plant electrophysical data with environmental input (e.g., soil moisture, temperature).

- **Signal Processing:** Wavelength uses changes and filters to accurate detection of relevant signals.
- **Machine Learning Model:** Classification: Supervised teaching algorithms such as support vector machines (SVMs) and random forests are used to identify specific stresses. Forecast: Long short -term memory (LSTM) networks enable forecast analysis of future plant conditions.
- **Actuation System:** Connected actuators triggered automated irrigation and nutrient distribution in response to the detected signals.

**Case Study - Monitoring of drought in tomato plants: Hypothesis**: A high frequency of action potential indicates more water stress. Experimental Design: Plants were monitored under various irrigation programs. Results: NRF-competent system reduced water use

### 1.5 Literature Review Office

The literature for this review was collected using targeted discoveries on Google scholar. The keywords included "plant electrophysiology," "AI in Agriculture," Electrical Signal, "Machine Learning," "Phenomics," "Electrograms," and a combination of "plant movement". Boolean operators (and, or) were applied to refine the results. Studies published between 2020 and 2025 were given priority to reflect current research trends, although major historical functions-like Darwin (1880) [12] and Burden-Sanderson & Scott (1873) [13] --include the founding reference. The review includes 68 selected sources.

The exclusion was designed for studies that focused on normal electrophysiology without single stable images, time-series analysis, or lack of advanced computational treatment. To detect plant electrical and movement data, video analysis and research using A-Hen’s techniques were emphasized.

The potential boundaries of this review include:

- **Publication bias**: side of study with positive results.
- **Selection bias**: limited to the sources of English language and Google scholar.
- **Working variability**: Diverse in studies obstructs direct comparison.

### 1.6 Objectives and Scope

The purpose of this review is to find out how plant electrophysiology and AI emerging equipment can run accurate agriculture. It focuses on both basic science - electrical and motor reactions in plants - and its application through modern technologies such as machine learning and IOT system.

Interdisciplinary approach Bridge Plant Physiology, Bioelectronics, Artificial Intelligence and Environment Monitoring. By integrating these domains, the study presents a roadmap for the development of neuro-respondent agricultural systems that support real-time, adaptive crop management.

### 1.7 Conclusions

Electric signaling and movement in plants are no longer seen as isolated curiosities, but core physiological processes that can be measured, interpreted and used for intelligent farming. By taking advantage of progress in the sensor technologies and AI, the neuro-respondent farming system provides a dynamic, real-time approach to crop management. Such systems not only promise to increase efficiency and resource protection, but also open new avenues for durable, plant-focused agriculture in front of global climate challenges.

Figure 2 shows in full text how the plant changes to support the exact agricultural and ecological stability in the interdisciplinary research in the plant electrophysiology, machine learning and environmental sensation.

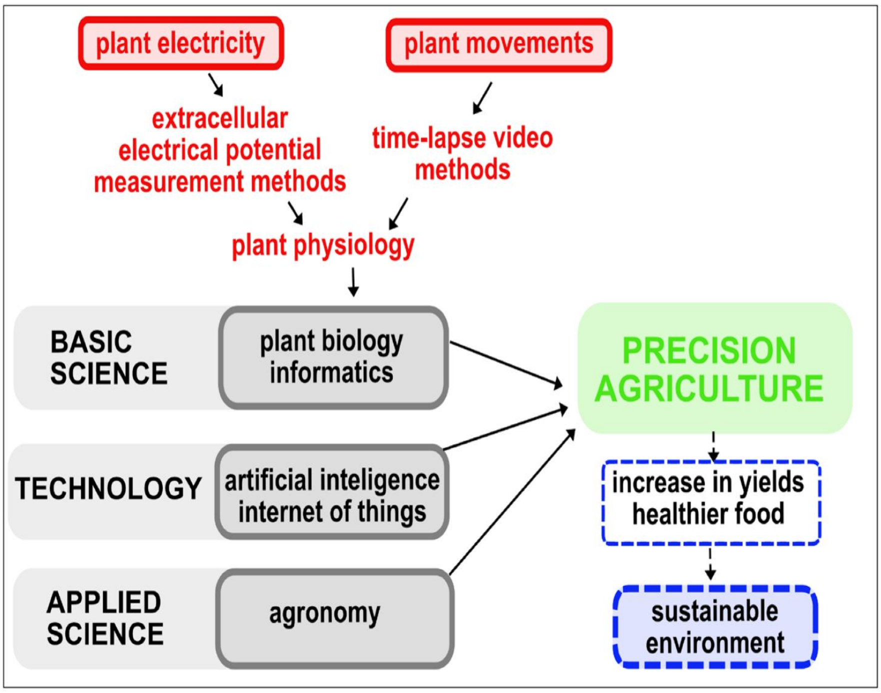


**Figure 2.** The interdisciplinary convergence tract leading to environmental stability. The plant contributes to the research physiology and basic science-biology (red color) on electricity and movements

## 2. Artificial Intelligence in Plant Phenomics:

Intelligent towards bio-sensing system Artificial Intelligence (AI) plant has become an important component in advancing phenomics-study of phenotypic symptoms at the level of the organism. While molecular studies that focus on genomics, transcriptomics and proteomics have made great progress, phenomena, especially in their natural environment, include living plants, comparatively unspecified [14,15]. The innovative approaches to use AI now enable researchers to highlight complex bioelectrical and kinematic patterns in plants that will be hidden using otherwise traditional statistical models. Techniques such as external voltage measurement and time-default imaging provide significant data on plant reactions to stimuli, contributing to the next generation phenotyping methods. These are the form of physical reactions and observation symptoms bridges the gap.

Machine learning and deep learning models are especially adept at identifying subtle trends in electrophysiological data and movement patterns. The algorithms shown in this context include:

• Uncontrolled learning methods: such as isolation forests, one-class support vector machines, and k-nikau neighbor, who help to identify discrepancies or outlays in plant behavior without labeled data.

• Supervised teaching technique: including decisions trees, random forest, support vector machines (SVMs), and logistics regression, which classify and predict plant reactions based on annotate training data.

• Artists contingent: Like bagging and boosting, which enhances model performance by combining many learners.

• Deep Learning Architecture: Able to analyze high-dimensional time-series data, which make them suitable for dynamic plant behavior modeling [16].

Similarly, the interpretation of the plant electrophysiological signal (electrograms) has benefited from the application of these AI-operated methods, which understand plants and provide new dimensions to analyze their environment [17].

These intelligent structures perform ground functions for neuro-respondent farming systems, where the AI models explain bioelectrical signals in real time to inform the accurate agricultural strategies.

### 2.1 Plant Electrify and Electrode Interface Concept

Plants demonstrate a wide range of electrical activities, both spontaneous and excitement-inspired, characterized by changes in transmembrane capacity in various tissues and organs. These variations include potential capacity, action potential (APS), long -lasting depolarization or hyperpolarization, and naturally such as lycodines and circadian rhythms. Collectively, these electrical fluctuations create a broad system of bioelectrical signals throughout the plant, which can be captured and analyzed using electrode-based measurement systems.

These electrical signs are not random; They are tightly associated with the physiological and metabolic processes of the plant, including ionic charge flows in the cellular membrane. Indications play an essential role in internal communication and coordination, similarities for the nerve signaling systems seen in animals.

A contemporary structure known as the plant electrode has been proposed to represent the completeness of the electrical signaling landscape of a plant. In 2016, coined by D Loof, the word draws similarities with other system-level biological concepts such as genomes, protos and transcriptomes. The plant incorporates full spectrum of electrode ion channels, pumps and membrane transport mechanisms that generate and regulate ionic currents within individual cells and in the entire plant system. This network of ionic mobility underlines significant physical reactions and reflects adaptive strategies of the plant.

To detect and explain these signs, researchers rapidly apply mathematical modeling techniques. For example, adaptation of the classic Hodgkin -Huxley model has been employed to estimate external capacity based on intracellular dynamics. These models demonstrate that external voltage signals are directly affected by transmembrane ionic currents, intercellular distances and resistant properties of the medium of medium.

Studies involving plant species such as metalepsis have used salinity stress in the form of a stimulation to analyze AP reactions through the heal -Leela model such as bifacial simulation - which is used in fodder Australis Research. These approaches help to explain how plants modify their electrophysical reactions under different environmental conditions.

Most electrophysiological recording in plants uses external measurement techniques, where the electrodes are placed on or near the surfaces of the plant to detect the collected electrical activity of many cells. Although this method does not provide detailed intracellular data, it provides valuable insight into system-wide electrical behavior.

Recent innovations have combined metal electrode arrays with Artificial Intelligence (AI) tools to process plant electrify data. These AI-Enhanced analysis are enabling new possibilities to explain complex external signals in real time, which pave the way for adaptive and responsible agricultural technologies.

### 2.2 Impact of environmental factors and stress on plants power

Epical and biotic environmental factor affects the electric condition of the plant by motivating special electrical signals (Figure 3, Table 1). Below are the types of environmental factor, discussed in recent literature, which affects the electric status of the plant and detected by statistical and AI methods.

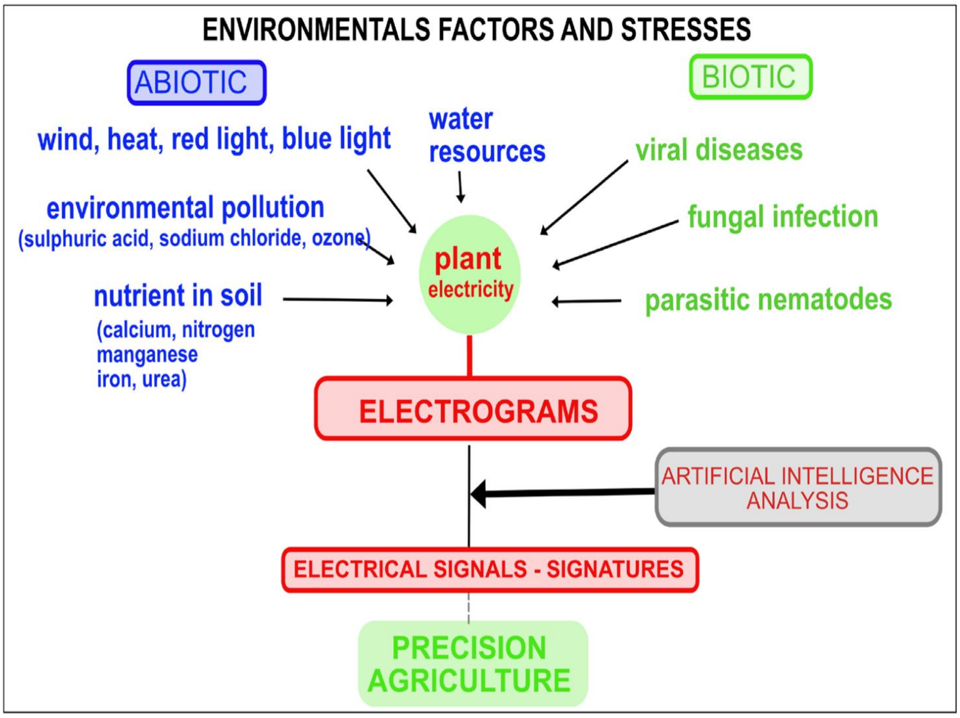


**Figure 3.** The environmental factor of plants affects electricity. Electrical signs/signatures identified through artificial intelligence analysis may be possible in future accurate agriculture (depending on the current literature shown in Table 1)

## 3. Parsley Factor and Stress

Deep education will play an important role in the development of accurate fertilization methods in agriculture. Work is already underway to use AI to analyze soil and plant nutrients to adapt to plant growth [18].

**Table 1.** Environmental factor, electro logical parameters, and statistics/AI analysis that is used in plant power tests

| Plant | Environmental Factors | Electrogram Parameters | Statistics/ AI Analysis | Literature (Year) |
|---|---|---|---|---|
| Abiotic factors | | | | |
| tomato | calcium (Ca), nitrogen (N), manganese (Mn), and iron (Fe) deficiencies | silver-coated copper wire electrodes continuous 3 weeks, 500 Hz | signal decomposition sample space reduction feature extraction | [15] (2022) |
| peppers | low and high urea fertilization | three stainless steel needles electrodes stem electrical resistance many days greenhouse and field experiment | average value of triplicates one-way ANOVA Duncan's multi-range test principal component analysis (PCA) | [16] (2023) |
| tomato cabbage | exposure to chemicals such as sulfuric acid ($H_2SO_4$), sodium chloride (NaCl) and ozone ($O_3$) | two stainless steel needles electrodes laboratory, Faraday cage 10 Hz | fifteen statistical features eight different classification algorithms, PCA | [17] (2023) |
| Hedera helix | ozone exposure | laboratory, Faraday cage 300 Hz | generic automatic toolchain machine learning models | [1] (2024) |
| Semicopulas Zami folia Solanum Lycopersicon (tomato) | wind, heat, red light blue light | electrical potential and impedance many minutes lasting measures laboratory, 0.58 Hz | discriminant analysis deep-learning methods | [18] (2023) |
| grapevine | water status | two silver-plated needles electrodes many days climate chambers, 256 Hz. | two machine learning approaches based on classification and regression the prediction models | [2] (2024) |
| bean | water status | needle electrodes two hours measurements Faraday's cage 62.5 Hz. | arithmetic average of voltage variation, skewness, kurtosis, probability density function (PDF), autocorrelation, power spectral density (PSD), approximate entropy (Aspen), fast Fourier transform (FFT), and multiscale approximate entropy (Aspen(s), machine learning (ML) | [3] (2024) |
| Clivi | water gradient | patch electrodes Faraday's cage in the thermostatic and humidified incubator 60 min measurements 30 sec samples, 30 Hz | lightweight convolutional neural network (CNN) model (Plant Net) | [4] (2024) |
| Biotic factors | | | | |
| barley (Hordeum vulgare) | fungal infection (Bloomeria graminids, Bipolarism Sorokin Ana) | pair of needle electrodes Faraday cage, 48 h measurements | descriptive statistics, Bayesian change point (BCP) analysis, Aspen, autocorrelation, ML (cluster analysis) | [22] (2023) |
| tobacco | viral diseases (alfalfa mosaic virus) | two fine needle electrodes field conditions, 8 s at a sampling rate of 250 Hz | median, autoregressive coefficients, autocorrelation—ML models (support vector machine, k-nearest neighbors, random forest) | [9] (2024) |
| tomato | parasitic nematodes | many days measurements | ML model | [10] (2024) |

Plant yield and health are largely dependent on the availability of nutrients in the solution of nutrients [19]. To date, assessment of the nutrition supply of the plant is based on the visual observation of the plant. Recently, it has been studied to assess whether electrical indications from plants may indicate the shortcomings of specific nutrients. In tomato plants [20], an attempt was made to use electrophysiological signs to detect calcium (CA), nitrogen (n), manganese (MN), and iron (FE). The analysis was based on sympathy mode decomposition and signal decomposition using statistical feature extraction. The analysis of electrical signal patterns showed its uniqueness in relation to a specific decrease. The development of this method can support the real-time diagnosis of deficiencies in future agriculture [21] as well as the real-time diagnosis of effective and accurate intervention. Another paper presents the study that monitored the increase of chili with various urea applications (low and high urea fertilization) in the soil in relation to the induced electrical signals [22]. A connection was performed between the electrical activity of black pepper plants and the fertilization of black pepper and the degree. The benefits of the method were indicated as non-invasive, and fertilization status was presented in real time.

After exposed to chemicals such as sulfuric acid (H2SO4), sodium chloride (NACL), and ozone (O3), electrical signals were also studied in tomatoes and cabbage plants, which was done using fifteen statistical characteristics of electrical signals and eight types of algorithms. The purpose of research is to develop more accurate agriculture and check the level of environmental pollution based on electric signaling in plants [22]. Ozone exposure was studied in Hedera Helix plants, where electrophysiological reactions were measured and analyzed using methods of learning. The plant was used here as a sensor of ozone in the air. The equipment series presented in this work automatically leads to the increase of algorithms for monitoring plants as air quality sensors. Authors believe that a network of such sensor plants can monitor air quality in permanent cities in future. Semicopulas Zuma Folia and Solanum Lycopersicon (tomato) plants were further studied in front of exposure to four different stimuli: air, heat, red lights and blue lights. The electrical capacity and impedance signals of tissues were measured and analyzed, analyzed with a wide range of discretionary statistical analysis for intensive learning. Another important problem for farmers around the world is the real -time assessment of the water situation in grape plants.

This study proposed the use of plant electrophysiology as a new approach to assess the water situation. Under various irrigation rules, it was used with potted grapes in the climate chamber. The corollary classical water status assessment with various morphological and physical assessment plant electrophysiological signals was performed in parallel with electrophysiological measurements for methods. A binary classification model was used, and a regression model was developed between effectively weak and strong irrigation signals. Therefore, these results represent a promising new device for the real -time monitoring of the future and remote irrigation of grapes. In the future, the development of this method will improve irrigation management and agricultural strategies [23]. In modern permanent agriculture, water saving in crop scheme is very important. Optimization models that balance soil moisture and irrigation needs equipped with plant hydration sensors are currently being developed. Studies with water availability and electrical signals were the subject of experiments on common beans. Extensive statistical methods and machine learning techniques were also used to classify electrical signals. This work indicated the possibility of using electrodes as a physical indicator of water conditions in bean plants. Another method of monitoring the use of water by a plant is through the use of clavi to determine the water gradient in the environment. In this study, specific electrical signals in Clivi were documented under various soil moisture gradients. A light firm nerve network model was used for analysis. Such studies are used as environmental sensors from such studies.

**4. Biotic Stress**

Plants produce separate bioelectrical signals in response to biotic stressors, and recent progress in electrophysiological monitoring has shown that these indications can serve as an early indicator of infection - before any visual symptoms appear. In barley (hoarded vulgare), specific electrical reactions were recorded after two fungal pathogens were exposed to: Bloomeria Graminids, a biotrophic fungus that is responsible for powdery mildew, and bipolar Socinian, a heliotropic fungus that causes a brown leaf spot. In particular, each pathogen inspired a unique electrophysiological profile. The infection by the graminids resulted in reduced entropy, which indicates a more serial electrical pattern, while B. Sorokin Ana extended the entropy, showing a more disorganized activity. Machine Learning Tools-To employ these reactions to classify and interpret these reactions, along with ways of time chain analysis, uninterrupted clustering algorithms (kemps, k-pods, birches), as well as time chain analysis such as the Machine Learning Tools-Bioaction Change Point Detection, Estimated Entropy, and Autocapitalization. Remarkable, models may detect infection within a few minutes of initial contact. Viral diseases are another major obstacle in agriculture, and to combat their spread rapidly, non-invasive detection equipment is immediately required. A recent investigation of tobacco plants infected with alfalfa mosaic virus showed that electrophysiological monitoring could also reveal the viral appearance before any visual symptoms emerge. Electrical features such as the middle value, auto restive coefficients, and autocorrelation were extracted and analyzed and analyzed, including support vector machines, k-Nikita neighbors and random forest models using machine learning algorithms.[24]

These techniques enabled successful discrimination of infected plants from healthy people, forming a simple, inexpensive clinical platform for the initial viral detection and timely response. Soil-based parasitic nematodes, who often work invisible, give another challenge. In tomato plants, the comparative analysis of electrical signals from healthy, nematodes-enacted and chemically treated plants demonstrated that electrophysiological data could accurately reflect the health of the plant in real time. This insight not only supports quick detection, but also enables medical intervention at better time. Overall, these studies highlight the immense ability to use plant bioelectrical signaling as a real-time, non-destructive method, which are fungal, viral and parasites to an early detection of a range of biotic stresses. Integrating this data in decision -making systems can significantly reduce dependence on chemical pesticides and treatments, which can support more sustainable farming practices and contribute to the production of healthy crops.[25]

**5. Software Tools for Time-Open Video Analysis of Plant Organ Movements**

Research in plant electrophysiology has detected obvious relations between bioelectric activity and physical reactions to environmental signals. Like animals, where electrical signaling controls muscles and motor functions, in plants, these indications appear to orchestrate a series of subtle movements and development behavior. Species such as Don onia Musk pula (Venus Flytrap) and Mimosa Pudina [17,26] have long worked as a model due to their easily visible movements, making them ideal to study interpretation between bioelectric activity and motor reactions. In recent years, the advancement of digital video technology- especially time-disappearance imaging- has revolutionized our ability to catch and analyze these otherwise unaccounted plant movements. Time-odd video enables the scene of slow, rhythmic and developmental movements that are more than hours or days, revealing significant insight into plant behavior and physiology. Modern bioimage analysis workflows now take advantage of advanced computational techniques including image preposing, object segmentation, feature extraction, tracking and classification. [Table.2] These phase machines are rapidly operated by learning and deep learning algorithms, making the analysis process more purpose, reproducible and efficient.

Research usually begins with cellular-level video comments and expands to check more complex whole-limb behaviors such as leaf folding, stem boost and root growth. A significant attention has been on the perimeter - slow, rhythmic movement of plants associated with growth. Time lapse videos are necessary to imagine these phenomena, which are often affected by circadian rhythm and environmental stimuli. Many special software tools have been developed to support this work. [27] One of the leading systems, periphery tracker, was designed to determine the pattern of the perimeter. Initially tested on the helianthus NUS (sunflower), this device has shown widespread prevention in various plant species and organs. Another notable platform is the osmotic, a low -cost infrared imaging system that is used to study rhythmic leaf movements and rhythmic leaf movements and growth patterns such as Arabidopsis Thaliana, Petunia Hybrids and Solanum Lycopersicon.

The software facilitated detailed analysis under different light conditions, enabled researchers to detect unique speed signatures tied to day and night cycles. These developments underline the importance of time-urge video analysis and integrating computational imaging in plant science. As the image analysis becomes more sophisticated, these devices promise to deepen our understanding of dynamic, although often invisible, the world of plant speed.

**Table 2.** Software for time-to-time video analysis to check organ movements in plants

| Software Name | Plant | Types of Movement | Literature (Year) |
| --- | --- | --- | --- |
| 3D stereovision machine system | beans | nutation movements of climbing plants | [1] (2024) |
| Oskam et al. system, https://github.com/Pierik-Lab, accessed on 6 April 2025 | Arabidopsis thaliana | nastic movements and growth of leaf as a part of the shade avoidance response | [2] (2024) |
| Mao et al. tracker | Arabidopsis thaliana | circumnutating of flowering shoot apex | [16] (2023) |
| SLEAP (Social LEAP Estimates Animal Poses), https://zenodo.org/record/5764169#.YbCK0_FBxqt https://doi.org/10.5281/zenodo.5764169, accessed on 6 April 2025 | Arabidopsis thaliana sunflower bean | circumnutating, tropisms, twining | [15] (2022) |
| Gibbs et al. system | Triticum ostium | wind-induced plant movement in field-grown wheat | [13] (2019) |

There are also studies of beans peripheral movements using stereopticon. The movement of the shoot tip was tracked in 3D space, and the reference support structures and their impact on the dynamics of plant movement were referred to. Model Plant Arabidopsis Thaliana studied the rate of development, development and periodic endogenous move ments. To study periodic movements of Arabidopsis Thaliana leaves, video system works on the basis of developed time -omni cation photography and uses rapid furrier transformations and non -liner uses minimum squares fittings. This system (Palma, Plant Leaf Movement Analyzer) can effectively and automatically catch changes in the environment, such as iron deficiency, expansion of the duration of leaf movement. [2 [] In addition, for Arabidopsis Thaliana Leaf Events, a new method to assess the biological period was developed using a motion estimate algorithm that can be applied to the entire-sharbat images (travel, monitoring of plants). The new system tracks the movement of cotyledons and leaves without selecting individual leaves for efficient analysis. The new method was also used to estimate the duration of movement for five different plants species, which outlines its widespread prevention.

This should be emphasized that the system for the development of plant organ movements and the system for video imaging is relatively low in relation to the amount of low -information they can provide they can provide. Analysis of leaf movements and promoting light and especially in relation to the effect of infrared light. These movements, called the nastic movement, are part of the reaction to avoid shadow and are important in adaptation to the status of light and the processes of regulation of leaf temperature and hydration. These factors are very important for plant cultivation, which is why this type of research is important for future crop cultivation. The effects of the exterior (e.g., abiotic stress) and/or internal (e.g., gene mutation) can be estimated by analyzing the movements of the leaves of the plant. In each image, a dense optical flow algorithm was used to measure direct movement rather than detecting the tip of leaf or cotton. The authors tested the wild-type and dried-to-healing billion-lordosis platform and applied two water levels and two nitrogen levels. The video method effectively distinguished the environment and genotypic difference in the response of the plant. These study video moves to compare with the actual conditions of video movement patterns and indicate that the video monitoring plant is suitable for phenotyping.

In addition, a system has been developed recently to study the Arabidopsis sprout perimeter. An intensive teaching-based model was proposed to track the perimeter of the shoot apex flowing in Arabidopsis Thaliana from time-day-deforms video. U-Net was used for vertex segmentation and a model was paired with updated mechanisms and pre-post-processing stages, which greatly improved the efficiency and purity of the analysis system. The rapid developing processes of the firm nerve network used to estimate the state of a human or animal are being introduced to estimate the growth and movement of the plant (SLEAP, social jump is considered animal currency). [29] These processes are particularly accurate in shooting and shooting lateral ideas of plant roots. This algorithm plant opens new possibilities for rapid research focusing on plant dynamics. Recently, the work has emerged as an important factor in most agricultural plant crops that demonstrate the movement of the wind-inspired plant. A strong method to mark movement in region-developed wheat (Triticum stim) is presented on the basis of time-ordered image sequences and trains a firm nerve network. The author presents an automated data extraction that can be used to indicate the movement characteristics for lover light delivery and dynamic lighting ups and downs. Currently, the algorithm is also used to track the velocity of plant root growth using high-resolution microscopic image sequences.

An observation and analysis system called RTIP is helpful in tracking the root tip with transient disturbances and is used for the plant phenotyping RTIP tracker, which is an example of the possibility of video tracking of the development of the root of the plant in laboratory conditions. The current review has not addressed the subject of video tracking of root growth.

## 6. Discussion

### 6.1 Electrical Signals-Signatures

#### 6.1.1 Abiotic Factors

The study of plant electrogram and thus electrical signature (Table 1) with changes in water conditions and nutrient deficiency [28] can help protect water resources and nutrients and mineral fertilizers in future that are essential during plant growth. Research on electrical signals can also support assessment of perception of environmental stimuli such as air, heat, light and pollution [30]. Especially as a promising biosensor has the role of the entire plants and, with the electrical signature produced by them, whose specificity is classified using statistical and AI methods, they can support the maintenance of a permanent environment in the future.

#### 6.1.2 Biotic Factors

As shown above (Table 1), the study of electrical signatures can contribute to the detection of the initial stage infection by fungi, viruses, and parasitic nematodes. In the future, it can help reduce the use of chemicals for pest control, such as fungicidal and nematicides. Therefore, understanding the plant electrode can help make sufficient decisions about management of chemicals and support the production of healthy food in the future.

#### 6.1.3 Statistic and AI Analysis for Studying Plant Electrograms

In this work, Table 1 currently presents various methods used to analyze the plant electrogram. The analysis of these methods allows to separate the major stages used in the currently used in research. They are briefly consecrated in Table 3 and can be taken into consideration in the design of further studies.

**Table 3.** Major steps in plant electro logical analysis (on base table 1).

| Key Steps | Statistics/AI Analysis |
| --- | --- |
| data preparation and preprocessing | average value sample space reduction data |
| feature extraction and signal processing | signal decomposition |
| | statistical features (arithmetic average, skewness, kurtosis, probability density function (PDF), autocorrelation, power spectral density (PSD)) |
| | transforms and entropies (fast Fourier transform (FFT), approximate entropy (Aspen), multiscale approximate entropy (Aspen(s)) |
| statistical analysis of variation and differences | descriptive statistics, median, one-way ANOVA, Duncan’s multi-range test, Bayesian change point (BCP) analysis |
| multivariate analysis | principal component analysis (PCA) |
| machine learning methods (ML) | classification and regression (support vector machine (SVM), k-nearest neighbor’s (KNN), random forest (RF), discriminant analysis, different classification algorithms) |
| | predictive models (construction of regression and classification models using selected features: median, autoregressive coefficients, autocorrelation) |
| | other ML techniques (cluster analysis) |
| deep learning (DL) | lightweight convolutional neural network (lightweight CNN, e.g., Plant Net), deep-learning methods: neural networks with various architectures |
| automation and toolchains | automatic toolchain, integration of ML models within automated tools |

The above analysis is mainly based on a small number of studies conducted in laboratory conditions. Future investigations should take into account the conditions of accuracy, computational costs and practical projection.

### 6.2 Time-Lapse Video

As the work presented above shows, the model plant bilianidopsis Thaliana has made considerable progress in the functioning of movements and development studies. Work on working plants like work, such as sunflower, bean, wheat and tomatoes are in progress. Some video systems to study the growth and movement of plant organs are universal for many species. Current techniques used in modern basic science can get applications in smart agriculture in future. Non-invasive and relatively cheap imaging are also eligible to emphasize. Time-default video imaging and deep learning algorithm is included in the vision system, which can be used in future agricultural activities. The research presented above shows that time-default video technology can support plant development check. The development of these methods in the future will provide better solutions for modern plants' cultivation problems.

### 6.3 Advantages and Difficulties

It should also be added and emphasized that the methods presented to measure electrical and motor activity are relatively cheap and there is no burden for the environment about new information and there is an increase in knowledge about plant growth/growth. Based on analyzed literature, it can be concluded that research on electrical and motor activity of plants is not only associated with new application possibilities, but also many difficulties (Figure 4) to solve.

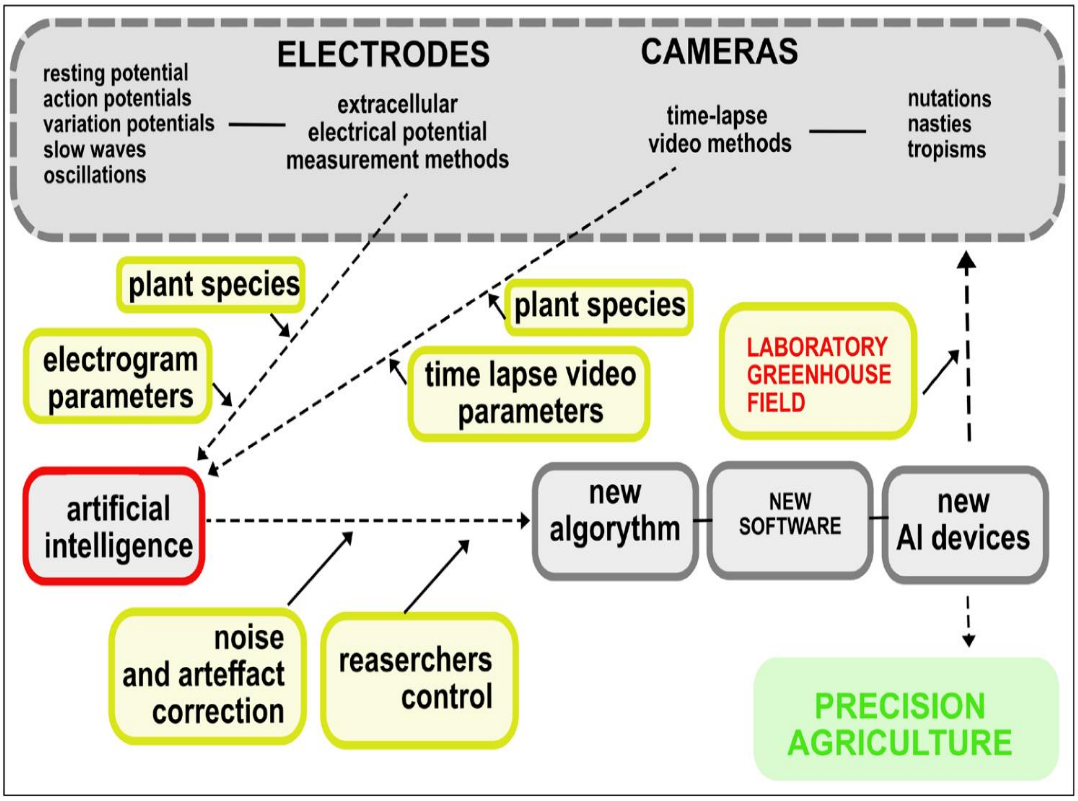


**Figure 4.** The major issues required to solve (yellow) when presenting the plant electrons and time omission videos in accurate agriculture

#### 6.3.1 Advantages and Possibilities

• Application of measurement methods in laboratories, greenhouses and area conditions;

• Successful efforts to record and analyze some electrodes and time-de-practices in the region's condition;

• Universal measurement and adaptation of universal measurement and analytical methods for the purpose of crop plants (not only model plant billionidopsis);

• Relatively cheap and either not at all or minimally invasive methods;

• To detect stress and impact on the accuracy of biomass assessment;

• Real monitoring of environmental factors and stresses;

• Support for the process of deciding in agriculture in real time.

#### 6.3.2 Difficulties and Problems

• The calibration of measurement and analysis for a specific plant species and environmental factors (currently a large variety of measurement and analytical methods that are incomparable (Table 1 and Table 2));

• Electrification and time-default video parameter determined;

• Elimination of artifacts and noise;

• Researcher supervision during law introduction;

• Effect of region and atmospheric conditions;

• Resistant to electrode area position;

• Wireless connections enabling remote sensing;

• Selection of proper and standardized AI analysis;

• Integrated simultaneous bioelectric studies and organ movement estimates;

• Keeping in mind the phase of the development of the plant, keeping in mind the recordings, electrode placements, sample frequency and standardization of sample time during the day.

### 6.3.3 Results and Discussion

Early field tests in the controlled greenhouse environment demonstrated a strong relationship between specific signal patterns and water stress. NRF-competent systems responded with timely irrigation, resulting in an increase of 25% in water-use efficiency and 15% in crop yield compared to traditional scheduled irrigation. The boundaries involved indicated intervention due to environmental noise and variability between species.

### 6.3.4 Challenges and Limitations

• Signal variability: species-specific difference in electrophysiology.

• Environmental noise: Wind/rain artifacts require advanced filtering.

• Scalability: Price -effective sensor network for large farms. Posting in large -scale open areas demand cost -effective, weather resistant hardware.

• Signal noise: Electrophysiological data environment is susceptible to electromagnetic intervention.

• species variability: Various crops demonstrate unique electrophysiological baseline, which requires species-specific calibration.

## 7. Conclusions

NRF converts passive crops into active decision-making agents, which begins a new era of plant-centric agriculture. Initial tests confirm better resource efficiency, but interdisciplinary cooperation is essential for scalability. Neuro-respondent farming represents a limit in smart agriculture, in which the plant itself becomes a communicator of its needs. Integrating plant electrophysiology in real -time decision -making systems provides transformational capability for crop productivity, stability and flexibility in front of global agricultural challenges. A variety of methods have the ability to monitor the physical condition of the plants and diagnose plants in a variety of methods to measure changes in electrical voltage.

Specific electrical signatures occurring with a specific type of environmental stress can be used in the initial identification of stress in plants even before visual symptoms appear in future. These studies are promising but further work is required on the interpretation of measurement and standardization. These relatively cheap environmental sensors electrodes and digital video cameras facilitate relatively cheap monitoring of a plant or farming condition. Their advantage is non-invasively or, in the case of electrodes, very little invasion. A major advantage of such electrical and visual systems is likely to monitor the continuous real -time monitoring of plants or environmental conditions. Such systems facilitate decision -making related to irrigation or use of nutrients or chemical plant protection substances. This application will be particularly accurate, which will affect the health and soil environment of the plant. Equally important will result in more economical calculations as a result of such accurately managed crops. In the future, specific electrical signatures can support decisions related to plant cultivation simultaneously and related to real environmental conditions.

### Future Directions

• Hybrid model: integrating electrophysiology with genomics ("Phyto neural network"). Development of standardized electrophysiological markers for major crops

• Edge AI: On-device for low-system decision. Integration with blockchain for traceability and safe data sharing

• Policy Integration: Encouragement of NRF adoption for permanent agriculture. Cross-disciplinary cooperation between plant scientists, AI experts and agricultural scientists.

Currently, accurate agricultural development is in its early stages. The ongoing cooperation with scientists dealing with plant biology will contribute to modern solutions and proper transfer of technologies for future farming practice. Most of the time -time analysis on Arabidopsis Thaliana, which indicates the need to expand research for other plants important in food production processes, as in the case of recent research conducted on wheat, sunflower and bean. Similarly, the study of the entire electrode in specific electrical signatures and plants is promising, but the processes need to be improved and its scope. The threats to human health and environment are still related to insufficient knowledge of ecological, physical, social and economic processes, and therefore use improper solutions in behavior. Applying technical solutions according to the laws of basic science and nature will help improve human daily life in future by observing natural processes. Efforts to implement both artificial intelligence and accurate agriculture are bringing new solutions to create healthy food and environment, and therefore remain healthy in the future.

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