

Article

Non-Invasive Multimodal and Multiscale Bioelectrical Sensor System for Proactive Holistic Plant Assessment

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Abstract

Global crop losses of 20–40% continue because traditional plant assessment methods are either invasive, damaging plant tissues, or reactive, detecting stress only after visible symptoms. Recent developments have remained fragmented, focusing on single modalities, individual organs, or limited frequency ranges. This study developed a unified bioelectrical sensor system capable of non-invasive, multimodal, multiscale, and integrative assessment by integrating capabilities that existing methods address only separately. The system combines spectroscopy and tomography within a single platform, enabling simultaneous evaluation of multiple organs. Unlike approaches confined to narrow frequencies, it captures complete physiological responses across scales. Validation on strawberry (*Fragaria × ananassa* ‘Sweet Charlie’) demonstrated comprehensive multi-organ assessment: 98.3% accuracy for fruit categorization, 95.8% for leaf water status, and 88.2% for stem productivity. Tomographic performance reached 2.6–2.8 mm resolution for 3D root mapping and 2.8–3.0 mm for 2D postharvest fruit sorting. Correlations with reference metrics were used exclusively for validation, confirming that the extracted features reflect genuine physiological variations. Importantly, the system detects stress before visible symptoms, enabling intervention within the reversible window. By unifying spectroscopy and tomography with complete frequency coverage and multi-organ capability, this platform overcomes existing fragmentation and establishes a foundation for proactive, comprehensive plant monitoring essential for sustainable agriculture.

Keywords: bioelectrical; spectroscopy; tomography; multimodal sensing; multiscale sensing; non-invasive; proactive; precision agriculture; machine learning; strawberry cultivation



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1. Introduction

Global agriculture loses 20–40% of crops each year because traditional plant assessment methods rely on invasive techniques that damage tissues and reactive management that detects stress only after symptoms appear [1–3]. Studies show that stress indicators emerge before visible symptoms, meaning early intervention windows are often missed [4–7]. Once

irreversible plant damage occurs, recovery is no longer possible [8,9]. This underscores the need for proactive rather than reactive strategies, with non-invasive methods becoming increasingly important as agriculture faces climate change and resource depletion [10–12].

Invasive techniques, such as tissue sampling and molecular extraction, remain limited because they require destructive sampling, laboratory facilities, and extended processing times. They are also hampered by low bacterial sensitivity, contamination risks, and extraction inhibitors, making them unsuitable for field use [13,14]. Non-invasive alternatives preserve tissue integrity but still depend on indirect measurements and limited data, delaying detection and contributing to yield losses [15–17]. Moreover, most of these approaches remain reactive, constrained by accuracy challenges and difficulties in interpreting field data [18–20].

These limitations explain why existing methods fail to provide a comprehensive assessment. They either damage tissues, focus only on surface properties, or remain limited to a single modality and a narrow physiological scale. Effective assessment requires preserving tissue integrity while capturing both features and spatial patterns across multiple scales [21–23]. Current technologies achieve only fragments of this integration. For example, hyperspectral imaging (350–2500 nm) and multispectral imaging (4–10 bands) capture surface reflectance but miss internal physiological changes [24–26]. Vis-NIR (400–1000 nm) can assess chlorophyll and water indices but provides no information on membrane integrity or ion transport [27]. Thermal imaging detects temperature variations with 73–89% accuracy but cannot identify ion deficiencies or membrane changes [28–30]. Chlorophyll fluorescence measures photosynthetic efficiency but not water status or structural integrity [31,32]. Electrochemical sensors are limited to specific analytes [33,34], while molecular methods still suffer from inhibitors and low bacterial sensitivity [35,36].

Attempts to integrate methods partially address these constraints. Wearable sensors enable multiple measurements at discrete points [37–39], and IoT systems link sensors for broader coverage but often miss physiological transitions between intervals [40,41]. Machine learning can enhance detection but remains limited by the quality of the sensor inputs [41–43]. Advanced methods such as X-ray micro-CT, Raman spectroscopy, terahertz spectroscopy, and magnetic resonance can measure multiple parameters, but they bring challenges, including radiation exposure, optical interference, limited penetration, high costs, and infrastructure requirements [44–51].

Bioelectrical measurements overcome many of these issues by directly probing cellular electrical properties through spectroscopy [52–55]. Unlike surface-limited methods, bioelectrical signals penetrate tissues, capturing internal physiological changes through frequency-dependent responses [56–61]. Specifically, α -dispersion (<10 kHz) reveals ion transport dynamics, while β -dispersion (100 kHz–1 MHz) reflects membrane integrity [62–64]. Recent studies have demonstrated strong correlations between bioelectrical properties and water potential [65–68], nutrient status [69–73], membrane integrity [74–76], and stress indicators [77–81]. Despite this promise, most bioelectrical studies remain fragmented: they employ either spectroscopy or tomography in isolation, often restricted to narrow frequency ranges, and they typically rely on raw bioelectrical data rather than systematic feature extraction with advanced machine learning [81–83].

Strawberry (*Fragaria* × *ananassa* ‘Sweet Charlie’) was chosen as the model crop to validate this integrated system for four reasons: (1) its rapid stress progression requires early intervention [84–86]; (2) complete organ accessibility allows for simultaneous multi-organ validation [85,87,88]; (3) its high economic value makes it particularly vulnerable to losses from reactive management [89–92]; and (4) its bioelectrical response patterns across physiological transitions are well documented [85,93].

This system targets critical gaps in strawberry production: reactive drought detection through proactive leaf water status classification; subjective fruit categorization through

physiological maturity assessment; inefficient allocation of resources to non-productive stems through productivity classification; hidden root stress through 3D conductivity mapping; and postharvest sorting limitations through 2D tomographic defect sorting

This study addresses the fragmentation in existing bioelectrical approaches through the following objectives:

- Unified platform development: Integrate multiple electrode configurations and operational modes, enabling both spectroscopy and tomography within a single deployable system.
- Organ-specific optimization: Establish a systematic methodology for identifying optimal frequency ranges and extracting physiologically meaningful features for each organ.
- Physiological validation framework: Correlate bioelectrical features with established reference metrics across all organs.
- Tomographic capability: Develop both 2D and 3D conductivity imaging for spatial physiological assessment.
- Proof-of-concept demonstration: Validate the integrated system on strawberry, establishing a transferable methodology for broader agricultural applications.

Together, these objectives culminate in a non-invasive, multimodal, and multiscale bioelectrical sensor system that transitions plant assessment from reactive detection to proactive intervention, providing the comprehensive assessment capability required for sustainable intensification under climate change.

2. Materials and Methods

The study comprises three phases, as shown in Figure 1: (1) system development and experimental preparation, (2) data acquisition and feature processing, and (3) dual-pathway spectroscopic and tomographic analysis. The analysis employs spectroscopic classification (solid arrows) for leaves, stems, and fruits with physiological correlation; tomographic reconstruction analysis (dotted arrows) for 3D root zone conductivity mapping; and 2D conductivity localization for postharvest fruit sorting. Both pathways converge in a unified performance evaluation.

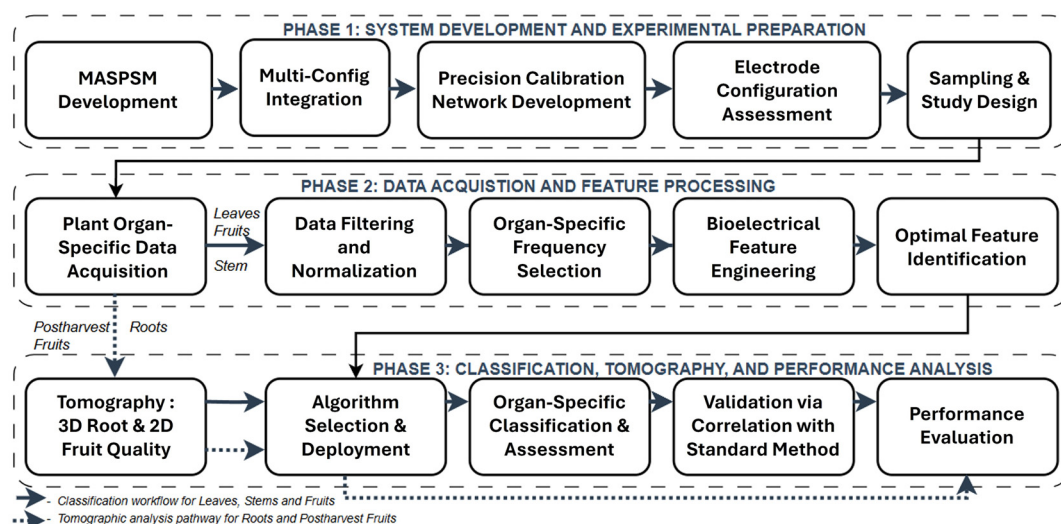


Figure 1. Comprehensive methodology workflow of the bioelectrical sensor system.

The methodology and framework in this study have been validated through rigorous experimental trials, statistical evaluations, and comparison with established reference measurements done by existing studies. All design choices and claims, specifically in strawberry model crops, are supported by evidence.

2.1. Modified Analog Signal-Processing Module for Multi-Configuration Integration

Figure 2 presents the measurement system with the modified analog signal-processing module (MASPM) architecture that provides multi-configuration switching and signal processing for all measurement modes.

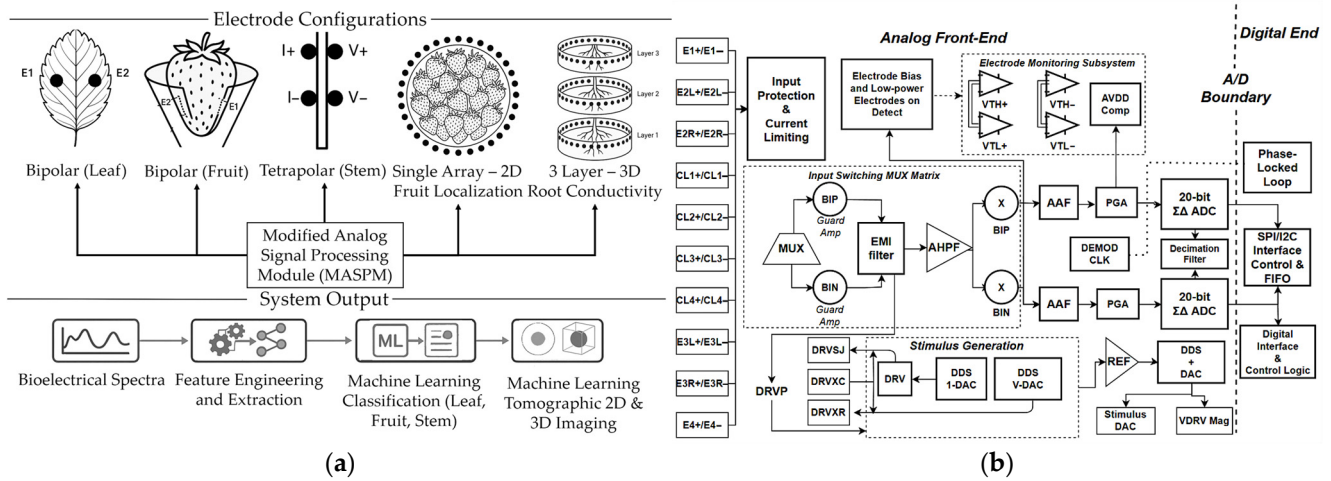


Figure 2. Non-invasive, multimodal, and multi-configuration bioelectrical sensing system: (a) organ-specific electrode configurations and signal-processing architecture; (b) internal architecture of the modified analog signal-processing module (MASPM) enabling multi-configuration switching.

Figure 2a illustrates the electrode configurations. Bipolar electrodes were used for leaves and fruits, tetrapolar for stems. A single 32-electrode array for 2D fruit tomography, and triple-layer arrays for 3D root tomography. Together, these setups allow the system to convert bioelectrical signals into both physiological state classifications and spatial conductivity maps. Figure 2b presents the internal architecture of the MASPM. Differential electrode pairs are connected through input protection and current-limiting circuits. A switching matrix with multiplexers and guard amplifiers provides noise reduction and EMI filtering. The electrode-monitoring unit ensures reliable connections by detecting voltage thresholds with supply compensation. Signal processing is carried out through dual channels, each employing anti-aliasing filters and programmable gain amplifiers feeding ADCs. Bioelectrical signals are simultaneously measured using cross-multiplication with phase-locked demodulation. The stimulus generation block uses dual DDS modules to deliver current and voltage outputs with programmable reference control, maintaining stable excitation across different plant tissues. Finally, digital control coordinates timing, data filtering, and communication protocols.

2.2. Multimodal Hardware Integration for Spectroscopic and Tomographic Operation

The bioelectrical measurement system employs configurations sharing core circuitry. Bipolar configuration (Supplementary Figure S1) implements two-electrode measurements for homogeneous tissues. Its H-bridge circuit establishes reference voltages using 4.7 k Ω resistors (0.1% tolerance), while OPA333 amplifiers (Texas Instruments, Dallas, TX, USA) minimize tissue loading. Protection combines SMAJ5.0A TVS devices (Littelfuse, Chicago, IL, USA) (± 5 V clamp) with EMI filtering. INA333 instrumentation amplifiers (Texas Instruments, Dallas, TX, USA) (CMRR >100 dB) with sense resistors enable overcurrent detection. The circuit interfaces with MASPM through DRVP/DRVN and BIP/BIN signal paths, controlled via SPI/I2C protocols. Signal conditioning employs three-stage RC networks (HPF, BPF, LPF) with corner frequencies and -60 dB/decade roll-off (detailed in Supplementary Figure S4). The tetrapolar configuration (Supplementary Figure S2)

separates current injection from voltage sensing to eliminate polarization artifacts in heterogeneous stem tissues. A Howland current source utilizing OPA2376 amplifiers (Texas Instruments, Dallas, TX, USA), controlled by an AD5171 potentiometer (Analog Devices, Wilmington, MA, USA) and an AD5663 DAC (Analog Devices, Wilmington, MA, USA), delivers programmable currents (1 μ A–10 mA) with ± 12 V compliance. Voltage paths use OPA333 buffers (Texas Instruments, Dallas, TX, USA) with guard drive techniques, reducing stray capacitance. Current monitoring combines INA333 (Texas Instruments, Dallas, TX, USA) with a 24-bit ADS1256 ADC (Texas Instruments, Dallas, TX, USA) for resolving differential voltages across channels. ADG1404 multiplexers (Analog Devices, Wilmington, MA, USA) manage electrode routing and source switching. Both spectroscopic configurations utilize ADG714 multiplexers (Analog Devices, Wilmington, MA, USA) for calibration resistor switching, AD9833 DDS (Analog Devices, Wilmington, MA, USA) with AD835 multipliers (Analog Devices, Wilmington, MA, USA) for frequency generation, and an STM32H755 dual-core processor (STMicroelectronics, Geneva, Switzerland). The Cortex-M7 core handles current source control, while the Cortex-M4 manages voltage acquisition and data processing, enabling parallel operation. Signal conditioning includes OPA4188 (Texas Instruments, Dallas, TX, USA) and REF5025 (Texas Instruments, Dallas, TX, USA) for reference stability. The system operates from linear ± 12 V supplies (LM7812/7912, STMicroelectronics, Geneva, Switzerland) with a <10 mVpp ripple.

For tomographic configuration, it employs 32-electrode arrays where four ADG1408 multiplexers cascade through dual ADG1409 multiplexers (Supplementary Figure S3), with an XC7A35RT controller managing switching, phase-locked sampling, and I/Q demodulation for reconstruction. The selection of 32 electrodes and phantom dimensions was not arbitrary but rather determined through optimization of measurement sensitivity and spatial resolution. This penetration depth is governed by the following equation:

$$\delta_{\text{penetration}} = \frac{1}{\sqrt{\pi f \mu \sigma}}, \quad (1)$$

where f is the excitation frequency, μ is the magnetic permeability, and σ is the nominal plant tissue conductivity. Reported tissue conductivity values range from 0.05–0.2 S/m based on physiological changes [94,95]. The 70 mm radius ensures current distribution based on the two-fold penetration depth criterion [96], while the 60 mm height provides 924 cm³ volume. Within these constraints, 32 electrodes were calculated via sensitivity optimization analysis, maximizing volume [97,98]. The angular electrode spacing is computed as follows:

$$\theta_{\text{res}} = 360^\circ / N_{\text{electrodes}}, \quad (2)$$

where θ_{res} represents the angular resolution between adjacent electrodes, and $N_{\text{electrodes}}$ denotes the total electrode count. This arrangement aims to balance circumferential coverage with the system. The parallelotope volume for measurement sensitivity, calculated as follows:

$$V_{\text{parallelotope}} = \sqrt{(\det(\mathbf{J}(\mathbf{M})\mathbf{J}^*(\mathbf{M}))),} \quad (3)$$

where $\mathbf{J}(\mathbf{M})$ represents the Jacobian matrix sensitivity matrix of selected measurements $\mathbf{M}$, with each row containing partial derivatives $\partial U_i / \partial \sigma_j$, relating voltage measurements U_i to conductivity changes $\partial \sigma_j$. The superscript “*” represents a conjugate transpose, and $\det$ indicates the determinant operation. This correlates voltage measurements to conductivity changes. Theoretical spatial resolution is estimated as follows:

$$\Delta s_{\text{spatial}} = r_{\text{phantom}} \times \sin(\theta_{\text{res}}/2) \quad (4)$$

where $\Delta s_{\text{spatial}}$ is the minimum resolvable feature size, r_{phantom} is the phantom radius (70 mm), and $\theta_{\text{res}}/2$ accounts for the half-angle between adjacent electrodes. This equation derives from geometric considerations where the spatial resolution depends on both the angular separation and radial distance from the array center. Current density distribution was modeled to evaluate penetration characteristics:

$$J(r, \theta) = (I_{\text{inj}}/2\pi r) \times \sum_{n=1}^{N/2} \cos(n(\theta - \theta_{\text{inj}})) \times e^{(-nr/R)}, \quad (5)$$

where $J(r, \theta)$ is the current density at coordinates (r, θ) , I_{inj} is the injection current, r is the radial distance from the center, θ is the angular position, θ_{inj} is the injection electrode angular position, n is the harmonic number, N is the total electrode count, and R is the phantom radius. This ensures current reaches the phantom center ($r = 0$) with <5% sensitivity loss compared to the boundary, consistent with prior simulations [96–98]. These computations generate conductivity slices and volumetric reconstructions (Figure 3).

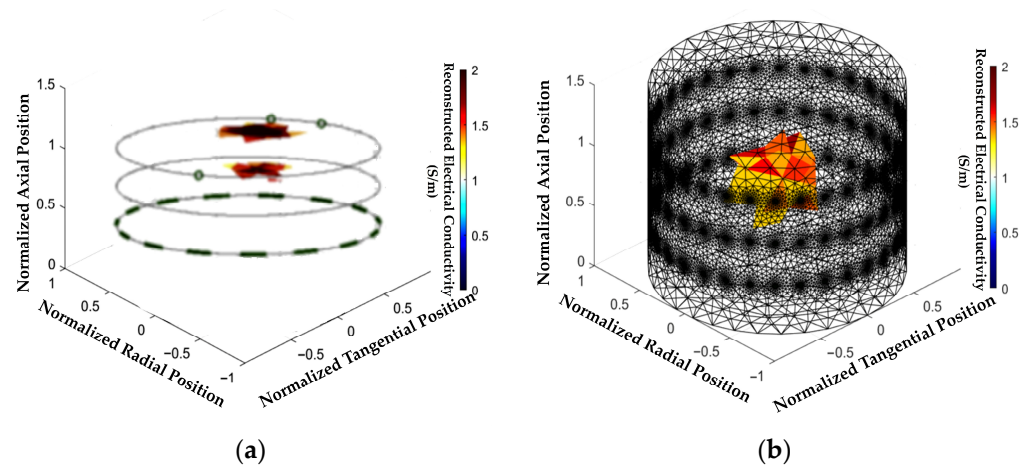


Figure 3. Tomographic setup simulation: (a) 2D conductivity slices used to form volumetric reconstruction; (b) 3D conductivity volumetric reconstruction and conductivity distribution.

2.3. Development of Calibration Network for Multi-Configuration and Multimodal Operation

The challenge in plant bioelectrical measurements is that different organs have vastly different electrical properties. The adaptive calibration network solves this problem by enabling one system to accurately measure all plant organs. The network centers on a precision resistor matrix that automatically adjusts to match each organ's measurement range (Supplementary Figure S4). Four programmable control signals manage this adaptation. PLANT_CAL_EN selects the organ type, while GSR_LOAD_EN handles conductivity variations. PLANT_GSR_RSEL sets the appropriate measurement range. Together, these signals allow the system to reconfigure itself for accurate measurements. To maintain non-invasive measurements, the network carefully manages electrode polarization. DC blocking uses 100 nF capacitors paired with 100 k Ω bias resistors to prevent polarization buildup. For frequency-specific responses, the system employs 10 nF and 10 k Ω networks to optimize α -dispersion measurements in the cellular response range, while 100 nH inductors with 4.7 k Ω resistors extend performance into higher frequencies of β -dispersion. All these parameters have been validated against traceable standards, including ENOB, noise floor, and THD specifications, ensuring consistent results across different organs and measurement sessions.

2.4. Electrode Design, Selection, and Performance Evaluation

The electrodes used to plant tissue connection influence the measurement quality. This requires the selection of optimal electrode types and configurations for both tomographic

and spectroscopic evaluation. For tomographic measurements, electrode materials were selected based on established agricultural applications. Gold-plated electrodes [99–103] were evaluated as the reference, given their proven conductivity and stability. Ag/AgCl electrodes [104–108] were included based on widespread adoption and cost-effectiveness. Performance was compared using the spatial resolution through point spread function (PSF) analysis, and current uniformity via FEM. For spectroscopic measurements, electrode selection followed established plant bioelectrical studies. For leaf measurements, hydrogel surface [109–111] and Ag/AgCl [112–115] electrodes were employed. For fruit measurements, adhesive patches [116–119] and screen-printed electrodes [120–123] for non-invasive surface contact were employed. For stem measurements, Ag/AgCl clip-type [124–127] and clamp-type [128–131] configurations were employed. Each electrode type was evaluated in both bipolar and tetrapolar configurations to identify optimal organ-specific pairings. Performance metrics included the signal-to-noise ratio (SNR), contact resistance, measurement repeatability, and contact area.

2.5. Sample Collection and Experimental Design

Having established the complete measurement platform, validation experiments were conducted using strawberries (*Fragaria* × *ananassa* ‘Sweet Charlie’) to demonstrate sensor system performance. Experiments were conducted at an existing controlled farm in Bukal, Majayjay, Laguna, the Philippines (14.1447° N, 121.4723° E, 750 m elevation). Environmental conditions were carefully controlled throughout the experiments. The measurement protocol drew from established bioelectrical studies and incorporated advice from local farmers familiar with the site’s microclimate. Three HOB0 U23-001 Pro v2 data loggers (Onset Computer Corporation, Bourne, MA, USA; ± 0.21 °C, $\pm 2.5\%$ RH) monitored conditions continuously, recording every 5 min. Measurements were conducted between 9:00 and 11:00 a.m. for several reasons. This window minimizes circadian-related measurement drift [132]. Local farmers confirmed temperature stability during these hours, which preliminary tests validated. Ten test runs showed that the temperature varied less than 2 °C during morning hours, compared to over 5 °C variations in the afternoon. The protocol successfully maintained conditions within the target range of 24–27 °C and 75–85% relative humidity. These ranges match those used in previous strawberry bioelectrical studies [85,86,120]. Measurement stability was verified through repeated testing. Twenty reference measurements yielded a coefficient of variation below 2.5% across the environmental range, consistent with the expected 2–3%/°C temperature coefficient for plant tissues. The stable electrode–tissue contact parameters shown in the results Section 3.1 further confirmed the protocol’s effectiveness.

For leaf water status classification, 400 leaf samples were collected from plants across eight beds. Water treatments utilized controlled irrigation: “well-watered” plants ($n = 200$) received 250–300 mL daily, maintaining more than 75% field capacity; “water-stressed” plants ($n = 200$) received 100–150 mL every third day, maintaining less than 40% field capacity. For validation, the soil moisture was monitored using capacitance probes at a 10 cm depth.

For market-based fruit categorization, two types were identified: (1) physiologically ripe (PR) fruits, with advanced internal changes that enhance flavor but shorten shelf life, and (2) commercially mature (CM) fruits, retaining firmness [133] and transport and storage potential [92]. These differences are natural from the farm’s environmental conditions: (1) Sunlight exposure accelerated internal physiological maturation, with bed-edge plants yielding more PR fruits and shaded inner plants producing CM fruits. (2) Primary crown fruits changed earlier than those from lateral branches. (3) Plants near irrigation emitters produced more PR fruits than those at line ends. (4) Topography is also a factor, with

elevated and well-drained areas favoring PR fruits, while lower, wetter areas favored CM fruits. A total of 300 fruits were collected with the help of experienced farmers in identifying the categories using a visual and firmness approach. PR fruits showed red color (including the tip), strong aroma, and softness. CM fruits displayed 85–90% red color (excluding the tip) and remained firm. For further validation, established postharvest assessment methods were employed. PR samples ($n = 150$) averaged 22–24 °Brix with a firmness of 0.8–1.2 N, while CM samples ($n = 150$) averaged 18–20 °Brix with a firmness of 2.0–2.5 N.

For stem productivity assessment, 200 samples were collected from plants that underwent a seven-week-long controlled-management period to create productivity categories (high vs. low productive). Productivity was generated using combined treatments. High-productive stems received daily watering (250–300 mL), weekly fertilization (20 g), and normal flowering, while low-productive stems received reduced watering (100–150 mL every third day), no fertilizer, and weekly flower removal. These treatments created clear phenotypic contrasts for system validation. Single-factor experiments were not conducted, as the focus of this study was classification of distinct productivity groups rather than isolating individual variable effects. For root zone conductivity mapping, four plants were utilized for tomographic mapping capabilities through contrasting root conditions. This validation employed a 2×2 factorial design (two irrigation levels $\times$ two replicates) monitored over seven weeks to allow for complete root system development. Plants were grown in the system's phantom with the same organic medium used in farm beds, ensuring relevance to field conditions. Since the roots were grown in the system's phantom, both water and fertilizer inputs were computationally reduced to prevent baseline conductivity shifts and ensure measurements reflected genuine physiological changes. Two plants received normal care, with 100 mL water daily with diluted 5 g organic fertilizer. Then, the other two plants underwent controlled stress, with only 50 mL daily, with no fertilizer. These treatment levels were calibrated to create detectable conductivity contrasts between healthy and stressed root systems while preventing plant death.

For conductivity localization for postharvest fruit sorting, tomographic validation focused on detecting fruits with internal defects, specifically hollow centers that appear normal externally but contain voids detectable through conductivity differences. Also, natural factors on farm conditions produced these defects: (1) Sun-exposed fruits create hollow centers despite normal appearance. (2) Irrigation inconsistencies at 15–20% water variation along drip lines caused cycles of dehydration and rehydration that collapsed internal tissues while external surfaces recovered. Uneven fertilizer distribution created nutrient-poor zones where fruits developed internal cavities due to insufficient ion availability. A total of 100 fruits were strategically harvested with guidance from an experienced farmer. Following 48 h of controlled storage at 25 °C and 35% RH to accentuate quality differences, bioelectrical prescreening via conductivity measurement was conducted. Fruits with high conductivity (≥ 0.5 S/m) were classified as good quality, indicating intact cellular structure, while those with low conductivity (≤ 0.3 S/m) were classified as poor quality, characteristic of internal voids. This correlated with visual inspection, confirming external appearance often masked internal defects detectable only through bioelectrical assessment. The prescreened fruits were allocated into three primary experimental configurations using 70 fruits, while the remaining 30 fruits were used for preliminary algorithm optimization and repeatability testing. Configuration 1 used 22 uniform good-quality fruits as the baseline validation; Configuration 2 assessed boundary detection with 10 poor-quality fruits centered among 12 good-quality fruits; and Configuration 3 tested resolution limits with 26 smaller poor-quality fruits arranged at a higher density. This distribution provided sufficient replication across scenarios to detect medium effect sizes (Cohen's $d \approx 0.5$) with $\geq 80\%$ statistical power, ensuring robust comparative analysis.

2.6. Bioelectrical Measurements Organ-Specific Protocols

The 1000 samples (400 leaves, 300 fruits, 200 stems, 100 postharvest fruits) from Section 2.5 were measured by the bioelectrical system using electrode configurations determined in Section 2.4. The methodologies are adapted from validated bioelectrical measurement approaches and tailored to strawberry-specific applications.

For leaf measurements, the hydrogel electrodes selected in Section 2.4 were specifically H-series models with integrated adhesive, comparable to Covidien and Medtronic types that represent the standard in plant bioelectrical studies. These particular specifications were chosen because the electrodes adhere through hydrogen bonding with leaf moisture, eliminating additional adhesives that could interfere with measurements. The measurement protocol involved surface preparation with deionized water cleaning and gentle drying, followed by application of Spectra-electrode gel to ensure consistent contact on irregular leaf surfaces. Unlike recent sensors designed for continuous growth monitoring [112,115], this study focused on measurement stability, physiological correlations, and absence of bioelectrical drift, rather than direct growth impacts. Figure 4 illustrates the electrode arrangement (Figure 4a) and the actual field implementation (Figure 4b). Bipolar electrodes were positioned on abaxial leaf surfaces with 15 mm center-to-center spacing.

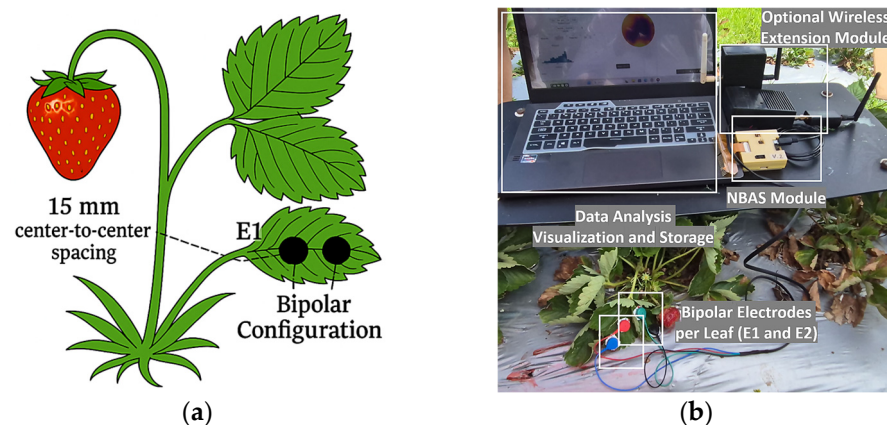


Figure 4. Bipolar electrode configuration for leaf bioelectrical measurements: (a) illustration showing electrode placement on abaxial leaf surface; (b) field implementation showing the complete leaf bioelectrical measurement setup.

Fruit measurements employed screen-printed electrodes embedded in conical substrates with a 60° apex angle, using bipolar configuration. This conical design was specifically chosen to conform to the fruit's curved surface, distributing pressure evenly to prevent damage while maintaining consistent electrode spacing. The electrodes were positioned at the fruit's equatorial plane. Each electrode's contact area of approximately 3 mm² was small enough to accommodate surface irregularities yet large enough to ensure proper current distribution across the tissue. The conical substrate design proved particularly effective for measuring attached fruits without causing tissue damage, an important consideration for non-invasive assessment. Figure 5 shows both the electrode arrangement schematic (a) and the actual field implementation (b).

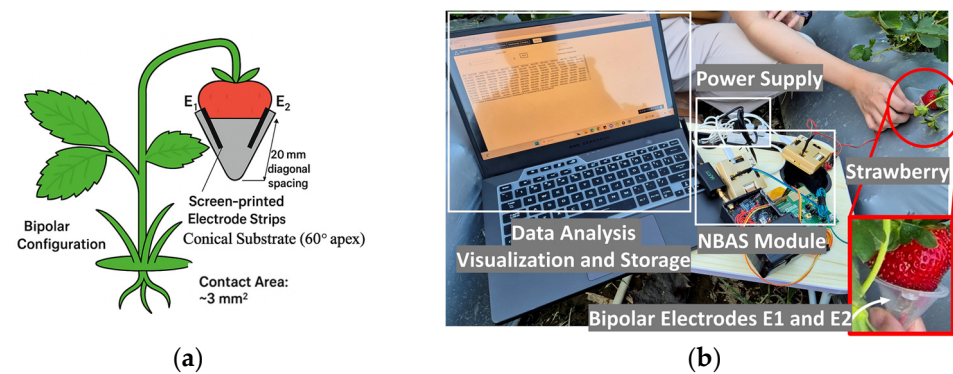


Figure 5. Bipolar configuration for fruit bioelectrical measurements: (a) illustration showing screen-printed electrodes embedded in conical substrate; (b) field implementation showing the complete strawberry fruit bioelectrical measurement setup.

For stem measurement, clip-on Ag/AgCl electrodes in tetrapolar configuration were selected based on their superior performance detailed in Section 3.2. This configuration excelled specifically because the stem's complex structure, with conductive vascular bundles requires separation of current injection from voltage sensing to minimize interface effects. The tetrapolar arrangement achieves this separation. Figure 6 illustrates the electrode arrangement in stem (Figure 6a) and the actual field implementation of it (Figure 6b). The electrode was placed linearly with 5 mm electrode spacing suitable for 5–8 mm diameter strawberry stem. This enabled complete current penetration while maintaining injection measurement separation, capturing the dual dispersion characteristics of stem tissues. While the clip-on mechanism of the electrodes provided consistent pressure accommodating diameter variations.

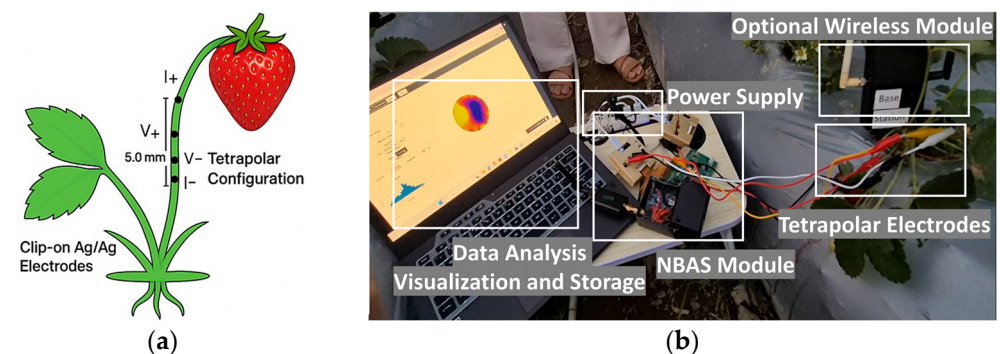


Figure 6. Electrode configurations for stem bioelectrical measurements: (a) tetrapolar clip-on Ag/AgCl electrode configuration schematic; (b) field implementation of NBAS system measuring strawberry stem.

Tomographic measurements utilized the computed 32-electrode array configuration, with gold-plated electrodes selected through comprehensive evaluation, including current uniformity via FEM to validate conductivity field distribution and spatial resolution through point spread function (PSF) analysis to verify localization accuracy and temporal stability. These measurements per frequency through adjacent-pair current injection and phase-locked FPGA acquisition, enabled both temporal monitoring and spatial reconstruction. Figure 7 illustrates the experimental setups for both 3D root conductivity mapping (Figure 7a) and 2D postharvest fruit quality assessment (Figure 7b).



Figure 7. Tomography measurement setups: (a) 3D roots zone conductivity mapping; (b) 2D conductivity localization for postharvest fruit sorting.

2.7. Data Preprocessing Filtering and Normalization

Raw bioelectrical data requires preprocessing to remove artifacts. Noise suppression employed Savitzky–Golay filtering through localized polynomial fitting:

$$y_j^{\text{smooth}} = \frac{1}{N} \sum_{i=-\frac{m-1}{2}}^{\frac{m-1}{2}} c_i y_{j+i}, \quad (6)$$

where y_j^{smooth} represents the filtered value at frequency point j , calculated as the weighted average of N neighboring points using polynomial coefficients c_i . The summation extends from $i = -(m-1)/2$ to $(m-1)/2$, where m defines the window size. The selection of m balanced noise reduction and feature preservation based on each organ: 5-point windows for leaves were selected to preserve sharp frequency transitions in narrow spectral peaks, 7-point for fruits broader spectral patterns, and 9-point for stems capturing dual-dispersion transitions. For anomaly detection, a modified z-score was utilized to identify electrode contact losses and transient interference:

$$M_i = \frac{0.67 \cdot |x_i - \tilde{x}|}{MAD}, \quad (7)$$

This metric compares each measurement x_i against the local median $\tilde{x}$, normalized by the median absolute deviation (MAD), with 0.67 ensuring equivalence to standard deviation units under normal distribution assumptions. Tissue-specific thresholds were established based on plant organ structural complexity: 3.0 for uniform leaf tissue, 3.5 for moderately variable fruits, and 4.0 for complex stem vascular tissue. Standardization through z-score normalization addressed electrode contact variations:

$$P(f)_{\text{normalized}} = \frac{P(f) - \mu_P}{\sigma_P}, \quad (8)$$

where bioelectrical parameters $P(f)$ at each frequency are centered by their dataset mean μ_P and scaled by standard deviation σ_P , producing zero mean unit variance distributions, enabling direct comparison across plant organ samples regardless of measurement scales.

2.8. Key Frequency Selection and Statistical Validation of Organ-Specific Ranges

After ensuring data quality through preprocessing, multi-frequency bioelectrical measurements were reduced to identify the most physiologically informative regions for each organ type. The selection process began with statistical evaluation of parameter differences at each frequency point using two-sample Welch's t -tests:

$$t = (\mu_1 - \mu_2) / \sqrt{(s_1^2/n_1 + s_2^2/n_2)}, \quad (9)$$

where μ_1 and μ_2 represent mean parameters for contrasting physiological states, s_1^2 and s_2^2 are sample variances, and n_1 and n_2 are group sizes. A Benjamini–Hochberg false discovery rate correction-controlled Type I error inflation from multiple comparisons was adopted, retaining frequencies with adjusted p -values less than 0.05. Significance was evaluated through Cohen’s d effect size to distinguish substantial from negligible differences, expressed as follows:

$$d = \frac{\mu_1 - \mu_2}{s_{\{pooled\}}}, \quad (10)$$

This metric expresses group mean differences in pooled standard deviation units (μ_1 and μ_2), providing scale-independent effect magnitude. And the pooled standard deviation accounts for unequal variances through weighted averaging:

$$s_{\{pooled\}} = \sqrt{\{((n_1 - 1)s_1^2 + (n_2 - 1)s_2^2) \text{ over } (n_1 + n_2 - 2)\}}, \quad (11)$$

where s_1^2 and s_2^2 represent group variances weighted by their respective degrees of freedom ($n_1 - 1$ and $n_2 - 1$). This provides an unbiased estimate of population standard deviation when group sizes differ. Only frequencies with $d \geq 1.0$ were retained, indicating separation greater than one standard deviation between states, ensuring detection beyond measurement variability. The final selection criterion employed mutual information (MI) analysis. Unlike correlation coefficients with limited linear relationships, MI captures both linear and nonlinear dependencies. MI is expressed as follows:

$$MI(X;Y) = \sum_{x,y} p(x,y) \log \left(\frac{p(x,y)}{p(x)p(y)} \right), \quad (12)$$

This measures uncertainty reduction about physiological state Y when the bioelectrical parameter X is known at each frequency. Joint probability $p(x,y)$ captures parameter-state co-occurrence, while the product $p(x)p(y)$ represents the independence expectation. Larger logarithmic ratios indicate stronger associations. Frequencies meeting all three criteria were selected for feature generation: statistical significance after FDR correction, effect size ≥ 1.0 , and normalized mutual information ≥ 0.7 . This integrated approach was designed to balance statistical rigor with physiological relevance.

2.9. Bioelectrical Feature Extraction for Physiological Interpretation

With optimal frequencies identified, the bioelectrical measurements underwent systematic feature extraction. This process transformed measurements into physiologically interpretable parameters, avoiding direct reliance on raw data. Central to this transformation is the Cole–Cole model, which describes the frequency-dependent bioelectrical response of biological tissues through physically meaningful parameters:

$$Z(\omega) = R_\infty + \frac{R_0 - R_\infty}{1 + (j\omega\tau)^\alpha}, \quad (13)$$

where $Z(\omega)$ is the complex impedance at angular frequency ω , R_0 represents resistance at low frequencies reflecting extracellular pathways, R_∞ represents resistance at high frequencies representing total tissue resistance, τ represents the relaxation time that indicates how quickly cells respond to electrical changes, and α is the dispersion parameter ranging from 0 to 1, which indicates tissue homogeneity. Derived parameters include membrane capacitance (C_m), indicating structural integrity and expressed as follows:

$$C_m = \frac{\tau}{R_0 - R_\infty}, \quad (14)$$

reflecting the charge storage capability, with higher values suggesting intact membranes. Characteristic frequency (f_c) identifies optimal measurement points, expressed as follows:

$$f_c = \frac{1}{2\pi\tau} \quad (15)$$

representing the resistive to capacitive transition where cellular effects dominate. Spectral energy distribution ($P(f)$) quantifies how magnitude varies across the frequency spectrum

$$P(f) = |Z(f)|^2 / \sum |Z(f)|^2, \quad (16)$$

where $|Z(f)|$ is magnitude at frequency f , normalized by total spectral energy. This reveals which frequencies contain maximum physiological information. While spectral centroid (f_c) locates the frequency response center:

$$f_c = \frac{\sum(f \times PSD(f))}{\sum(PSD(f))} \quad (17)$$

Lower values indicate slow cellular processes, and higher values suggest faster responses. The spectral bandwidth (BW) measures the spread around this center:

$$BW = \sqrt{\frac{\sum((f - f_c)^2 \times PSD(f))}{\sum(PSD(f))}} \quad (18)$$

Narrow bandwidths indicate uniform tissue; wide bandwidths suggest heterogeneous structures. Dynamic analysis examines rapid bioelectrical changes with frequency, revealing tissue complexity:

$$\frac{dZ}{df} = \frac{Z(f + \Delta f) - Z(f - \Delta f)}{2\Delta f} \quad (19)$$

Steep derivatives indicate tissue boundaries, while gradual slopes suggest uniform regions. Large derivatives occur at critical frequencies where conduction transitions from ionic to electronic pathways. Morphological analysis extracts patterns from reactance vs. resistance trends. Extreme phase angles indicate capacitive and resistive dominance at physiological transitions.

2.10. Optimal Parameter Identification and Feature Selection

Following feature extraction in Section 2.9, this section will discuss the selection of the most discriminative features from the expanded feature pool for organ-specific classification. Recursive Feature Elimination with Cross-Validation (RFECV) was implemented to remove features with minimal classification contribution. This was evaluated through fivefold cross validation. Feature retention followed these criteria: (1) feature had to yield at least 1.0% improvement in accuracy, (2) the training to validation performance gap was kept below 3.0% to avoid overfitting, and (3) individual feature importance exceeded 5.0% of the model contribution, as determined by permutation testing. Redundancy was addressed via hierarchical clustering of correlation, with features showing correlation coefficients above 0.85 considered redundant. Among these, only the representative feature with the highest MI was retained, computed as follows:

$$MI(F; Y) = -p(f, y) \log \sum \left[\frac{p(f, y)}{p(f)p(y)} \right] \quad (20)$$

This metric captures the nonlinear dependencies between features F and target labels Y that linear correlation overlook.

This selection process identified organ-specific optimal features reflecting physiological traits: fruits 12 features (sample-to-feature ratio 25:1), leaves 10 features (ratio 40:1),

and stems 8 features (ratio 25:1). This feature subsets enable also balance classification performance with efficiency.

2.11. Multi-Frequency Tomographic Data Acquisition Method

While spectroscopic measurements utilized selected frequencies for feature extraction, tomographic imaging required comprehensive frequency sweeps to enable spatial conductivity reconstruction. Frequency sweeps were designed based on penetration depth calculations for the standard phantoms detailed in Section 2.4, and computed as follows:

$$\delta(f) = \frac{1}{\sqrt{\pi f \times 4\pi \times 10^{-7} \times \sigma_0 [1 + (j\omega\tau)^\alpha]^{-1}}}, \quad (21)$$

where $\delta(f)$ represents the penetration depth (m), f is the excitation frequency (Hz), σ_0 is conductivity (S/m), $\omega = 2\pi f$ represents the angular frequency, τ is the Cole–Cole relaxation time (s), and α represents the dispersion parameter. Logarithmically spaced frequency points were implemented to optimize sampling, expressed as follows:

$$f_k = f_{\min} \times 10^{k \cdot \frac{\log_{10}(\frac{f_{\max}}{f_{\min}})}{N-1}}, \quad (22)$$

This spacing ensured adequate coverage while maintaining acquisition times less than 100 ms per frequency. Spatial data organization employed adjacent electrode current injections. For the 32-electrode array, systematic rotation yields the following matrix:

$$Z_{(spatial)(i,j)} = \frac{V_{(measured)(i,j)}}{I_{(injected)(i,j)}} \times \exp(j\phi_{i,j}), \quad (23)$$

where $V_{(measured)(i,j)}$ represents differential voltage between electrode pair (i,j) , $I_{(injected)(i,j)}$ is constant current, and $\phi_{i,j}$ denotes the measured phase angle. The frame synchronization maintains coherence across the multi-electrode array through the equation below:

$$t_{(sync)(k)} = k \cdot T_{frame} + \phi_{offset}, \quad (24)$$

where T_{frame} represents the frame acquisition period (s), and ϕ_{offset} compensates for system propagation delays, achieving a synchronization accuracy of $\pm 10 \mu\text{s}$, which is essential for demodulation across all channels. The reconstruction domain employed cylindrical coordinates with homogeneous Neumann boundary conditions ($\partial\phi/\partial n=0$), at phantom walls and mixed conditions at electrode interfaces. Multi-frequency data integration was implemented using weighted averaging, calculated as follows:

$$\sigma_{(reconstructed)(x,y,z)} = \frac{\sum_{k=1}^{50} w_k \cdot \sigma_{k(x,y,z)}}{\sum_{k=1}^{50} w_k}, \quad (25)$$

where frequency-specific weights (w_k) combine SNR with penetration depth characteristics. The weighting scheme assigns higher importance to low frequencies for central region reconstruction and emphasizes higher frequencies for boundary definition, represented as follows:

$$w_k = \text{SNR}(f_k) \times \delta(f_k)^\beta, \quad (26)$$

with $\beta = 0.5$ for balanced depth and resolution. This multi-frequency approach provides the spatial richness necessary for conductivity differentiation.

To validate these penetration depth calculations and frequency-dependent weightings, a comprehensive evaluation was performed through established methods of assessment: (1) penetration depth via progressive electrode measurements, (2) spatial resolution through

point spread function analysis (PSF), (3) sensitivity via conductivity perturbation tests, and (4) calculation of a performance index

2.12. Algorithm Selection and Implementation

Following feature extraction and protocol establishment, algorithms were selected to match each organ's data characteristics and reconstruction requirements. For classification tasks, four machine learning approaches were evaluated. TabPFN was chosen as the primary classifier due to its effectiveness with the extracted features from raw spectral data. Three gradient-boosting methods provided comparative baselines: CatBoost for its robust handling of mixed features and overfitting resistance, LightGBM for computational efficiency with feature sets, and XGBoost as the established benchmark with strong regularization capabilities. Tomographic reconstruction required different approaches for 2D and 3D applications. The 3D root conductivity mapping employed a U-Net architecture, whose skip connections excel at reconstructing detailed conductivity patterns from sparse electrode measurements. Filtered Back Projection (FBP) served as the analytical standard for comparison. For 2D fruit quality assessment, SIRT was selected for its stability with circular electrode arrays and effective noise suppression. Additionally, a Modified Back-Projection (MBP) algorithm was developed specifically for detecting defect boundaries:

$$\sigma^* = \operatorname{argmin}_{\sigma} \left[\|J\sigma - \Delta V\|^2 + \lambda \|\nabla \sigma\|^1 \right] \quad (27)$$

where σ^* is the conductivity distribution, J is the Jacobian sensitivity matrix, ΔV is the measured voltage differences, λ controls the regularization strength, and $\|\nabla \sigma\|^1$ is the L1 norm of the conductivity gradient. The $\nabla \sigma$ preserves edges while suppressing noise, essential for localizing defect boundaries.

2.13. System Validation and Physiological Correlation

Following standard bioelectrical protocols, we employ (1) classification accuracy (%) as the primary performance metric and (2) correlation (r) to validate physiological relevance only. Leaf validation employed computation of the relative water content (RWC) through gravimetric analysis. The direct relationship between RWC and bioelectrical properties is well-established through ionic conductivity changes, evidence correlations across multiple crop species [134,135]. It is computed as:

$$RWC (\%) = \frac{W_f - W_d}{W_t - W_d} \times 100, \quad (28)$$

where W_f , represents fresh weight, W_d , represents dry and W_t represents turgid weights. W_f was recorded immediately after harvest. W_t , was recorded after leaves were immersed in distilled water for 4 h at 20 °C. After hydration, surface water was blotted by filter papers before weighing. W_d , followed 12 h desiccation at 70 °C. Constant mass was confirmed every hour checking for less than 0.005 g threshold change. Values outside 50–100% indicated measurement error. Replicate variation remained below 5%. Key requirements included turgid weight exceeding fresh weight, complete surface water removal, and gentle sample handling. Second validation is chlorophyll content. This was measured via SPAD-502Plus that affect cellular capacitance and ion transport. SPAD validations demonstrate high correlations with water stress indicators [135]. The temporal precedence of electrical changes over chlorophyll decline provides additional validation support. Leaf thickness demonstrates correlations with bioelectrical parameters through effects on current distribution pathways.

For fruits, features were correlated with reference metrics using established strawberry assessment protocols, as consistently applied in previous studies. Sugar content (°Brix) was

measured at the equatorial plane, 90° from the ventral suture, validated for representative sugar content in strawberry [136]. Measurements were made using an Atago PAL-3 refractometer. Firmness (N) was measured using a TA.XT2 texture analyzer with a 5 mm probe applied at two opposite cheeks on the equatorial plane [133].

Stem validation employed correlation with its diameter and attached fruit quality (using fruit validation metrics). Productive stems yielded normal-sized fruits with standard quality metrics, and non-productive stems produced smaller, poorly developed fruits. A correlation analysis of all plant organ's optimal features and established reference measurements employed Pearson coefficients, calculated as follows:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}}, \quad (29)$$

where selected bioelectrical features (x_i) (12 features in fruits, 10 features in leaves, 8 features in stems) correlated with validation metrics y_i . Multiple comparison correction employed Bonferroni adjustment with $\alpha = 0.05/m$ for m parameter-metric pairs; 72 for fruits (12 features $\times$ 6 quality metrics), 30 for leaves (10 features $\times$ 3 quality metrics), and 56 for stems (8 features $\times$ 7 quality metrics). Reference measurements followed standardized protocols with uncertainties documented in Table A1.

For tomographic localization quality, relative residual error was calculated as the normalized difference between measured and reconstructed voltage patterns following established tomography protocols.

3. Results

This section presents the experimental results for the validation of the sensor system, which was comprehensively evaluated and calibrated using model crops, strawberries (*Fragaria* $\times$ *ananassa* 'Sweet Charlie').

3.1. Comparative Performance of Electrode Types and Configurations for Organ-Specific Measurements

Electrode performance varied significantly across plant organs, reflecting their distinct properties (Table 1). Values represent mean $\pm$ standard deviation from measurements per configuration. While comprehensive visualization of electrode performance evaluation across all configurations is provided in Supplementary Figure S5.

These stable parameters confirm the non-invasive nature of the contact-based measurements. Tissue damage would normally produce measurement drift, degrade SNR, or increase measurement variation, but none of these effects were observed across all samples. Established electrodes and configurations from previous studies was also employed and validated for non-invasiveness. Hydrogel patches providing minimize stress on leaves, screen-printed electrodes shown to be safe for repeated fruit assessments, and Ag/AgCl electrodes validated for continuous stem monitoring without vascular damage. Combined with stable repeatability (CV < 2.5%), these results verify that the tissue integrity was preserved.

Table 1. Comparative performance of electrode types and configurations for organ-specific spectroscopic measurements.

Organ	Electrode Type	Configuration	Signal Quality (SNR, dB)	Contact Resistance(Ω)	Repeatability (CV, %)	Contact Area (mm ²)
Leaf	Hydrogel Patch	Bipolar	48.2 $\pm$ 1.8	950 $\pm$ 120	2.1 $\pm$ 0.4	3.14
		Tetrapolar	46.1 $\pm$ 1.9	1050 $\pm$ 140	2.6 $\pm$ 0.5	3.14
	Clip Ag/AgCl	Bipolar	42.8 $\pm$ 2.3	1280 $\pm$ 170	3.4 $\pm$ 0.7	3.14
		Tetrapolar	39.6 $\pm$ 2.6	1450 $\pm$ 195	4.1 $\pm$ 0.9	2.83
Fruit	Conical Screen Printed	Bipolar	47.8 $\pm$ 1.6	890 $\pm$ 115	2.3 $\pm$ 0.4	7.07
		Tetrapolar	45.2 $\pm$ 1.8	1020 $\pm$ 135	2.7 $\pm$ 0.5	7.07
	Adhesive Patch	Bipolar	41.3 $\pm$ 2.2	1320 $\pm$ 185	3.5 $\pm$ 0.8	2.83
		Tetrapolar	38.9 $\pm$ 2.5	1480 $\pm$ 210	4.2 $\pm$ 0.9	3.14
Stem	Clip-on Ag/AgCl	Bipolar	42.3 $\pm$ 2.1	1180 $\pm$ 165	3.3 $\pm$ 0.7	7.07
		Tetrapolar	46.8 $\pm$ 1.7	920 $\pm$ 125	2.4 $\pm$ 0.5	5.31
	Clamp Ag/AgCl	Bipolar	35.6 $\pm$ 2.8	1580 $\pm$ 245	5.1 $\pm$ 1.2	4.91
		Tetrapolar	40.1 $\pm$ 2.4	1350 $\pm$ 190	3.8 $\pm$ 0.9	2.83

The tomographic reconstruction required different electrode configurations to ensure uniform current distribution across 32-electrode arrays. Both gold-plated and Ag/AgCl electrodes were evaluated in 2D single-layer and 3D three-layer configurations. Gold-plated electrodes outperformed Ag/AgCl across all metrics: spatial resolution reached 5.5 ± 0.4 mm versus 6.3 ± 0.5 mm in 2D configuration and 5.9 ± 0.4 mm versus 6.8 ± 0.5 mm in 3D configuration, while current injection uniformity achieved $89.2 \pm 1.8\%$ versus $83.7 \pm 2.4\%$, as validated through PSF analysis and FEM modeling in EIDORS. This baseline performances improved further with frequency optimization discussed in the next section.

3.2. Optimal Multi-Scale Frequency Across Plant Organs

The frequency selection protocol in Section 2.8 identified which frequencies produced the strongest bioelectrical signatures for each organ. Statistical analysis revealed distinct dispersion patterns that proved useful for both spectroscopic and tomographic measurements. These optimal frequency ranges matched the dispersion characteristics previously documented in plant studies [62–64]. Table 2 lists the specific frequencies selected for spectroscopic measurements, while Supplementary Figure S6 shows statistical validation and selection process.

All selected frequencies show $p < 0.001$ (statistical significance), Cohen's $d > 1.0$ (effect size), and mutual information $MI > 0.7$. This validation confirms the representation of changes, not random noise or equipment errors.

While in the tomographic frequency selection, detailed in Section 2.11, different frequency ranges were evaluated based on penetration depth, spatial resolution, sensitivity, and overall performance. Lower frequencies penetrated deeper but gave coarser resolution, while higher frequencies provided finer resolution with shallower penetration, as shown in Supplementary Figure S7. Table 3 presents the quantitative results from this evaluation.

Table 2. Optimal multi-scale frequency with statistical validation across plant organs.

Organ	Frequency (kHz)	Cohen's d	Mutual Information
Leaf	0.5	1.34	0.847
	1.0	1.28	0.823
	5.0	1.67	0.912
	10.0	1.45	0.876
	25.0	1.23	0.798
	50.0	1.18	0.765
Fruit	1.0	1.12	0.734
	10.0	1.41	0.856
	50.0	1.78	0.934
	75.0	1.65	0.898
	100.0	1.52	0.867
	200.0	1.34	0.812
Stem	1.0	0.98	0.687
	25.0	1.15	0.743
	100.0	1.34	0.798
	250.0	1.28	0.776
	500.0	1.22	0.754
	1000.0	1.08	0.712

Table 3. Evaluated frequency ranges for tomographic reconstruction.

Application	Frequency Range	Penetration Depth (mm)	Spatial Resolution (mm)	Sensitivity	Performance Index
3D Root	0.01–0.1 kHz	70 ± 8	6.2 ± 0.8	0.85	0.68
Conductivity	0.1–10 kHz	48 ± 3	3.8 ± 0.3	0.71	0.92
Mapping	10–100 kHz	22 ± 3	2.7 ± 0.3	0.34	0.42
2D Fruit	0.1–1 kHz	55 ± 6	5.1 ± 0.6	0.78	0.72
Conductivity	1–50 kHz	28 ± 2	3.1 ± 0.2	0.62	0.94
Localization	50–500 kHz	12 ± 2	2.1 ± 0.3	0.23	0.35

Table 3 reveals that successful conductivity reconstruction requires balancing multiple parameters rather than optimizing any single metric. The performance index (PI) captures this balance and identifies optimal frequency ranges. For 3D root zone mapping, three distinct patterns emerged. The lowest frequencies (0.01–0.1 kHz) penetrated deepest at 70 mm with 0.85 sensitivity, but their poor 6.2 mm resolution merged adjacent zones, making it impossible to distinguish localized water and nutrient uptake regions (PI = 0.68). Mid-range frequencies (0.1–10 kHz) offered the best compromise: 48 mm penetration reached active root zones, 3.8 mm resolution separated individual conductivity gradients, and 0.71 sensitivity detected meaningful changes, yielding the highest PI of 0.92. Higher frequencies (10–100 kHz) achieved 2.7 mm resolution but penetrated only 22 mm, missing deeper variations entirely, with sensitivity dropping to 0.34 (PI = 0.42). Similar trade-offs appeared in 2D fruit localization. Low frequencies (0.1–1 kHz) detected conductivity differences with 0.78 sensitivity but blurred fruit boundaries at 5.1 mm resolution (PI = 0.72). The middle range (1–50 kHz) again proved optimal, balancing 28 mm penetration for complete fruit coverage, 3.1 mm resolution to separate quality regions, and 0.62 sensitivity above discrimination threshold (PI = 0.94). High frequencies (50–500 kHz) provided 2.1 mm resolution but penetrated only 12 mm with an inadequate 0.35 sensitivity (PI = 0.35). These results establish 0.1–10 kHz as optimal for root zone monitoring and 1–50 kHz for fruit quality assessment.

3.3. Optimal Features for Classification

Feature extraction and selection (Sections 2.9 and 2.10) identified organ-specific parameter subsets achieving optimal classification, all with statistical significance ($p < 0.001$). Table A2 lists these parameters and weights. Supplementary Figure S8 shows the RFECV results for optimal feature selection. Each organ has different bioelectrical features matching its physiology. Fruits have 12 parameters dominated by high-frequency measurements (50–100 kHz) that detect ripening-related membrane changes and sugar accumulation. Leaves have 10 features primarily at low frequencies (0.5–5 kHz), where water stress directly affects ionic conductivity. Stems have 8 parameters, including two separate Cole–Cole relaxation times, revealing distinct pathways for water versus nutrient transport. Despite organ differences, a clear hierarchy emerged. Basic electrical properties (phase angles, resistances) always ranked highest, followed by Cole–Cole relaxation parameters capturing tissue dynamics, then derived metrics providing Supplementary Information. This consistent pattern across organs aligns with bioelectrical theory and demonstrates why effective plant monitoring requires organ-specific feature selection rather than one-size-fits-all approaches.

3.4. Performance Matrix and Confusion Matrices for Classification

Comparative evaluation of machine learning algorithms revealed TabPFN outperformed CatBoost, LightGBM, and XGBoost across all organs, achieving 98.3% accuracy for fruits, 95.8% for leaves, and 88.2% for stems (Figure 8). These accuracy levels reflect the directness of electrical–biological coupling in each organ. Fruit classification succeeded best because ripening creates clear conductivity shifts through sugar accumulation and cell wall softening. Leaf assessment performed well since the water content directly determines ionic conductivity. Stem productivity assessment measured current vascular transport properties to indicate production potential. Misclassification patterns provided additional insights. Errors clustered at physiological transition points rather than occurring randomly. Fruits misclassified were typically transitioning between commercial maturity and physiological ripeness, where electrical properties naturally overlap. Similarly, leaves at intermediate water stress levels and stems transitioning between high- and low-productivity states showed higher error rates, as their electrical signatures occupied the boundary zones between distinct categories.

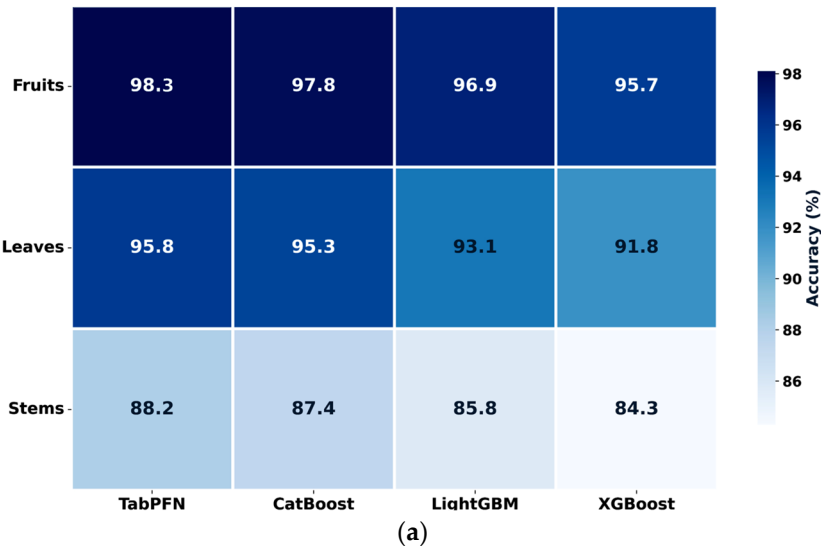


Figure 8. Cont.

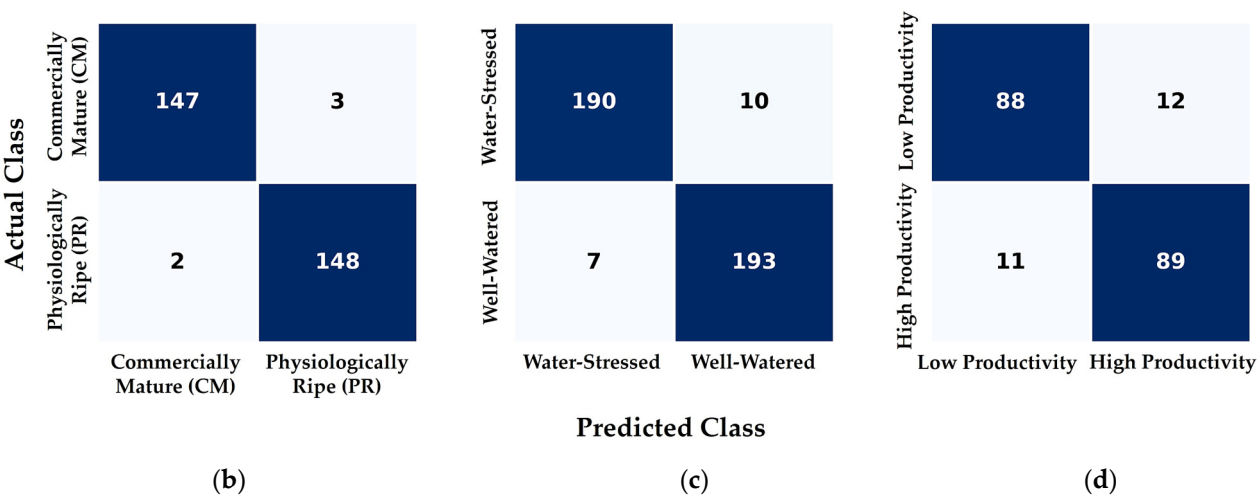


Figure 8. Algorithm performance comparison and TabPFN classification results: (a) algorithm performance heatmap showing accuracy percentages across four machine learning algorithms (TabPFN, CatBoost, LightGBM, and XGBoost) for three organ types; (b–d) TabPFN confusion matrices detailing classification performance for (b) fruit, (c) leaf water status, and (d) stem productivity.

3.5. Correlation Results

The correlation analysis served solely to validate that bioelectrical measurements reflect real physiological changes. Full correlation details appear in Tables A4–A6 and Figure S9. A clear pattern emerged across organs that mirrors measurement directness. Fruits showed the strongest correlations because ripening directly alters electrical properties through sugar and ion changes. Leaves performed well since water loss immediately affects conductivity. Stems had the weakest correlations, which makes sense given that current vascular activity must predict productivity. Interestingly, chemical parameters consistently outperformed physical ones. In fruits, sugar content and pH correlated better than weight or size. This suggests bioelectrical measurements excel at detecting internal chemical changes rather than external physical or morphological traits. The measurement frequencies also matched organ physiology. Fruits responded best at higher frequencies where internal changes dominate, while leaves preferred lower frequencies where water-related ion transport occurs. This validation approach follows standard practice in bioelectrical studies, where classification provides practical performance while correlations confirm physiological relevance.

3.6. Tomography Results

Temporal 3D root zone conductivity mapping over 49 days revealed conductivity patterns between stressed and control plants (Figure 9). Both groups initially showed blue regions (0.4–0.5 S/m) during the first week, indicating adaptation to the environment following transplantation.

Control plants subsequently developed healthy root systems visible as high-conductivity zones (orange to red, 0.7–0.8 S/m) concentrated in the upper root zone where primary water uptake occurs. These values remained stable throughout monitoring. In contrast, stressed plants under water and nutrient reduction showed progressive decline from an initial 0.6 S/m to below 0.4 S/m by day 49, appearing as expanding cyan blue regions. This 33% reduction suggests reduced ionic transport due to water and nutrient deprivation affecting the metabolic activity. The color progression from warm to cool tones reveals three distinct stress phases: initial resilience (days 0–14) with minimal change, rapid deterioration (days 14–28) as blue zones expanded inward from the root periphery, and stabilization at degraded levels after day 28 with persistent blue coloration. These measurements represent

electrical conductivity patterns. While in algorithm evaluation, U-Net achieved a better resolution (2.6 ± 0.3 mm) than FBP (2.8 ± 0.3 mm), though FBP processed faster (8.7 ± 1.4 vs. 24.3 ± 3.2 s per timepoint).

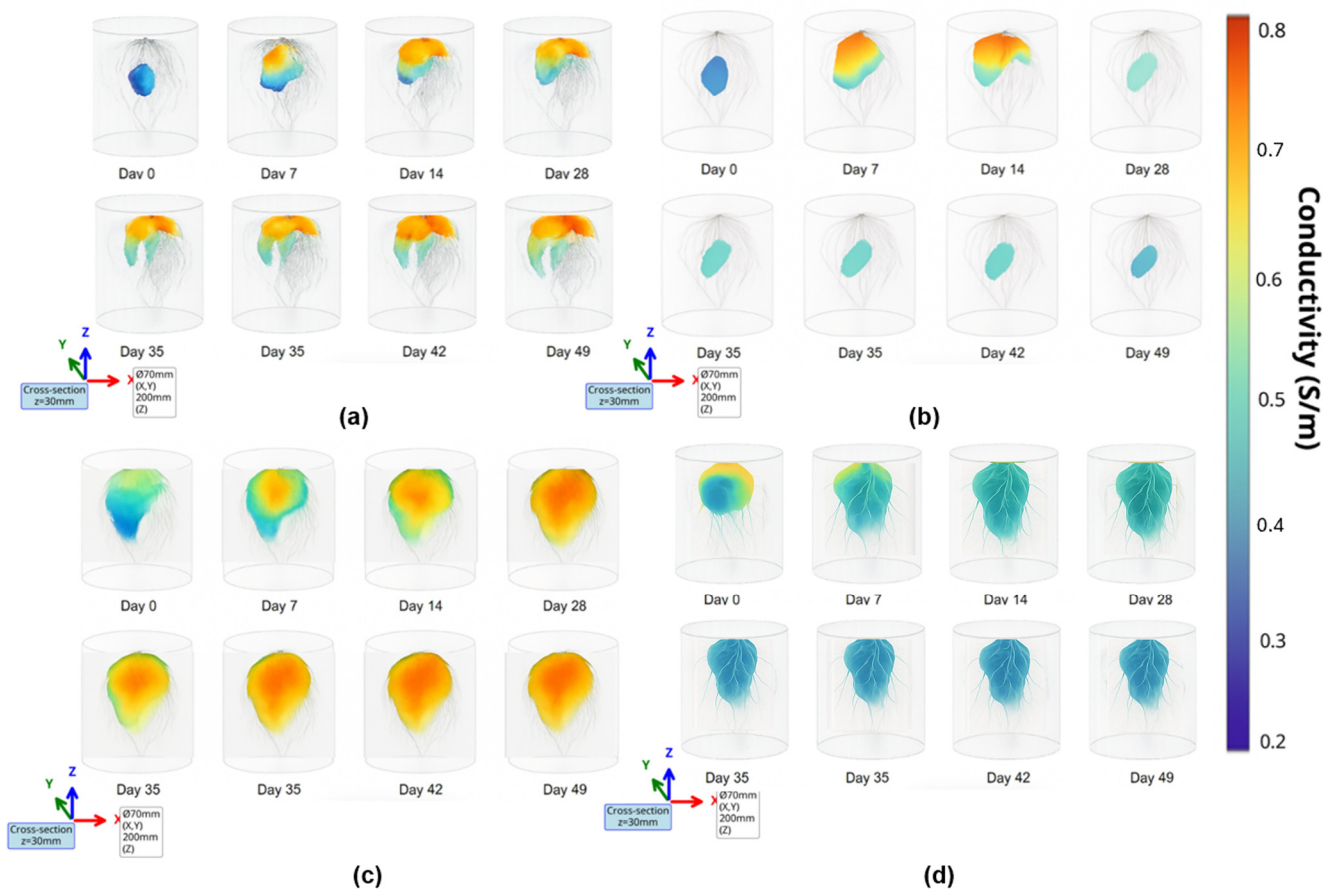


Figure 9. Temporal 3D root conductivity mapping showing (a) normal management with U-Net reconstruction, (b) stressed management with U-Net, (c) normal management with FBP, and (d) stressed management with FBP over 49 days.

Figure 10 illustrates the postharvest strawberry quality assessment through conductivity localization starting from setup configurations (a–c), followed by SIRT (d–f) and Modified Back-Projection (g–i) reconstructions. Figure 10a–c shows the 2D tomographic reconstruction for postharvest fruit quality sorting using the three test configurations: uniform good-quality fruits, mixed quality with central defects, and uniform poor-quality fruits. Good-quality fruits showed high conductivity (≥ 0.5 S/m), while poor-quality fruits exhibited low conductivity (≤ 0.3 S/m), enabling clear differentiation.

Conductivity values were normalized (0–1 scale) to enable direct comparison between reconstruction algorithms using a unified color bar. Both SIRT and Modified Back-Projection successfully differentiated fruit quality across all three test configurations. SIRT reconstructions (Figure 10d–f) clearly identified uniform good quality, central poor-quality clusters, and distributed defects through distinct conductivity patterns. Modified Back-Projection (Figure 10g–i) produced the same quality differentiation but with notably sharper boundaries between good and poor fruit regions, particularly visible at quality transition zones. This boundary sharpness advantage aligns with MBP’s superior resolution metrics reported above. Modified Back-Projection achieved better resolution (2.8 ± 0.3 mm) and lower error ($8.1 \pm 0.9\%$) while processing faster at 13.7 ± 2.1 s per frame. SIRT required 19.2 ± 3.1 s with slightly coarser resolution (3.0 ± 0.3 mm) and higher error ($10.3 \pm 1.2\%$).

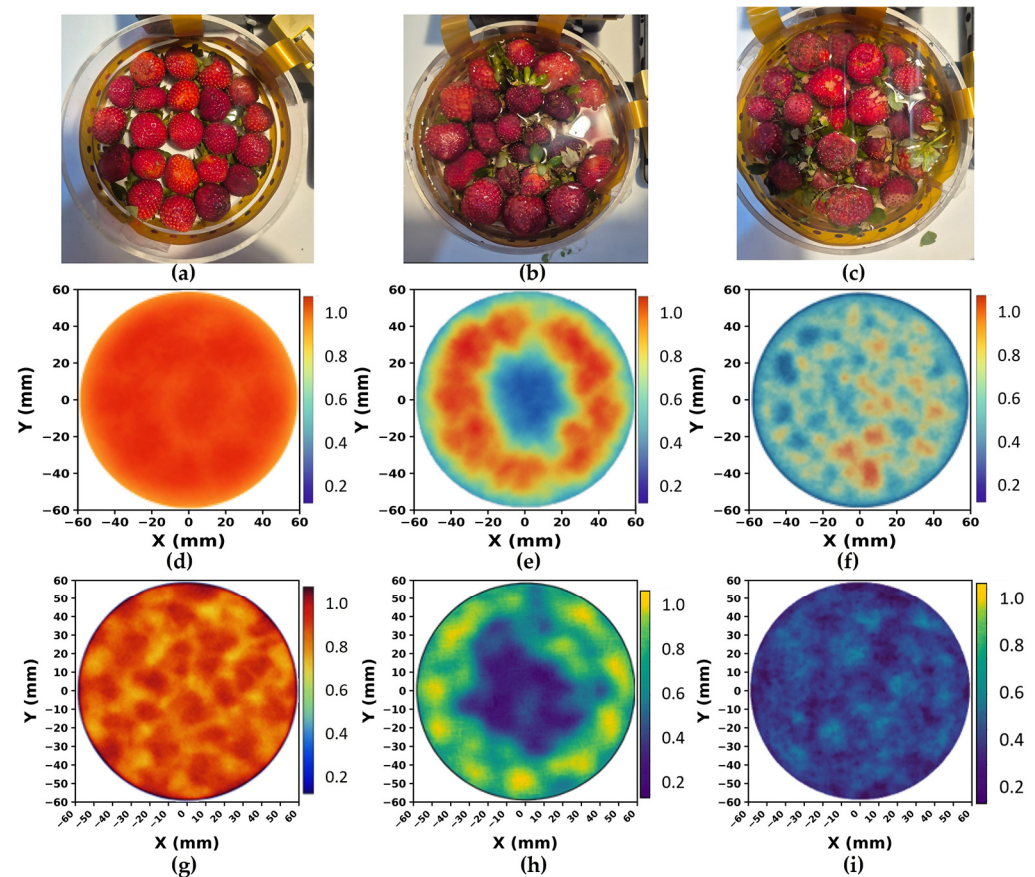


Figure 10. Postharvest strawberry quality assessment through conductivity localization showing (a–c) original fruit arrangements with (a) uniform good quality, (b) mixed quality with central defects, (c) uniform poor quality, (d–f) SIRT reconstructions, and (g–i) Modified Back-Projection reconstructions. Color bar indicates conductivity (S/m).

These tomographic capabilities were validated through focused sample sizes designed for system demonstration. Root measurements were performed on four plants, generating 41,664 individual observations (7 time points $\times$ 1488 measurements per scan), while fruit assessment involved 100 specimens, producing 34,720 measurements. This measurement density approach is consistent with established tomography validation protocols [60,94,106], where spatial and temporal multiplicity provide statistical power for technology validation despite limited biological replication. Similar studies have successfully demonstrated system capabilities with limited samples [44,45,51,94], as the emphasis is on validation rather than biological variation [96–98]. While these sample sizes were sufficient to demonstrate system performance, future agricultural deployment will require expanded trials across cultivars and seasons to establish population-level validity.

4. Discussion

This study presents a non-invasive, multimodal, and multiscale bioelectrical sensor system achieved through unified hardware integration and systematic methodology for organ-specific feature extraction. These features were correlated with physiological reference metrics for validation. The system further incorporates multimodality through 2D and 3D tomographic imaging. A proof-of-concept demonstration across multiple organs of *Fragaria* $\times$ *ananassa* (cv. ‘Sweet Charlie’) confirmed the system’s capability for holistic plant assessment and established a transferable foundation for broader applications across cultivars and crops.

This study addresses the fragmentation that limits existing bioelectrical approaches. Spectroscopy and tomography, previously deployed separately, here function as complementary outputs of a single system. Spectroscopy provides organ-specific indicators in leaves, fruits, and stems, while tomography enables spatial conductivity imaging in roots and postharvest fruits, offering converging physiological views across all plant organs. Direct cross-validation between modalities was not performed as biological metrics remain organ-specific, but the integrated framework (Table A3) enabled the following validated results.

Fruit categorization achieved 98.3% accuracy, comparable to standard and advanced optical methods. Leaf water status reached 95.8%, matching hyperspectral and developed approaches [137]. Stem productivity attained 88.2%, similar to existing electrochemical methods (detailed comparisons in Table A4). While some methods report higher accuracy, they detect only surface changes after symptom onset. This system identifies internal physiological changes within the reversible stress window, enabling proactive intervention.

These classification accuracies reflect the integrated assessment approach employed. The stem productivity assessment applied integrated stress variables, recognizing that plant responses arise from multiple interacting factors as documented in stress assessment literature [5,10,23]. This approach is consistent with methodologies reported in previous studies [53,68,73]. Similarly, fruit and leaf assessments were based on established studies, incorporating multiple parameters linked to standard quality traits [138–141] and to progressive water stress effects [142–144], respectively.

The correlation analysis further validates these results by confirming that the extracted features capture genuine physiological processes (Appendix A, Tables A5–A7), with the correlation map presented in Supplementary Figure S9. Specifically, each organ exhibits distinct mechanisms that simultaneously affect both bioelectrical properties [145,146] and reference parameters.

In leaves, water stress drives parallel changes in RWC and bioelectrical conductivity through altered ionic regulation and conductivity [68,85]. SPAD correlations reflect stress pathways affecting both photosynthesis and conductivity, with electrical changes preceding chlorophyll decline [135,147,148]. Leaf thickness further influences current distribution pathways [149,150]. In fruits, ripening simultaneously triggers pectinase activity, ATPase modulation, and vacuolar changes that affect factors like sugar accumulation (Brix), conductivity, and structural changes [95,132,136], explaining strong correlations with quality metrics [70,89,95,120]. In stems, vascular transport processes, like xylem flow, phloem loading, and cambial activity, influence productivity metrics and electrical conductivity [125,127,131]. These parallel processes generate strong correlations without implying causation, following established bioelectrical validation approaches where classification accuracy provides primary performance metrics while correlations confirm physiological relevance [53,68,73,95,125]. This validates that bioelectrical measurements capture genuine physiological processes rather than artifacts.

Beyond these spectroscopic assessments, the system's tomographic capabilities extend measurements to spatial imaging. Root system 3D mapping achieved 2.6–2.8 mm resolution, with conductivity patterns (0.8 to 0.4 S/m decline) matching documented stress responses [60,94,106,147,148], though direct physiological validation remains future work. Postharvest 2D fruit tomography achieved 2.8–3.0 mm resolution. These capabilities provide localized physiological information impossible with spectroscopic point measurements alone, demonstrating multimodal integration.

The system's technical innovations succeeded through organ-specific electrode matching. Leaves and fruits have homogeneous tissues that maintain stable conductivity with bipolar measurements [95,109,111,120]. Stems, however, contain conductive vas-

cular bundles within resistive tissue, creating heterogeneity that causes errors in bipolar mode [61,93,125,127,131]. Tetrapolar configuration corrects this by separating current injection from voltage sensing [61,125,131], consistent with bioelectrical theory [54,63]. This tissue-electrode matching explains why homogeneous organs achieve high SNR with bipolar configurations while heterogeneous stems require tetrapolar arrangements.

To address how the system achieves multimodal, multiscale, and holistic assessment, Table A3 summarizes the validation framework. Detailed technical specifications are provided in Table A8.

These technical capabilities involve practical trade-offs. Unlike rapid advanced optical methods, the system detects cellular changes before visible symptoms, enabling intervention to prevent the 20–40% losses typical of reactive management. As of now, the system's architecture incorporates parallel multiplexing capability, though deployment awaits field validation for future scalability. This positions the system as a complementary tool for high-value crops or research requiring early stress detection or detailed physiological data.

While the current validation focused on strawberry (*Fragaria × ananassa* 'Sweet Charlie'), the system's capabilities demonstrated here apply across crops. Each crop will require threshold calibration, which is standard practice for any assessment method, with this study providing the methodological framework. Future work involves multi-cultivar validation, automated calibration algorithms, and integration with farm management systems.

5. Conclusions and Recommendations

This study developed and validated a unified bioelectrical sensor system for non-invasive, multimodal, and multiscale plant assessment. As a proof of concept using strawberry (*Fragaria × ananassa* 'Sweet Charlie'), the system achieved high accuracy across multiple organs: 98.3% for fruit categorization, 95.8% for leaf water status, and 88.2% for stem productivity. Additionally, tomographic imaging reached 2.6–2.8 mm resolution for 3D root mapping and 2.8–3.0 mm for 2D fruit defect sorting. The platform integrates spectroscopy, which captures multiscale responses from cellular to tissue levels, with tomography, which provides spatial visualization. Strong physiological correlations confirmed that the features detected represent genuine physiological variations.

While validation was limited to a single cultivar and stem assessment remained indirect, these represent development opportunities rather than fundamental limitations. Future work should focus on enabling parallel measurements, expanding to other crops, and building automated calibration algorithms. Integration with farm management systems and standardized deployment protocols will allow for field-scale adoption. In the longer term, IoT implementation, controlled single-factor experiments, and crop-specific bioelectrical libraries will establish comprehensive assessment networks.

By detecting stress before irreversible damage, this proactive approach helps prevent the 20–40% yield losses typical of reactive management. It also supports the 40% production increase required by 2050, contributing to sustainable intensification in the face of climate change.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/technologies13110496/s1>, Figure S1. Bipolar (2-electrode) configuration circuit implementation for bioelectrical spectroscopy. Figure S2. Tetrapolar (4-electrode) configuration circuit implementation for bioelectrical spectroscopy. Figure S3. 32-electrode array configuration with multi-stage multiplexing architecture for tomographic applications. Figure S4. Precision programmable resistor load network for bioelectrical sensor system calibration. Figure S5. Electrode performance evaluation for bioelectrical spectroscopy (a–c) and tomography (d–f) measurements across strawberry plant organs. Figure S6. Statistical validation and multi-criteria frequency selection showing (a–c) $-\log_{10}(p\text{-values})$ from *t*-tests and (d–f) normalized scores integrating sta-

tistical significance, effect size, and mutual information for leaves, fruits, and stems respectively. Figure S7. Frequency-dependent sensitivity and penetration analysis for tomographic applications showing (a) radial sensitivity profiles, (b) frequency response optimization, (c) 3-layer array root conductivity reconstruction, and (d) 2D fruit conductivity reconstruction. Figure S8. Recursive feature elimination with cross-validation (RFECV) results for optimal feature selection across (a) fruit maturity, (b) leaf water status, and (c) stem productivity classification tasks. Figure S9. Bioelectrical feature-validation metric correlation matrices for (a) fruits showing 12 features vs. 6 established validation metrics, (b) leaves showing 10 features vs. 3 metrics, and (c) stems showing 8 features vs. 7 metric.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Reference methods and uncertainties for validating bioelectrical correlations with physiological parameters.

Organ	Parameter	Instrument/Method	Measurement Uncertainty	Range	References
Fruit	Sugar content (°Brix)	Atago PAL-3 refractometer (Atago Co., Ltd., Tokyo, Japan)	±0.2 °Brix	6–14 °Brix	[95,132,136]
	Firmness (N)	TA.XT2 texture analyzer (Stable Micro Systems, Godalming, UK)	±0.15 N	1.5–4.5 N	[133,136]
	Weight (g)	Mettler Toledo MA204 balance (Mettler Toledo, Columbus, OH, USA)	±0.003 g	8–25 g	[86,95,136]
	Diameter (mm)	Mitutoyo 500-196-30 caliper (Mitutoyo Corporation, Kawasaki, Japan)	±0.03 mm	20–40 mm	[90,91,95]
	pH	Mettler Toledo FP20 pH meter (Mettler Toledo, Columbus, OH, USA)	±0.02 pH	3.2–4.0	[132,136]
	EC (mS/cm)	HI 9033 conductivity meter (Hanna Instruments, Woonsocket, RI, USA)	±0.05 mS/cm	2.0–5.0 mS/cm	[95,120,132]
Leaf	RWC (%)	Gravimetric method	±3%	65–95%	[68,85,134]
	Chlorophyll (SPAD)	SPAD-502Plus chlorophyll meter (Konica Minolta, Tokyo, Japan)	±1.5 units	25–45 SPAD	[85,88,135]
	Thickness (mm)	Mitutoyo 500-196-30 caliper (Mitutoyo Corporation, Kawasaki, Japan)	±0.03 mm	0.25–0.45 mm	[68,85,86]

Table A1. Cont.

Organ	Parameter	Instrument/Method	Measurement Uncertainty	Range	References
Stem	Diameter (mm)	Mitutoyo CD-6AX caliper (Mitutoyo Corporation, Kawasaki, Japan)	± 0.03 mm	4–12 mm	[93,125]
	Sugar content (°Brix) *	Atago PAL-3 refractometer (Atago Co., Ltd., Tokyo, Japan)	± 0.2 °Brix	6–14 °Brix	[95,132,136]
	Firmness (N) *	TA.XT2 texture analyzer (Stable Micro Systems, Godalming, UK)	± 0.15 N	1.5–4.5 N	[133,136]
	Weight (g) *	Mettler Toledo MA204 balance (Mettler Toledo, Columbus, OH, USA)	± 0.003 g	8–25 g	[86,95,136]
	Diameter (mm) *	Mitutoyo 500-196-30 caliper (Mitutoyo Corporation, Kawasaki, Japan)	± 0.03 mm	20–40 mm	[90,91,95]
	pH *	Mettler Toledo FP20 pH meter (Mettler Toledo, Columbus, OH, USA)	± 0.02 pH	3.2–4.0	[132,136]
	EC (mS/cm) *	HI 9033 conductivity meter (Hanna Instruments, Woonsocket, RI, USA)	± 0.05 mS/cm	2.0–5.0 mS/cm	[95,120,132]

* Quality metrics measured from fruits attached to the assessed stems.

Table A2. Optimal bioelectrical features for plant organ classification.

Organ Type (Sample Size, Accuracy)	Rank	Feature Name	Type/Frequency	Relative Weight
Fruits ($n = 300$, $98.3\% \pm 1.0\%$)	1	θ (fruit _{50kHz})	Phase angle at 50 kHz	0.187
	2	τ (fruit _{50kHz})	Cole-Cole parameter	0.172
	3	L (fruit _{100kHz})	Inductance at 100 kHz	0.158
	4	Q (fruit _{50kHz})	Derived at 50 kHz	0.144
	5	α (fruit _{β-dispersion})	Dispersion parameter	0.131
	6	C_m (fruit _{50kHz})	Capacitance at 50 kHz	0.118
	7	R_0 (fruit _{1kHz})	Resistance at 1 kHz	0.105
	8	R_∞ (fruit _{200kHz})	Resistance at 200 kHz	0.092
	9	Z (fruit _{10k/100k})	Impedance ratio	0.087
	10	Morphological (asymmetry)	Derived geometric	0.081
	11	Spectral centroid (fruit _{β-dispersion})	Statistical	0.074
	12	Peak power (fruit _{50kHz})	Derived	0.068
Leaves ($n = 400$, $95.8\% \pm 1.6\%$)	1	θ (leaf _{5kHz})	Phase angle at 5 kHz	0.156
	2	R_0 (leaf _{0.5kHz})	Resistance at 0.5 kHz	0.142
	3	C (leaf _{5kHz})	Capacitance at 5 kHz	0.134
	4	τ (leaf _{5kHz})	Cole-Cole at 5 kHz	0.128
	5	R_∞ (leaf _{50kHz})	Resistance at 50 kHz	0.121
	6	Z (leaf _{1k/25k})	Impedance ratio	0.115
	7	α (leaf _{α-dispersion})	Dispersion parameter	0.108
	8	Z (ratio leaf _{5k/50k})	Impedance ratio	0.102
	9	Spectral centroid (leaf _{α-dispersion})	Statistical	0.096
	10	Derivative magnitude (leaf _{α-average})	Derived	0.089
Stems ($n = 200$, $88.2\% \pm 1.9\%$)	1	θ (stem _{100kHz})	Phase angle at 100 kHz	0.198
	2	τ_1 (stem _{100kHz})	Cole-Cole parameter	0.176
	3	τ_2 (stem _{500kHz})	Cole-Cole parameter	0.149
	4	Z (ratio stem _{1k/250k})	Impedance ratio	0.132
	5	α (stem _{α-dispersion})	Dispersion parameter	0.118
	6	C_m (stem _{100kHz})	Capacitance at 100 kHz	0.097
	7	R_0 (stem _{25kHz})	Resistance at 25 kHz	0.084
	8	Coupling factor (stem)	Derived	0.073

Table A3. Framework for achieving multimodal, multiscale, and holistic plant assessment.

Assessment	Implementation	Organ Coverage	Validation Outcome
Multimodal	Spectroscopy (bipolar/tetrapolar)	Leaves, Fruits, Stems	Accurate classification (95.8%, 98.3%, 88.2%)
	Tomography (2D & 3D arrays)	Fruits, Roots	Spatial resolution 2.6–3.0 mm; conductivity-based root zone mapping and fruit defect sorting
Multiscale	α -dispersion	Leaves	Captures water status dynamics
	β -dispersion	Fruits	Market-based fruit quality sorting
	Dual dispersion	Stems	Reflects vascular transport and stem productivity
Holistic	Multi-organ protocol on single platform	All four organs	Unified hardware with physiologically validated features

Table A4. Comparison of the proposed bioelectrical sensor system with standard and advanced methods reported in the literature.

Method	Performance Type and Metrics	Detection Type	Key Limitations	References
Fruit Quality Assessment				
Hyperspectral imaging + AI	Classification: 90–99%	Reactive	Equipment cost, surface only,	[24,26,137,140]
VIS-NIR spectroscopy	Regression (R^2): 0.73–0.91	Reactive	Cost, Species-specific, Lighting dependent	[27,139]
Portable VIS-NIR	Regression (R^2): 0.82–0.89	Reactive	Single species, Lighting dependent, Inconclusive	[27,65,141]
Advanced optical spectral	Classification: 85–98%	Reactive	Limited to optical parameters, affected by light	[87,88,138]
Thermal imaging	Classification: 73–89%	Reactive	Environment dependent, surface temp only	[28–30,83]
Chlorophyll fluorescence	Detection: 82–87%	Semi-proactive	Limited to single parameter	[28–32]
Electrochemical spectroscopy	Classification: 82–95%	Semi-proactive	Limited features, Limited penetration,	[52,53,64,95]
Molecular	Detection: 70–85%	Reactive	Destructive sampling	[33–36]
This Study	Classification: 98.3%	Proactive	Contact required, Low-throughput	Present work
Leaf Relative Water Content				
Spectral indices	Regression (R^2): 0.65–0.78	Semi-proactive	Surface only, Inconclusive in field calibration	[27,88,142]
Hyperspectral reflectance	Regression (R^2): 0.71–0.83	Semi-proactive	Equipment cost, Lab conditions only	[24,88,143]
Hyperspectral stress	Classification: 83–89%	Semi-proactive	Complex, Equipment cost, Lab conditions only	[24–26]
Plant-based sensors	Correlation (r): 0.75–0.85	Monitoring	Fixed installation, Environment dependent	[40,77,144]
Thermal imaging	Detection: 73–89%	Semi-proactive	Environment dependent, surface temp only	[28–32]
Chlorophyll fluorescence	Classification: 80–85%	Semi-proactive	Dark adaptation, affected by light and radiation	[31,32,147–149]
Terahertz spectroscopy	Detection: 76–82%	Semi-proactive	Limited features, Limited penetration	[48–50]
Electrochemical spectroscopy	Classification: 87–90%	Semi-proactive	No feature extraction, Limited features, Limited penetration	[53,67,68,85]

Table A4. Cont.

Method	Performance Type and Metrics	Detection Type	Key Limitations	References
Wearable sensors, IoT networks	System dependent	Monitoring	Power/durability, Integration complexity	[37–41]
This Study	Classification: 95.8% ± 1.6%	Proactive	Contact required, Low-throughput compared to advanced imaging	Present work
Stem Assessment				
Visual inspection	Accuracy: 70–75%	Reactive	Subjective	[70,92,93]
Electrochemical spectroscopy	Classification: 87%	Proactive	Specific to peduncle only	[124–131]
Pedicle Assessment	Correlation (r): 0.65–0.72	Reactive	Subjective Manual measurement, Operator-dependent	[92,93]
Sap flow sensors	Correlation (r): 0.70–0.80	Reactive	Limited point measurement	[77,127,144]
This Study	Classification: 88.2%	Proactive	Indirect validation	Present work
Root Mapping				
Electrochemical Tomography	Resolution: 5–10 mm	Sequential	Low resolution	[56,57,94]
X-ray micro-CT	Resolution: 0.5–2 mm	Static	Radiation exposure	[43–45]
MRI	Resolution: 1–3 mm	Time-series	Expensive equipment	[50,51]
Ground penetrating radar	Depth: 50–200 mm	Single sweep	Soil dependent	[57,60,94]
Conductivity root mapping	Resolution: 8–12 mm	Continuous	Limited penetration	[56,59,60]
This Study	Resolution: 2.6–2.8 mm	Real-time	Phantom-grown only	Present work
Fruit Defect Detection				
X-ray imaging	Detection: 85–92%	Static	Radiation required	[44,45]
NIR transmittance	Classification: 78–86%	Single scan	Translucent only	[27,65,139]
Acoustic analysis	Classification: 75–83%	Pulse response	Noise sensitive	[89–91]
Previous 2D EIT	Resolution: 4–6 mm	Sequential	Poor boundaries	[56,61,95]
MRI internal imaging	Resolution: 1–2 mm	Time-series	Very expensive	[49–51]
This Study	Resolution: 2.8–3.0 mm	Non-invasive	Binary defect detection only	Present work

Table A5. Correlation coefficients between optimal bioelectrical features and key quality attributes across all fruit samples (*n* =300), spanning both physiologically ripe and commercially mature categories.

Bioelectrical Parameter	Brix Content (° Bx)	Firmness (N)	Weight (g)	Diameter (mm)	Juice pH	Juice EC (mS/cm)
θ (fruit _{50kHz})	0.923	0.912	0.687	0.654	0.843	0.896
τ (fruit _{50kHz})	0.908	0.894	0.672	0.641	0.829	0.881
L (fruit _{100kHz})	0.896	0.887	0.698	0.665	0.856	0.874
Q (fruit _{50kHz})	0.887	0.878	0.681	0.648	0.834	0.869
α (fruit _{β-dispersion})	0.874	0.865	0.663	0.631	0.821	0.856
C _m (fruit _{50kHz})	0.869	0.858	0.656	0.624	0.812	0.847
R ₀ (fruit _{1kHz})	0.856	0.847	0.649	0.617	0.798	0.834
R∞ (fruit _{200kHz})	0.863	0.852	0.671	0.639	0.805	0.841
Z (fruit _{10k/100k})	0.847	0.836	0.692	0.659	0.789	0.823
Morphological (asymmetry)	0.834	0.823	0.678	0.645	0.776	0.812
Spectral centroid (fruit _{β-dispersion})	0.821	0.812	0.665	0.632	0.763	0.798
Peak power (fruit _{50kHz})	0.812	0.801	0.658	0.625	0.754	0.789

Table A6. Correlation coefficients between optimal bioelectrical features and key quality attributes across all leaf samples ($n=400$), spanning both well-watered and water-stressed categories.

Bioelectrical Parameter	Water Content (%)	Chlorophyll (SPAD)	Thickness (mm)
θ (leaf _{5kHz})	0.834	0.821	0.808
R_0 (leaf _{0.5kHz})	0.823	0.812	0.798
C (leaf _{5kHz})	0.812	0.801	0.789
τ (leaf _{5kHz})	0.801	0.789	0.776
R_∞ (leaf _{50kHz})	0.789	0.778	0.765
Z (leaf _{1k/25k})	0.778	0.767	0.754
α (leaf _{α-dispersion})	0.767	0.756	0.743
Z (ratio leaf _{5k/50k})	0.756	0.745	0.732
Spectral centroid (leaf _{α-dispersion})	0.745	0.734	0.721
Derivative magnitude (leaf _{α-average})	0.734	0.723	0.712

Table A7. Correlation coefficients between optimal bioelectrical features and key quality attributes across all stem samples ($n=200$), spanning both productive and non-productive categories.

Parameter	Stem Diameter (mm)	Fruit Brix (° Bx) *	Fruit Firmness (N) *	Fruit Weight (g) *	Fruit Thickness (mm) *	Fruit pH *	Fruit EC (mS/cm) *
θ (stem _{100kHz})	0.712	0.698	0.584	0.521	0.487	0.634	0.671
τ_1 (stem _{100kHz})	0.698	0.685	0.571	0.508	0.474	0.621	0.658
τ_2 (stem _{500kHz})	0.685	0.672	0.558	0.495	0.461	0.608	0.645
Z (ratio stem _{1k/250k})	0.672	0.659	0.545	0.482	0.448	0.595	0.632
α (stem _{α-dispersion})	0.659	0.646	0.532	0.469	0.435	0.582	0.619
C_m (stem _{100kHz})	0.646	0.633	0.519	0.456	0.422	0.569	0.606
R_0 (stem _{25kHz})	0.633	0.620	0.506	0.443	0.409	0.556	0.593
Coupling factor (stem)	0.620	0.607	0.493	0.430	0.396	0.543	0.580

* All fruit metrics were taken from fruits attached to the stem.

Table A8. Hardware implementation and core processes in the bioelectrical measurement system.

Process	Hardware Implementation
Signal Generation	AD9833 DDS + AD835 multiplier
Electrode Routing	ADG714, ADG1404, ADG1408/1409
Input Protection	SMAJ5.0A TVS + EMI filtering
Signal Conditioning	3-stage RC networks: HPF + BPF + LPF
Current Source	Howland: OPA2376/AD5171/AD5663
Voltage Buffering	OPA333 with guard drive
Instrumentation	INA333 + sense resistors
Reference Elements	4.7 k Ω (H-bridge), calibration resistors
Data Acquisition	ADS1256 (24-bit) + OPA4188 + REF5025
System Control	STM32H755 + XC7A35RT FPGA
Power System	Linear ± 12 V (LM7812/7912)

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