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Machine learning-based analysis of electrical impedance spectroscopy for predicting plant gravimetric dynamics

Harpreet Singh [a,*,1], Divisha Garg [a,1], Lee Bar-On [b,d], Adi Avni [c], Yosi Shacham-Diamand [b,d]

[a] Department of Computer Science Engineering, Thapar Institute of Engineering and Technology, Patiala, 147004, India
[b] Department of Electrical Engineering, Tel-Aviv University, Israel
[c] School of Plant Sciences and Food Security, Tel Aviv University, Israel
[d] Scojen Institute of Synthetic Biology, Reichman University, Israel

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ABSTRACT

Sensor-driven field monitoring in precision agriculture requires innovative solutions for real-time plant assessment. This study introduces a novel four-point impedance spectroscopy technique integrated with machine learning algorithms to evaluate plant physiological status under field conditions. A dual experimental setup, combining a gravimetric system with a custom electrical impedance module, enabled synchronized data acquisition. The proposed machine learning ensemble achieves a coefficient of determination (R^2) of 0.855 in predicting plant gravimetric dynamics, thus, outperforming conventional models and reducing error significantly. These findings support the advancement of impedance-based analytics as a scalable, non-invasive approach for large-scale agricultural monitoring.

1. Introduction

1.1. Background and importance of the study

Food security and rising agricultural yields have emerged as one of this century's most critical and complex subjects (Omokpariola et al., 2025; FAO, 2020). Many large projects focus on integrating science and technology into agricultural methods to improve both the availability and quality of produce, an approach known as precision agriculture. The success of precision agriculture relies heavily on efficient data handling, management, and decision-making (Liu et al., 2021b). Advances in science and technology have driven the development of precision agriculture, a field that integrates cutting-edge technologies for real-time monitoring, analysis, and decision-making in farming. Precision agriculture employs a range of sensing technologies, including remote sensing, hyperspectral imaging, and sensor networks, to optimize resource utilization and improve crop yield (Liu et al., 2021b). However, the effective handling and processing of large-scale agricultural data remains a significant challenge. The integration of Machine Learning (ML) and Artificial Intelligence (AI) has shown great promise in overcoming these challenges by enabling automated decision-making based on complex sensor data (Shu et al., 2021). Among various sensing techniques, Electrical Impedance Spectroscopy (EIS) has emerged as a non-invasive and cost-effective method for assessing plant health and physiological responses under varying environmental conditions (Abdalla et al., 2021; Lin et al., 2021). EIS measures the electrical properties of plant tissues, providing insights into water content, nutrient uptake, transpiration rates, and metabolic activities. The impedance of a plant refers to the opposition to the flow of electrical current within a plant. The higher the impedance, the harder it is for the current to flow. It is a complex electrical quantity composed of two key components: resistance (R) and reactance (X), both of which reflect different physiological aspects of the plant (Macdonald, 1992). Resistance determines the plant's ability to conduct electrical energy (Macdonald, 1992) and reactance represents the plant's ability to store electrical charge. Changes in impedance can indicate variations in plant hydration, stress conditions, and overall health status, making it a valuable tool for precision agriculture (Lopez et al., 2024).

Plant gravimetric behavior refers to the changes in mass or weight of the plant system due to external factors such as fluid movement, moisture retention, or mechanical interactions. In this study, gravimetric behavior is analyzed to understand how the plant responds to varying conditions, which plays a crucial role in monitoring plant health and optimizing agricultural practices. The assessment of these variations helps in evaluating the efficiency and effectiveness of the model used. Given the strong relationship between plant hydration,

* Corresponding author.
E-mail addresses: akalharpreet@gmail.com, harpreet.s@thapar.edu (H. Singh).
[1] These authors contributed equally to this work.

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biomass accumulation, and physiological responses, gravimetric behavior provides critical insights into plant growth dynamics and stress adaptation, making it a key parameter in precision agriculture.

The gravimetric monitoring system operates by continuously measuring the weight of the plant or substrate using high-precision load cells or balance-based sensors. These sensors detect minute changes in mass, which correspond to variations in water uptake, transpiration rates, and biomass accumulation. By recording real-time weight fluctuations, the system enables researchers to track plant hydration status, growth patterns, and stress responses under different environmental conditions. This non-invasive monitoring technique provides an accurate and reliable means to assess plant water dynamics and overall health, complementing other physiological and spectral measurement methods.

Despite its potential, the application of EIS in real-world agricultural settings has been limited due to challenges in data interpretation, variability in environmental conditions, and the need for robust predictive models. Agricultural monitoring technologies continue to evolve, with EIS emerging as a promising tool in plant assessment (Jócsák et al., 2019). EIS has been used to evaluate fruit and crop quality, leveraging different impedance measurement configurations to gain insights into plant physiology. EIS measures electrical resistance in biological specimens under test by passing current through plant tissues. The resulting impedance, expressed as a complex number, provides key physiological indicators linked to plant health, water status, and structural integrity. A recent study highlights that impedance can reveal insights into plant transpiration rates and stress levels (Voroney, 2019).

1.2. Limitations of existing methods

Despite its potential, EIS-based plant monitoring faces key limitations, including:

1. Variability in Impedance Readings: Impedance measurements are influenced by multiple factors, including temperature, soil moisture, plant species, and developmental stages, leading to inconsistent results (Voroney, 2019).
2. Lack of Standardized Data Processing Techniques: There is no universally accepted method for analyzing impedance data in plant monitoring, resulting in fragmented approaches across different studies.
3. Limited Use of ML for EIS Analysis: While ML has been widely applied in hyperspectral imaging and remote sensing, its potential for enhancing impedance-based plant health assessment remains underutilized (Liu et al., 2021a).
4. Sensitivity to Environmental Factors: Impedance measurements are influenced by moisture levels, temperature variations, and plant structure (Jócsák et al., 2019).
5. Interpretation Complexity: The relationship between impedance and plant health is highly nonlinear, requiring sophisticated analytical techniques (Lopez et al., 2024).
6. Need for Real-Time Data Processing: Conventional methods struggle to process impedance data efficiently for immediate decision-making (Liu, 2024).

Plant monitoring also traditionally relies on destructive sampling and biochemical assays, which are time-consuming and invasive (Geldhof et al., 2021). Thus, advanced data-driven methods, particularly ML approaches, are needed to optimize real-time plant monitoring.

1.3. Advancements in EIS and role of ML in plant analysis

Recent studies indicate that plant impedance data analytics plays an essential role in precision agriculture, providing deeper insights into plant health, growth dynamics, and environmental responses (Liu et al., 2021a). EIS measurements offer multiple advantages: (1) Non-destructive and real-time monitoring: unlike conventional techniques, EIS enables continuous plant health assessment without damage (Zhou et al., 2025). Aybar et al. (2024) introduced an innovative approach for real-time water quality monitoring in irrigation systems using impedance spectroscopy and ML. Their study demonstrated that bioimpedance-based measurements could effectively estimate sodium chloride and magnesium sulfate concentrations in water, offering a more accurate and efficient alternative to traditional electrical conductivity methods. By leveraging random forest and Multi-layer Perceptron (MLP) models, their proposed method achieved significant improvements in solute concentration prediction, supporting continuous monitoring. Their findings suggest that automated water quality monitoring systems could enhance precision agriculture by enabling threshold-based alerts and automated responses, optimizing irrigation management and crop health (Aybar et al., 2024). (2) Correlation with physiological traits: impedance is linked to transpiration rate, nutrient uptake, and weight variations of water molecules (Matuszewski et al., 2025).

Furthermore, impedance analysis is highly frequency-dependent (Bassham and Lambers, 2023, June 28): Low-frequency signals are more sensitive to water content and hydration levels. High-frequency signals capture nutrient absorption and metabolic activity (Balliu et al., 2021). These findings highlight the strong potential of EIS for long-term plant monitoring in precision agriculture.

Recent studies also illustrate the versatility of bioimpedance spectroscopy in plant stress monitoring (Garg et al., 2025), crop management, and postharvest quality assessment, emphasizing its potential for smart agriculture applications. Altana et al. (2024) explored bioimpedance as a tool for monitoring iron stress in tomato plants. Their study demonstrated that EIS can effectively track plant responses to iron deficiency over time. By employing ML techniques, they achieved high classification accuracy, suggesting that bioimpedance-based monitoring could be a valuable tool for precision agriculture and early stress detection (Altana et al., 2024). Hamed et al. (2024) investigated the use of bioimpedance spectroscopy to assess water stress in tomato plants. By analyzing impedance spectra with equivalent circuit models, they identified patterns corresponding to different stress levels. Their findings highlight the potential of ML algorithms, particularly the MLP, for accurately classifying water stress conditions in plants (Hamed et al., 2024). Allará et al. (2025) extended the application of bioimpedance to the postharvest quality assessment of potatoes. Their study focused on using supervised ML models to predict dry matter content and classify potato varieties based on bioimpedance parameters. They demonstrated that bioimpedance can serve as a non-destructive, rapid alternative for potato quality evaluation, achieving high prediction accuracy for both dry matter content and variety classification (Allará et al., 2025). Thus, ML has emerged as a powerful tool in data-driven plant monitoring and disease detection, addressing challenges in interpreting complex impedance measurements. ML models can process large datasets efficiently, improving real-time decision-making (Buja et al., 2021). They can identify plant health patterns based on impedance variations (Ruiz-Gonzalez, 2025), as well as optimized irrigation and fertilization strategies, thereby reducing resource wastage (Akhtar et al., 2021). Recent advancements in data analytics for precision agriculture also suggest that ML-based approaches can automate plant monitoring and early stress detection (Aman et al., 2025). However, despite these advancements, ML-based impedance analysis is still in its early stages, requiring rigorous evaluation, hyperparameter tuning, and validation (Geldhof et al., 2021).

1.4. Research objectives and contributions

To overcome the limitations of traditional plant monitoring techniques, this study aims to implement and compare ML approaches for analyzing impedance spectroscopy data. The key contributions of this research are:

1. Application of ML techniques to a plant impedance spectroscopy dataset for enhanced decision-making in precision agriculture.
2. Development of an improved voting-based ensemble method for normalized plant weight prediction, with hyperparameter tuning via randomized search.
3. Comparative evaluation of the proposed ensemble model against existing methods, considering various training data sizes.
4. Validation of the proposed approach using k-fold cross-validation to ensure robustness and reliability.

Thus, by enabling real-time, non-invasive plant monitoring, this study contributes to large-scale agricultural data analysis and precision farming advancements.

1.5. Structure of the paper

The rest of this paper is organized as follows: Section 2 describes methodology, detection principle and mechanistic basis, experimental setup, sensor configuration, data acquisition process, dataset description, exploratory data analysis, data preprocessing, and model development through machine learning methods and proposed approach. Section 3 presents the results of the study, including feature importance and validation technique. This Section 3 also discusses the impact of frequency ranges on plant weight prediction, distinction of EIS from optical methods, mechanistic interpretation, advantages of the proposed approach, practical implications, and real-world applications. The last Section 4 concludes the study, discusses the limitations of the study, and outlines future research directions.

2. Methodology

Electrical impedance spectroscopy measurements were collected for a duration of 30 to 60 days per experiment across different plants (Bar-On et al., 2021). The measurements were set to measure across a frequency range of 40 Hz–1 MHz, while in this domain, the impedance analyzer was fully calibrated with the additional multiplexing circuit and the cables and connectors to the plant. Calibration included all wires except the actual probes that were in contact with the plant, as they were assumed to be perfect conductors (Au wires of approximately 4 cm in length and 0.6 mm in diameter were used). Voltage was set to 500 mV Vrms. This setup allowed the collection of data across a wide range of frequencies as well as across time, so that examining the results can be done in various ways. The selected frequencies were 100 Hz, 1 kHz, 10 kHz, 100 kHz, and 1 MHz.

To ensure measurement consistency over the 30–60 day experimental period, the impedance electrodes were fixed at a predefined location using a rigid mounting mechanism, maintaining constant inter-electrode spacing despite plant growth. The experimental setup is described in the subsequent subsection. The methodology employed for the current study is depicted in Fig. 1.

2.1. Detection principle and mechanistic basis

Sensors based on impedance measurements are commonly used for biological specimens, as impedance spectroscopy is a well-established method for material characterization. The electrical impedance is a function of the dielectric properties of the plant, which, among other parameters, depend on its structure, water content, and distribution, and the ionic concentration in the flowing electrolytes in the Xylem and Phloem. It is often used to evaluate changes in biological materials and structures. In plant research, it has been used to evaluate response at the cell level, differentiating between the response of the cell membrane, the vacuole in the cytoplasm, etc. Plant tissue, from different sections of the plant, has also been evaluated for several phenomena such as disease detection, fruit ripening, and the evaluation of frost response (Jócsák et al., 2019). Models used to interpret the spectrum data have generally been based on available models, with adaptations to the specific specimen studied (Zhang and Willison, 1991). The use of impedance to monitor plants is mentioned in many papers (for example, see recent reviews: Liu et al. (2021a) and Van Haeverbeke et al. (2023)).

From a physiological and bioelectrical perspective, plant gravimetric behavior is intrinsically linked to biomass accumulation, cellular proliferation, and water uptake. Variations in plant weight are accompanied by changes in cellular density, intercellular spacing, and the volume of intracellular and extracellular fluids. These structural and compositional modifications directly influence ionic conduction pathways and membrane polarization effects, which together determine the resistive and capacitive components of plant electrical impedance.

The frequency-dependent nature of EIS provides further insight into this relationship. At lower excitation frequencies, the applied current predominantly flows through extracellular pathways, rendering the measured impedance sensitive to tissue compaction and intercellular water distribution. At higher frequencies, the current increasingly penetrates cell membranes and reflects intracellular fluid content and membrane capacitance. As a result, changes in plant biomass and water status, key contributors to plant weight, manifest as measurable, frequency-dependent variations in impedance. This provides a mechanistic basis for relating impedance spectra to plant gravimetric dynamics.

Furthermore, the proposed system employs a four-point probe configuration operated in Kelvin mode, which significantly reduces the influence of electrode-tissue contact resistance compared to conventional two-probe measurements. In addition, this configuration minimizes sensitivity to minor geometric variations, including small changes in effective electrode spacing that may arise from plant growth over the 30–60 day experimental period. As a result, the observed impedance variations predominantly reflect physiological and compositional changes within the plant tissue, rather than artifacts associated with electrode positioning or contact effects.

2.2. Experimental setup and data collection

The data studied in this work were experimentally collected through multiple measurement techniques to evaluate the physiological condition and health status of the plant. This data was later studied using various methods in machine learning for further application and prediction in precision agriculture. The experimental activity was completed in an outdoor greenhouse facility. A wide range of experiments was run, allowing to acquire significant data regarding the plant response and activity measured by accepted plant physiological monitoring methods. Fig. 2 demonstrates the experimental system setup in the greenhouse using the PlantArray™ system and a monitored environment. A virtual model representation of the EIS instrument and its connection to the plant is illustrated in Fig. 3. The probe design was optimized, allowing good mechanical stability for the relatively long period of measurements that in some cases lasted for a few months. Hence, we designed with a relatively large spacing. It should be noted that further research optimizing the spacing and size of the electrodes to maximize the signal-to-noise ratio is still needed; however, the current setup provides a significantly "clean" signal. The temperature was monitored separately since it was done in a greenhouse under a controlled environment. The dependence on the temperature is also observed; however, it was less significant than the dehydration and lighting effects. In addition, the collection of data has been done simultaneously using the electrical impedance response across a variety of frequencies. This comparative approach and study, providing reliable data from multiple systems simultaneously across time, opens the way for the design and application of various artificial intelligence algorithms to predict plant health.

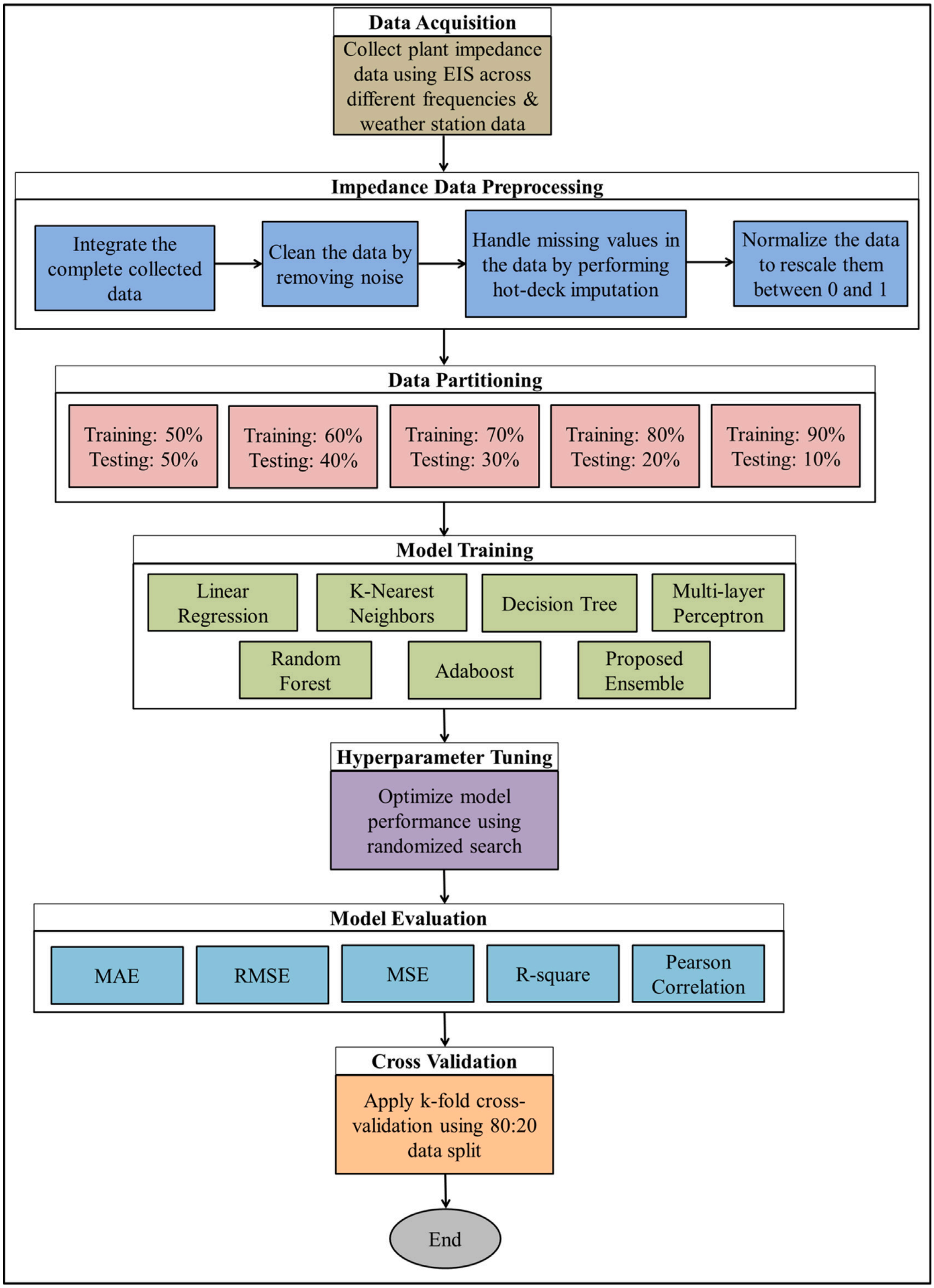

Fig. 1. The flowchart describes data acquisition filtering and learning.

1. Four-Point-Probe Electrical Impedance Spectroscopy System
   The first is the novel four-point probe impedance spectroscopy setup. The measurements were obtained directly from the *Nicotiana tabacum* L. cv. Samsun-NN plant stems in an ongoing manner across long time periods ranging from weeks to two months. For each experimental run, 10–14 uniform plants were monitored using the Plantarray™ high-throughput phenotyping platform. Plants were selected at a comparable vegetative stage, with stem diameters ranging from 0.7 to 1.0 cm (measured at the collar region), to ensure experimental consistency. The samples from these plants were collected every 9 min. This setup is described in detail and physically modeled in Bar-On et al. (2021). A four-point probe configuration was applied to verify accuracy and reliability. Impedance magnitude and phase values were measured across a frequency range of 50 Hz to 4 MHz. Errors in impedance magnitude and phase are estimated at 0.12% and 0.08%, respectively (Bao et al., 2024). The impedance magnitude exhibited daily fluctuations and demonstrated sensitivity

Table 1
Summary of the acquired dataset.

SN	Column name	Description	Units
1	Frequency	The frequency value at which measurements were collected.	Hz
2	Impedance	Resistance to the alternating current (AC).	Ω
3	Phase	The angular component of a periodic wave.	Degree
4	Relative Humidity (RH)	The proportion of water vapor in the air compared to the maximum amount that the air can hold.	%
5	Temperature	The temperature at which the plant is preserved.	°C
6	Vapor Pressure Deficit (VPD)	The difference between the moisture content in the air and the maximum amount of moisture air can hold.	kPa
7	Volumetric Water Content (VWC)	The amount of water present in a given volume of soil.	%
8	Weight	The weight of the plant.	kg

to induced water stress. Under controlled conditions, the mean impedance magnitude was estimated at 3.5 ± 0.5 kΩ (Bar-On and Shacham-Diamand, 2021).

2. Gravimetric System
The next system is a cutting-edge gravimetric plant monitoring system, which is designed for automated whole-plant phenotyping. Here, the plant weight and water use efficiency data were collected. These measurements are based on the gravimetric approach to plant physiological monitoring that is known to indicate plant well-being and growth factors. Furthermore, the water consumption monitoring allows for the study of additional aspects of the plant development and status.
3. Environment Monitoring - Outdoor Greenhouse
Given the facility, the greenhouse is in Tel-Aviv University, Israel, and is located outdoors, allowing exposure to natural light conditions. The greenhouse environment is regulated and monitored in terms of temperature and humidity. The weather station located in the center of the greenhouse logs the parameters explained in Table 1.
These include the temperature, relative humidity, and vapor pressure deficit. Monitoring the growth of a plant involves obtaining information about the plant's physiological reactions and condition from environmental parameters, such as temperature, humidity, and other physical factors that impact plant growth. For instance, temperature plays a vital role in fostering plant growth, as it affects plants under heat and cold stress. This can help attain a deeper comprehension of plant growth, identify potential issues, and optimize plant growth conditions to achieve the desired outcomes.
In the greenhouse environment, the plants were grown in 3.9 L pots filled with coarse sand of "Negev Industrial Minerals" Ltd., Israel, where the controlled temperature was 19-28 °C and natural light conditions. Irrigation was performed using 2 L of water per pot, supplemented with Shaphir nitrate fertilizer solution (4:2:6; Deshen Gat Ltd.), to maintain proper saturation and promote healthy plant growth. It was done daily during the night hours (9 PM) except when they were subject to drought for 24 to 48 h.

Fig. 4 provides an overview of the experimental setup and the synchronized acquisition of impedance, gravimetric, and environmental parameters.

2.3. Dataset description and exploratory analysis

A description of the dataset is provided in Table 1, and a sample data set is presented in Table 2. A total of 796,830 entries out of all the collected data were considered for modeling. Histogram distributions of the collected parameters over frequency and weight have been added in Figs. 5 and 6, respectively, to illustrate the characteristics of the dataset better. It offers insights into the variability of the features and represents the statistical distribution of the gathered data.

2.4. Data processing and model development

Although the dataset is inherently time-series, where the data points were collected at different time intervals, an initial examination revealed that there was no linear variation over time. Consequently, it was observed that incorporating the time-series aspect into the analysis would not provide additional insights. Therefore, the analysis was conducted without considering the time variable. This approach was further validated with a graph (Fig. 7) illustrating the lack of temporal variation across the dataset, which supports the decision to exclude time as a factor in the statistical analysis. It can be observed from Fig. 7 that the graph does not show steady weight gain, linear growth, or any meaningful long-term trends. It rather depicts mostly constant plant weight, with data integrity issues, including outliers and discontinuities.

2.4.1. Data handling

The experimentally acquired data were cleaned and pre-processed using data pre-processing techniques. The raw measurements were collated into a single file and handled as follows:

a. Missing Data:
Missing data can adversely affect data analysis and model building, as it reduces the sample size and potentially introduces bias. Therefore, it is crucial to impute missing values to ascertain the accuracy and validity of the analysis. Several methods could be used to fill in missing entries. In the current study, hot deck imputation has been used. As per this imputation, a comparable entry from the column is considered and imputed in the place of the missing value (Marycz et al., 2025). The imputation was performed on the complete dataset.
b. Data Normalization:
Data normalization is the procedure of converting data into a standardized format, typically to improve its usefulness in data analysis and modeling. The data samples in the current study are individually normalized to the unit norm so that the values are rescaled to a common range, typically between 0 and 1.
c. Partitioning the Data into Training and Test Sets:
The data was segmented into subsets for training and testing the ML models. To rigorously assess the robustness of the predictive model, the dataset was partitioned into training and test sets with varying proportions, ranging from 50% to 90%. Specifically, for each partition, the percentage of data used for training and testing was as described in Table 3. This partitioning strategy was adopted to evaluate the model's performance across different training set sizes and assess its generalization ability.

2.5. Model training

Training a machine learning model means that the model will use this data to learn and adjust its parameters. This step comprises an artificial intelligence-based solution to predict the required parameters like the normalized weight of the plant using the acquired data. The models used in this study are described below.

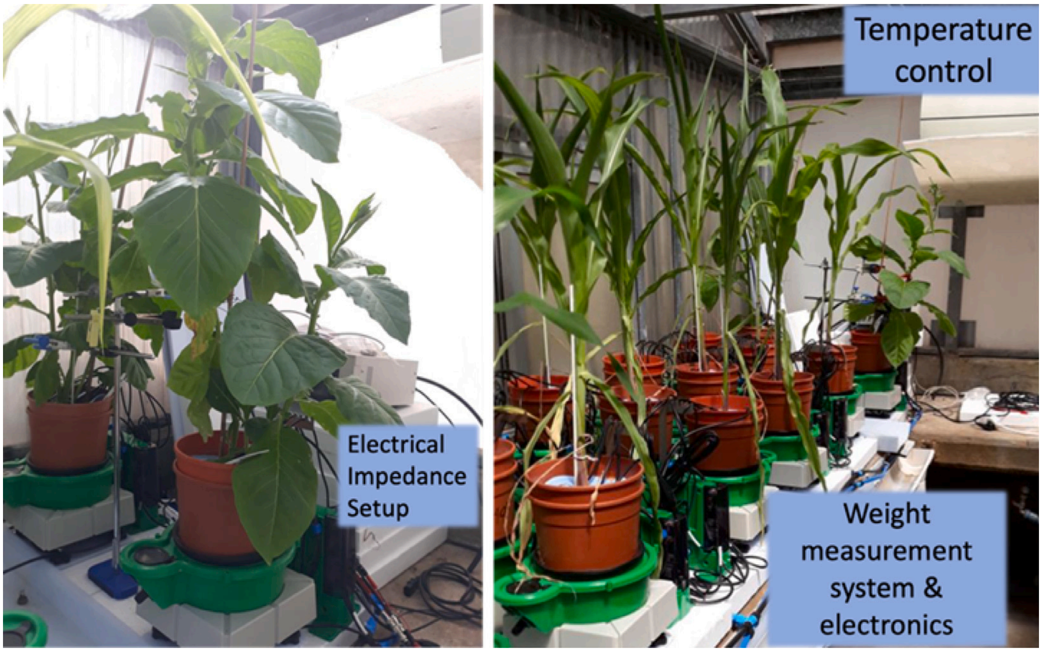

Fig. 2. Experimental systems setup in greenhouse utilizing monitored environment and PlantArray system.

Table 2
Sample of raw data collected.

Frequency	Impedance	Phase	RH	Temperature	VPD	VWC	Weight
1 000 000	327	−20.541	81.1	20	0.44159	0.18251	1.01719
101	4529.482	−3.563	87.5	20	0.29206	0.18429	1.01821
1010	3892.253	−16.043	87.6	20	0.28972	0.1835	1.0172
10 100	1869.21	−32.47	85	19	0.32935	0.18468	1.01668
101 000	785.5841	−34.239	76.8	20	0.54206	0.18291	1.01812
1020	3821.377	−15.933	84.4	19	0.34252	0.18311	1.01747
10 200	1846.688	−32.441	89.2	20	0.25234	0.18291	1.01771
102 000	775.136	−34.205	89.4	20	0.24767	0.18311	1.01713

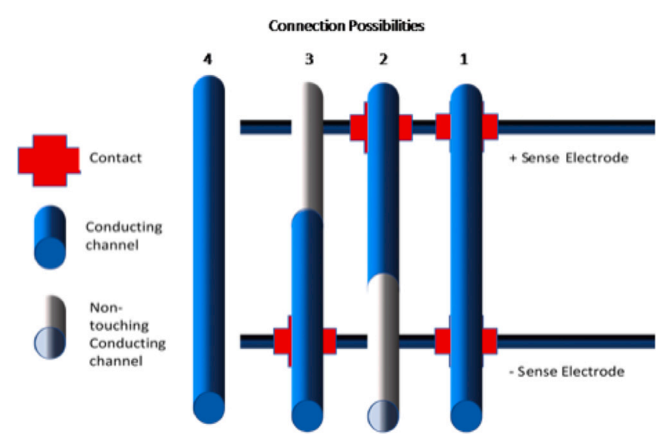

Fig. 3. Schematic description of the stem vascular vessels contact options with the electrode configuration (Bar-On et al., 2021).

Table 3
Details of data partitions.

Data partition (%)	Train %	Test %	Train size	Test size
50	50	50	398 415	398 415
60	60	40	478 098	318 732
70	70	30	557 781	239 049
80	80	20	637 464	159 366
90	90	10	717 147	79 683

1. Linear Regression:
It determines the optimal linear association between the independent features and the output value. It is represented by a hyperplane in higher dimensions. The equation for multiple linear regression is:

$$y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n \quad (1)$$

where y represents the output value, $x_1, x_2, \ldots, x_n$ represent independent features, and $b_0, b_1, b_2, \ldots, b_n$ denote coefficients that are determined during the training phase of the model. Here, the least squares regression technique was applied, finding coefficients of the prediction error (Montgomery et al., 2021).

2. K-Nearest Neighbors:
K-Nearest Neighbors (KNN) regression is a non-parametric algorithm in machine learning. It predicts a new instance considering k number of close neighbors and averages the target values. The k parameter requires fine-tuning to avoid overfitting (Zhou et al., 2025).

3. Decision Tree:
The decision tree regressor operates by iteratively dividing input data into increasingly smaller subsets according to a set of splitting criteria, continuing until each subset exclusively comprises data points with similar target variable values. The splitting criteria used by the algorithm are chosen based on a measure of impurity or error, such as mean absolute error or mean squared

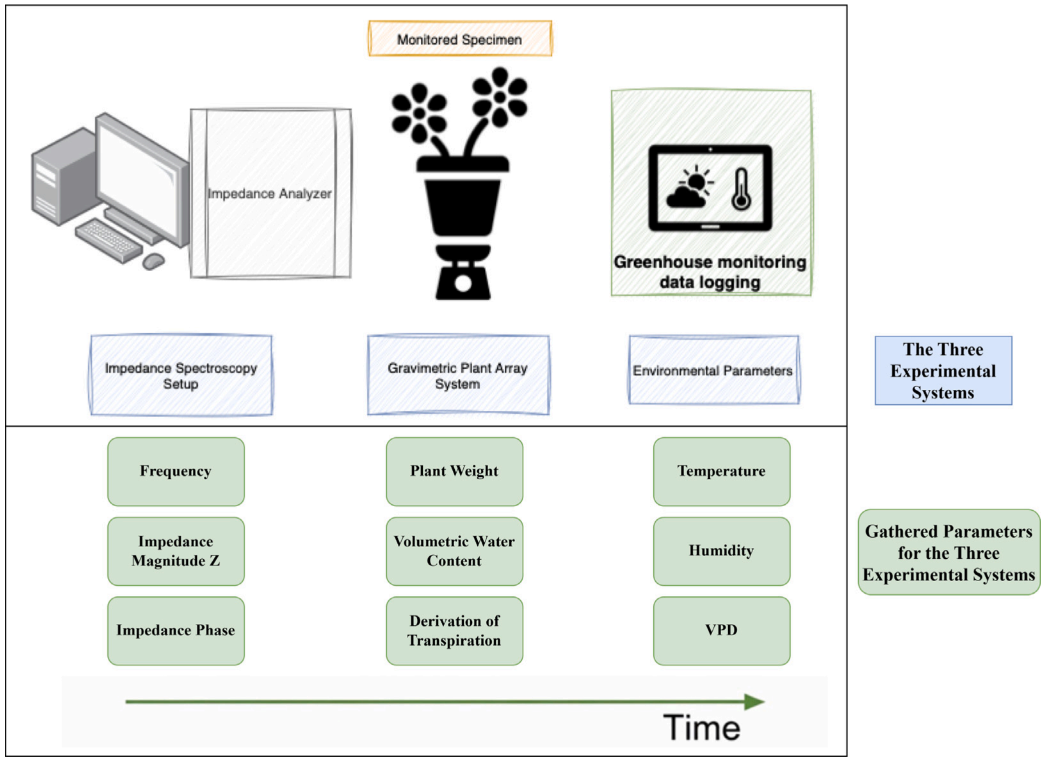

Fig. 4. Schematic representation of the experimental setup and data acquisition framework.

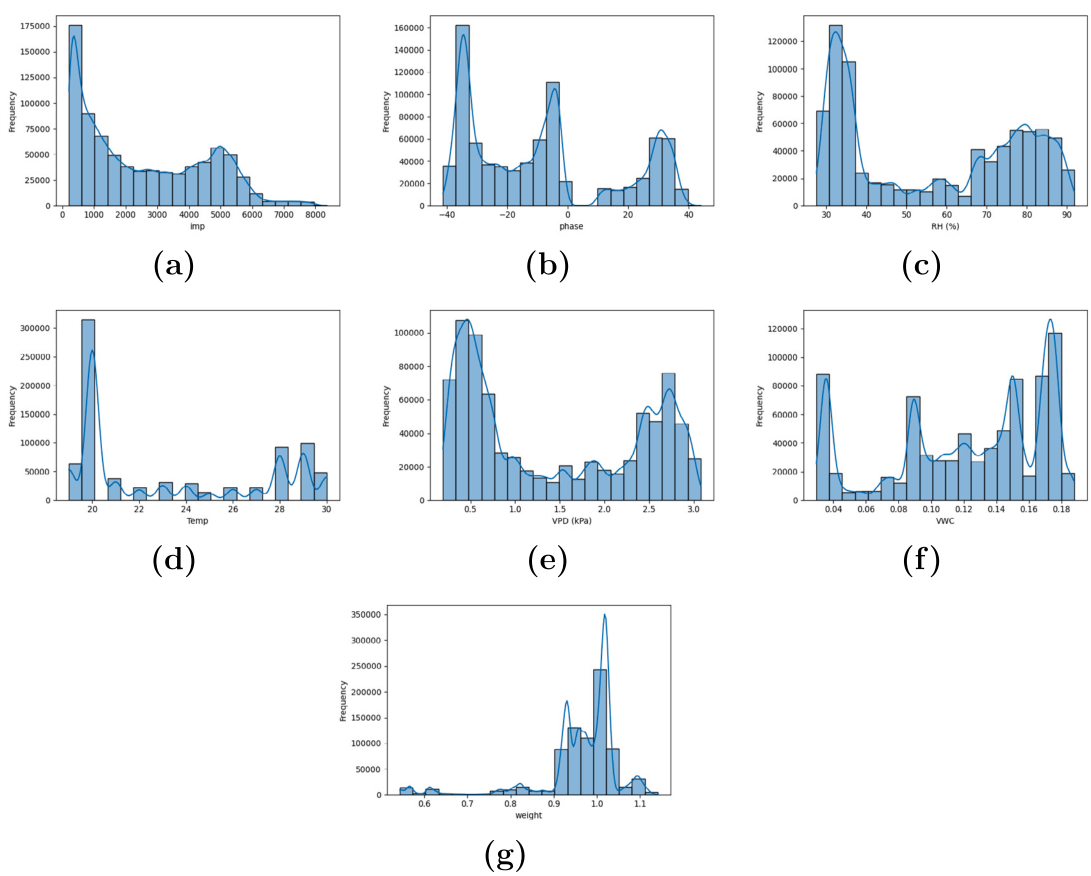

Fig. 5. (a) Impedance Distribution over Frequency (b) Phase Distribution over Frequency (c) Humidity Distribution over Frequency (d) Temperature Distribution over Frequency (e) VPD Distribution over Frequency (f) VWC Distribution over Frequency (g) Weight Distribution over Frequency.

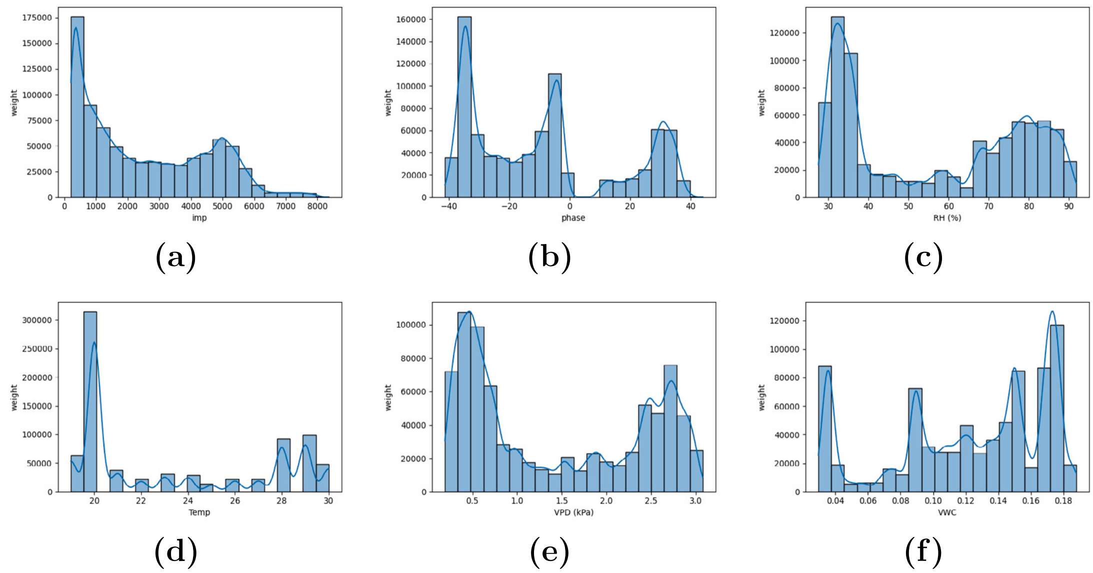

Fig. 6. (a) Impedance Distribution over Weight (b) Phase distribution over weight (c) Humidity distribution over weight (d) Temperature distribution over weight (e) VPD distribution over weight (f) VWC distribution over weight.

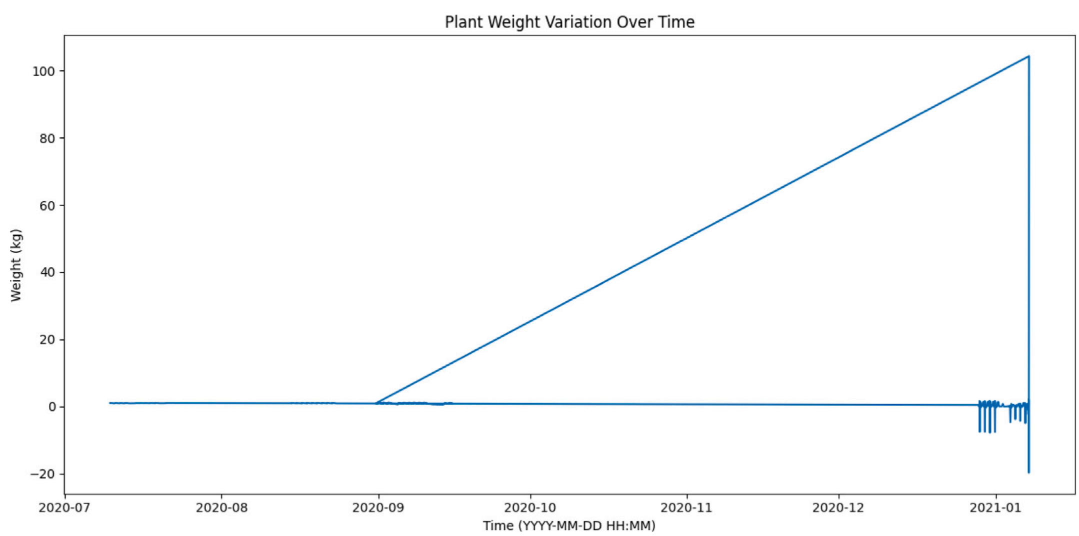

Fig. 7. Variation of plant weight over time.

error. Once the tree is constructed, a prediction for a new data point is made by traversing the tree from root to leaf node, where the predicted output value is the mean or median of training examples contained within that leaf node. However, decision tree regressors can be prone to overfitting (Kruse et al., 2022).

4. Multi-Layer Perceptron:
A Multi-Layer Perceptron (MLP) regressor works by taking in input values and passing them through a series of hidden layers, where each layer utilizes an activation function on the weighted sum of its inputs (Kruse et al., 2022).
5. Ensemble Models:
Ensemble models are often used in machine learning competitions where accuracy is critical. These models combine predictions from various individual models to enhance the overall performance of the system. The concept behind ensemble modeling posits that the combination of multiple models frequently produces superior predictions than any single model alone (Garg et al., 2025).
6. Random Forest:
A type of decision tree-based ensemble model, random forests involve training multiple decision trees on random subsets of the training dataset and its features. The final prediction is determined by consolidating the predictions from each decision tree. It can handle many input variables and can capture intricate nonlinear relationships between the independent and dependent variables. It also helps to reduce the overfitting of data (Zhang et al., 2025).
7. Adaboost:
Adaboost regressor is an adaptive method that adjusts the weights of individual models to enhance the overall system performance. It works by combining several weak learning models to construct a robust and more precise model. In each iteration of the algorithm, a weak learning model is trained using a subset of the training data, and its efficacy is assessed. The instances that are misclassified by the weak model are then assigned higher weights, and the process continues until the desired accuracy level is attained. The final forecast is the weighted mean of all weak model predictions (Garg et al., 2025).

Table 4
List of ML ensemble models and their parameters.

SN	Model	Tuning parameters
1	Linear Regression (LR)	None
2	K-Nearest Neighbors (KNN)	n_neighbors = 2
3	Decision Trees (DT)	criterion = 'gini'
4	Multi-Layer Perceptron (MLP)	hidden_layer_sizes = (20, 30); max_iter = 200; alpha = 0.001; solver = 'adam'
5	Random Forest (RF)	n_estimators = 300
6	Adaboost (Ab)	n_estimators = 100

The parameters of the machine learning models used in the current study are tabulated in Table 4.

2.5.1. Proposed ensemble approach

The voting ensemble method is a machine-learning approach that integrates predictions from various individual models to generate a final prediction. The rationale behind this technique lies in: (1) The combination of the predictions of multiple models; (2) Variance in our predictions could be reduced, and a more accurate model could be created. The procedure of the voting ensemble method can be summarized as follows:

Step 1: Create multiple individual models: The first step in the voting ensemble method is to create multiple individual models. These models can be machine learning models. It is significant to choose models that have different strengths and weaknesses so that when combined, they create a more robust model.

Step 2: Train each individual model: Once the individual models have been created, every model is trained on a small unit of the training dataset. This can be done using any standard machine learning training algorithm.

Step 3: Make predictions with each individual model: After each individual model has been trained, it is utilized for predicting outcomes on the test dataset. These predictions are then aggregated to formulate a final prediction.

Step 4: Choose a voting approach: The voting ensemble method offers two types of voting methods: soft voting and hard voting. With hard voting, the final prediction is determined by taking the majority vote of individual models. Conversely, with soft voting, the final prediction is made by taking the mean of predicted probabilities generated by individual models.

Step 5: Make the final prediction: The final step in the voting ensemble method is to make the final prediction according to the chosen voting method. This final prediction is then used as the output of the ensemble model.

The algorithm of the proposed ensemble approach is explained in Algorithm 1, while Fig. 8 demonstrates the working procedure of the proposed approach.

Algorithm 1 Proposed Ensemble Learning Approach

Require: List of base models $\mathcal{M} = \{M_1, M_2, \ldots, M_n\}$, training data X, true labels y
Ensure: Trained ensemble model with aggregated predictions
Initialize EnsembleModel with base models $\mathcal{M}$
for each base model $M_i \in \mathcal{M}$ **do**
  Train M_i using training data (X, y)
end for
Define prediction function for EnsembleModel
for each data point $x_j \in X$ **do**
  Initialize empty vote dictionary V
  for each base model $M_i \in \mathcal{M}$ **do**
    Obtain prediction $p_i = M_i(x_j)$
    if $p_i \notin V$ **then**
      $V[p_i] \leftarrow 1$
    else
      $V[p_i] \leftarrow V[p_i] + 1$
    end if
  end for
  Select final prediction $\hat{y}_j = \arg\max V$
end for
return EnsembleModel

3. Results and discussion

The testing of the machine learning model is done by feeding the test set data into the model and seeing how well it can predict the outcomes. A prediction score is computed based on the accurate predictions compared to the total possible predictions. This score measures the performance and efficacy of the machine learning and ensemble model on the available dataset using various evaluation metrics.

1. **Analysis of Mean Absolute Error (MAE):**
MAE represents the mean of absolute differences between predicted and actual values. The comparative analysis of machine learning and ensemble models for mean absolute error for normalized plant weight prediction is described in Table 5.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - \hat{y}_i \right| \tag{2}$$

It is noticed that the proposed approach has superior results in comparison to alternative computational methods. It indicates that the proposed system outperforms others.

2. **Analysis of Root Mean Squared Error (RMSE):**
RMSE represents the square root of MSE, quantifying the standard deviation of differences between predicted and actual values. Table 6 presents a comparative analysis of machine learning algorithms and ensemble models for root mean squared error for predicting the normalized weight of plants.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2} \tag{3}$$

Table 6 clearly shows that the proposed system demonstrates superior performance compared to others because it exhibits a lower RMSE when contrasted with all others. It is seen that despite the training data being increased consistently, the proposed system still outperforms others. Analysis using other metrics like Mean Squared Error (MSE), R-Square (R^2), and Pearson correlation was also conducted. Tables 7, 8, and 9 represent a comparative analysis of ML and ensemble models for MSE, R-squared, and Pearson correlation, respectively, for normalized plant weight prediction.

The findings of the study indicate that the proposed model effectively predicts the normalized weight of the plant. The system exhibited the capability of forecasting the weights with an R-square value of 0.855 on 90% data partition by the proposed method.

3.1. Feature importance

Feature importance analysis helps identify the most influential variables contributing to the performance of the predictive model. This study employed Pearson correlation analysis and Variance Inflation Factor (VIF) to assess the dependency between input features and the target variable, providing insights into the most relevant predictors for

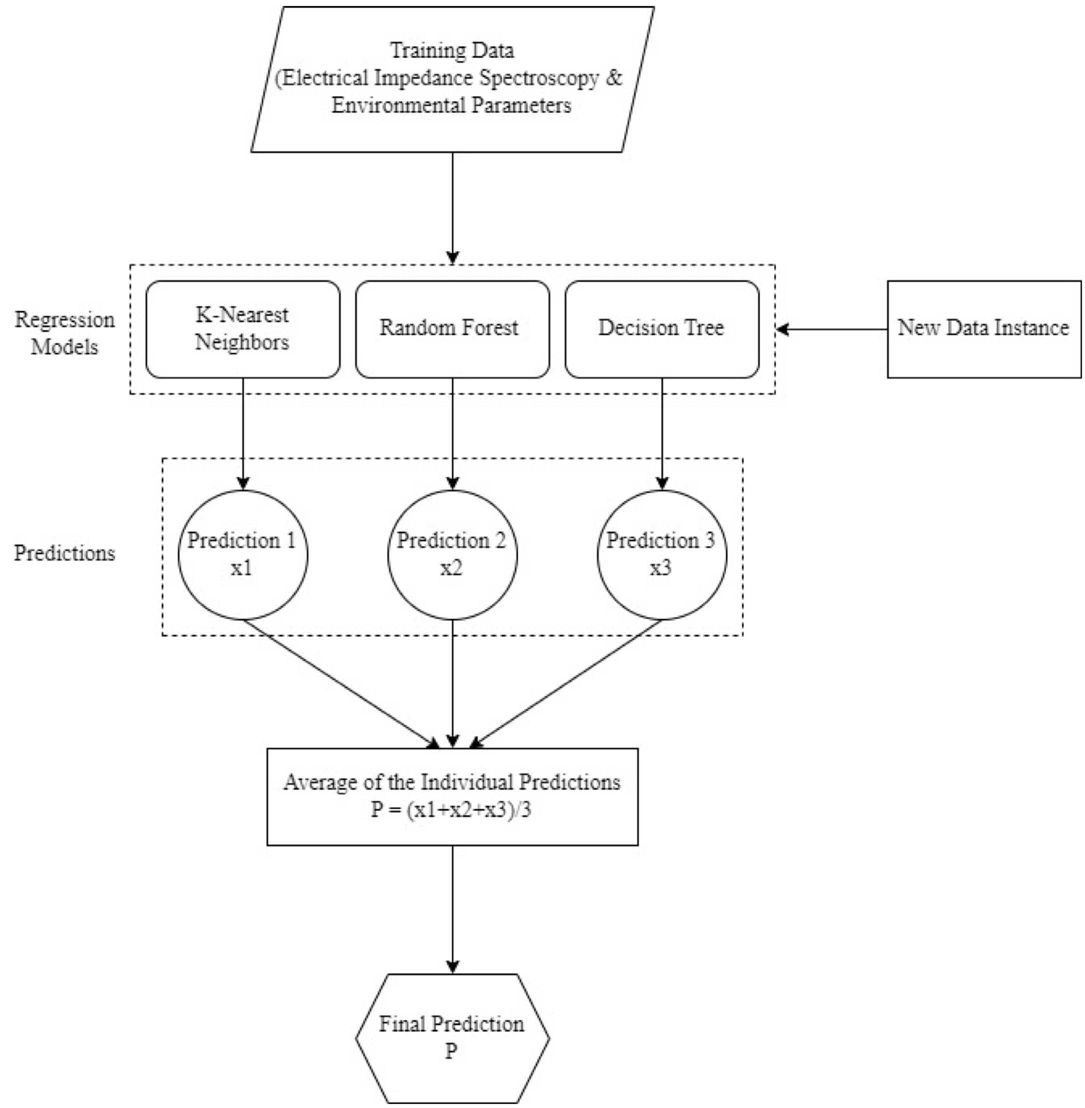

Fig. 8. Diagram illustrating the proposed algorithm.

Table 5
Mean absolute error comparison for different partitions.

ML and ensemble models	50%	60%	70%	80%	90%
LR	0.046	0.046	0.046	0.046	0.046
KNN	0.039	0.038	0.037	0.037	0.036
DT	0.014	0.013	0.012	0.011	0.01
MLP	1.8	40.17	0.228	0.272	3.3
RF	0.022	0.021	0.02	0.02	0.019
Ab	0.049	0.049	0.05	0.049	0.049
Proposed	0.015	0.014	0.013	0.012	0.011

Table 6
Root mean squared error comparison for different partitions.

ML and ensemble models	50%	60%	70%	80%	90%
LR	0.09	0.09	0.09	0.09	0.09
KNN	0.078	0.077	0.076	0.076	0.075
DT	0.06	0.057	0.054	0.052	0.051
MLP	3.808	105.378	0.313	0.389	8.52
RF	0.05	0.047	0.046	0.045	0.043
Ab	0.091	0.091	0.091	0.091	0.091
Proposed	0.044	0.041	0.039	0.038	0.037

Table 7
Mean squared error comparison for different partitions.

ML and ensemble models	50%	60%	70%	80%	90%
LR	0.008	0.008	0.008	0.008	0.008
KNN	0.006	0.006	0.005	0.005	0.005
DT	0.003	0.003	0.002	0.002	0.002
MLP	14.502	11 104.66	0.098	0.151	72.6
RF	0.002	0.002	0.002	0.002	0.001
Ab	0.008	0.008	0.008	0.008	0.008
Proposed	0.001	0.001	0.001	0.001	0.001

Table 8
Comparative analysis of R-Square on different data partitions.

ML and ensemble models	50%	60%	70%	80%	90%
LR	0.152	0.153	0.152	0.152	0.151
KNN	0.356	0.372	0.385	0.397	0.407
DT	0.621	0.652	0.689	0.719	0.723
MLP	0.067	0.071	0.092	0.147	0.065
RF	0.74	0.762	0.777	0.789	0.799
Ab	0.133	0.133	0.13	0.136	0.138
Proposed	0.797	0.819	0.836	0.848	0.855

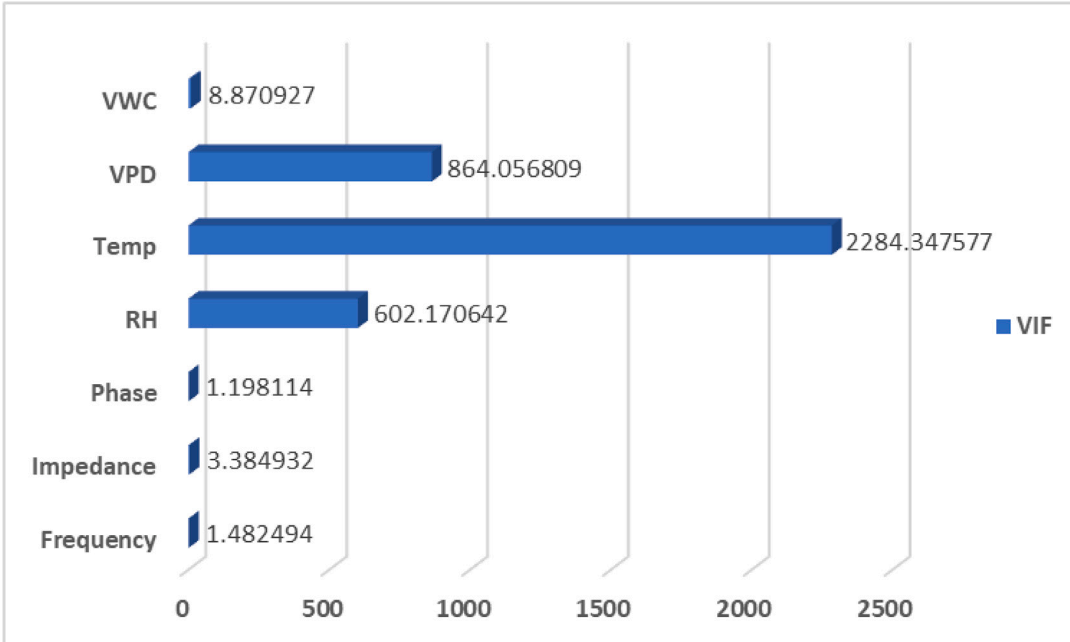

Fig. 9. Feature importance using variance inflation factor.

Table 9
Comparative analysis of Pearson correlation on different data partitions.

ML and ensemble models	50%	60%	70%	80%	90%
LR	0.391	0.392	0.39	0.39	0.389
KNN	0.641	0.65	0.66	0.665	0.671
DT	0.811	0.826	0.844	0.859	0.861
MLP	0.05	0.054	0.111	0.004	0.056
RF	0.863	0.876	0.884	0.891	0.897
Ab	0.432	0.432	0.427	0.432	0.434
Proposed	0.894	0.906	0.915	0.922	0.925

plant growth estimation. Fig. 9 shows the VIF-based feature importance scores. If $VIF > 5$ or 10, the feature is highly collinear and may not add much value. Thus, it is evident from Fig. 9 that the features vapor pressure deficit, temperature, and relative humidity are highly correlated features that do not add much contribution in predicting the plant weight, while features phase, frequency, and impedance had low VIF. To better understand the relationships between the key features, a Pearson correlation analysis was also performed. The correlation matrix was visualized using a heatmap, as shown in Fig. 10. The Pearson correlation analysis reveals several interesting relationships between the plant's physiological parameters. The inverse correlation between temperature and RH and also between VPD and RH could be explained by the environmental conditions under which the measurements were taken, suggesting that higher temperatures lead to lower humidity and vapor pressure in the environment. These correlations provide valuable insights into the interactions between environmental factors and plant health.

3.2. Validation

The k-fold cross-validation method is favored above other validation methods for assessing the robustness of the ensemble model. It is because of its iterative nature, randomness, and simplicity. K-fold cross-validation stands as a widely adopted method for assessing the efficacy of machine learning models. It entails partitioning the dataset into k equal-sized segments, or "folds". Subsequently, the model undergoes training and evaluation k times, with every iteration employing a distinct fold as the validation set and the remaining folds as the training set. This method enables a thorough evaluation of the model's performance by obtaining k different performance metrics. It helps alleviate the effects of variability in the training and testing data, providing a more reliable estimation of the model's generalization capabilities (McAlinn and Takanashi, 2025). In the current study, the value of k is chosen as 10. This means that the model would undergo 10 rounds of training and testing. 10-fold cross-validation was specifically conducted for the 80% data partition because the 80:20 split ensures a balance between sufficient training data and reliable model evaluation. For the other partitions (50%, 60%, 70%, and 90%), the model was trained and evaluated directly without cross-validation to assess its performance across different training set sizes. The outcomes attained via 10-fold cross-validation with 80% data partition for each ML and ensemble model, including the proposed model, are demonstrated in Fig. 11. Notably, in every iteration, the proposed model consistently either achieves a lower error or higher R^2 and Pearson correlation values than the other models. This serves as evidence that the proposed model is more efficient and robust than the individual models.

3.3. Impact of frequency ranges for plant weight prediction

The impedance spectroscopy captures distinct physiological characteristics of plants across varying frequency ranges: (1) Low frequencies (below 5 kHz) primarily reflect extracellular resistance and ionic movement in plant tissues. (2) Mid frequencies (5 kHz to 2 MHz) capture cell membrane charging effects and hydration levels. (3) High frequencies (more than 2 MHz to 4 MHz) provide insights into intracellular capacitance and dielectric properties of plant cells. The highlight of the four-point measurement is that since the voltage is measured using separate probes, there is significantly less noise from the contact, and the signal is not affected by the surrounding environment (except at 50 Hz from the power lines).

In our study, we have identified the most relevant frequencies through Mutual Information (MI) analysis, as depicted in Fig. 12. Our findings (from Fig. 12) suggest that 1.43 MHz to 3.89 MHz frequency bands contribute more to plant weight prediction, due to their relationship with hydration status. Also, the weight of the testing apparatus included the plant weight, including its water content, as well as the water content in the soil. The amount of water is expected to

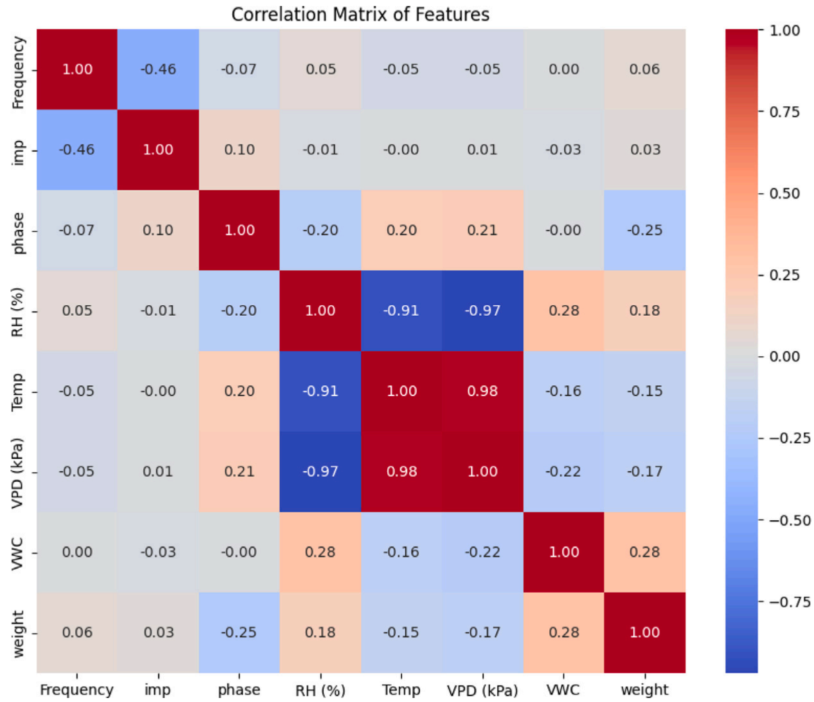

Fig. 10. Heatmap of the Pearson correlation analysis.

be related to the plant dehydration rate, which is important in the evaluation of the plant compatibility with the irrigation constraints and the environmental conditions.

3.3.1. Impact of impedance measurement on selected frequency ranges for plant weight prediction

The relationship between impedance and plant weight is analyzed to further explain the gravimetric behavior of the measured results. The analysis is represented in the scatterplot and boxplot visualizations in Figs. 13 and 14, respectively. In Fig. 13, the x-axis represents impedance values, and the y-axis represents plant weight. The data points are color-coded by frequency, indicating impedance measurements at different frequencies. The spread of data points suggests that impedance values vary significantly across different weight values. There appears to be a dense clustering of data points in the 219–290 impedance range, which suggests that most plant weight measurements correspond to this range of impedance. The plant weight values are tightly clustered between 0.92 and 1.04, which indicates a small variation in weight for the dataset. At higher impedance values (beyond 300 Ω), the number of data points decreases significantly, which may indicate that only certain frequencies contribute to weight measurement in this range. Some frequencies (e.g., cyan, pink, and orange points) seem to dominate certain impedance ranges, while others are more scattered across different impedance values. The overlap of colors suggests that multiple frequencies contribute to plant weight estimation. However, no clear linear relationship is visible between impedance and plant weight, suggesting that the relationship is nonlinear.

In Fig. 14, the x-axis represents plant weight categories (Low, Medium, High, Very High). The y-axis represents impedance values. Color-coded boxes represent impedance measurements at different frequencies. Whiskers and outliers show the spread of impedance values for each category. The median impedance values are higher in the "Low" weight category and decrease progressively for "Medium" and "High". This suggests an inverse relationship between impedance and plant weight—higher plant weight is associated with lower impedance. The "Low" weight category has a higher spread of impedance values (larger interquartile range), meaning more variation in impedance at lower weights. The spread becomes narrower as weight increases, suggesting impedance values stabilize for heavier plants. The "Low" category has a significant number of high-impedance outliers (black circles above the whiskers). This indicates that at low plant weights, plants exhibit exceptionally high impedance values. The impedance values for different frequencies follow a similar trend. No single frequency stands out as an extreme outlier, meaning most frequencies behave similarly across weight categories. Overall, the observed decrease in impedance with increasing plant weight is consistent with the physiological interpretation that higher biomass and water content enhance ionic conductivity within plant tissues. The reduced variability in impedance at higher weight categories indicates more stable electrical properties in mature or well-hydrated plants. This result provides experimental evidence supporting the feasibility of using multi-frequency EIS features as informative predictors for plant gravimetric dynamics and justifies their inclusion in the proposed machine learning framework.

3.4. Distinction of EIS from optical methods

Traditional plant monitoring techniques, such as multispectral reflectance and other optical sensing methods, have been widely explored in the literature for assessing plant health. These approaches rely on analyzing reflected light from plant surfaces to infer physiological and biochemical properties. Multispectral reflectance techniques analyze the absorption and reflection of light at different wavelengths to infer surface-level characteristics such as chlorophyll content, stress levels, and overall plant health. It is widely used for remote sensing applications. However, our study employs EIS, a unique approach that evaluates plant health by analyzing electrical properties rather than optical characteristics. It enables direct in-situ measurements, offering a more detailed assessment of internal plant functions. Unlike multispectral reflectance, which provides insights into surface-level plant traits, EIS captures internal physiological variations, offering a novel and data-driven perspective for assessing plant health. This methodological distinction from conventional methods demonstrates its potential as an alternative or complementary approach for assessing plant health. Moreover, by combining multi-frequency EIS with machine learning,

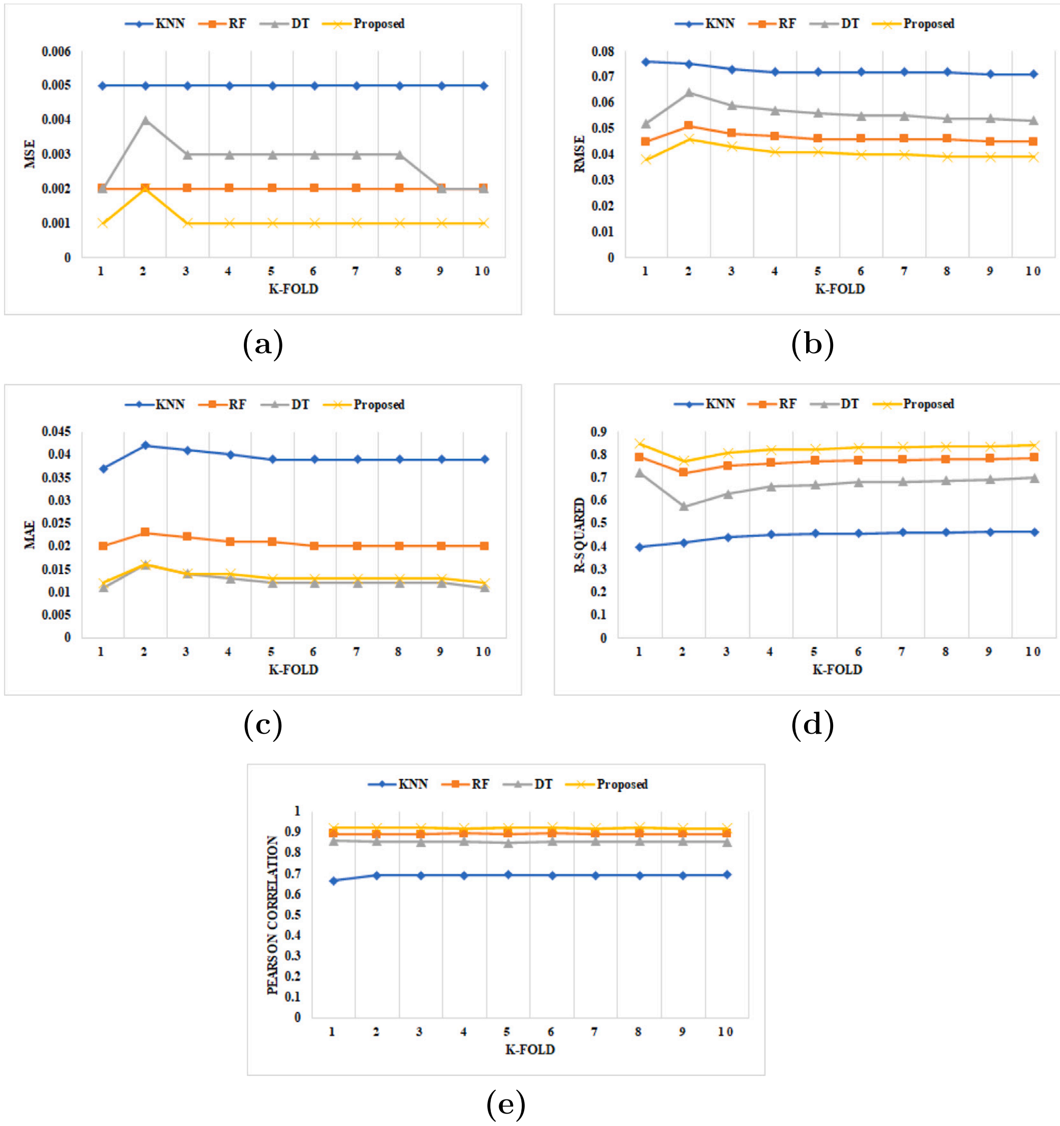

Fig. 11. (a) K-fold validation for MSE with 80% data partition (b) K-fold validation for RMSE with 80% data partition (c) K-fold validation for MAE with 80% data partition (d) K-fold validation for R-square with 80% data partition (e) K-fold validation for Pearson correlation with 80% data partition.

the method enables continuous and non-destructive inference of plant gravimetric dynamics, which is particularly relevant for data-driven decision support in precision agriculture.

3.5. Mechanistic interpretation

Although electrical impedance spectroscopy has traditionally been applied to assess plant moisture, maturity, and stress conditions, its relationship with plant gravimetric behavior can be explained through fundamental bioelectrical and physiological mechanisms. Plant weight is inherently linked to biomass accumulation, cellular density, and water content. As plant biomass increases, both the number and size of cells increase, leading to higher intracellular and extracellular fluid volumes. These changes directly influence the conductive pathways within plant tissues.

At lower frequencies, electrical current primarily flows through the extracellular space, which is affected by tissue compaction and intercellular water content. At higher frequencies, the current penetrates cell membranes and is influenced by intracellular fluid volume and membrane capacitance. Consequently, variations in cellular density, tissue hydration, and structural organization—factors that collectively contribute to changes in plant weight—manifest as measurable impedance variations across frequencies.

3.6. Strengths of the proposed EIS-based machine learning framework

A key strength of the proposed approach lies in the use of complex electrical impedance spectroscopy for modeling plant gravimetric dynamics. Although plant weight is a macroscopic parameter, its temporal variation is governed by complex physiological processes such as water transport, transpiration, and biomass accumulation at the cellular and tissue levels. Simple gravimetric or moisture-based measurements provide limited insight into these underlying dynamics. In contrast, electrical impedance spectroscopy offers frequency-dependent information that reflects both extracellular and intracellular electrical pathways, membrane properties, and fluid distribution. The use of complex impedance features, including magnitude and phase across multiple frequencies, enables the capture of subtle physiological changes that collectively influence plant gravimetric behavior. Thus, the application of complex EIS represents a physiologically meaningful and complementary sensing modality for modeling plant weight dynamics.

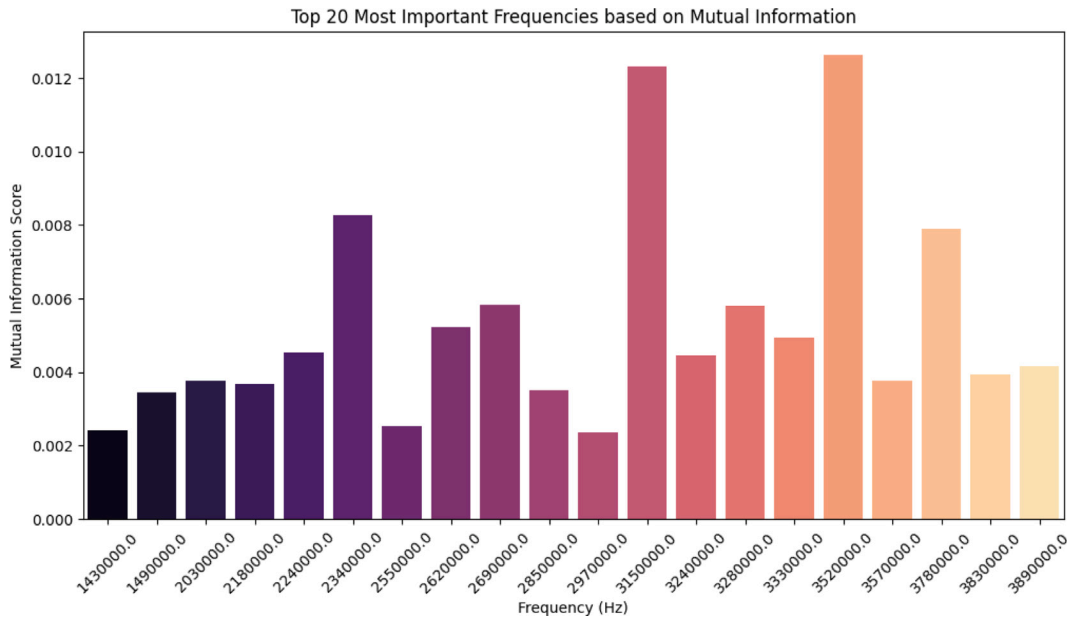

Fig. 12. Top 20 frequencies based on mutual information.

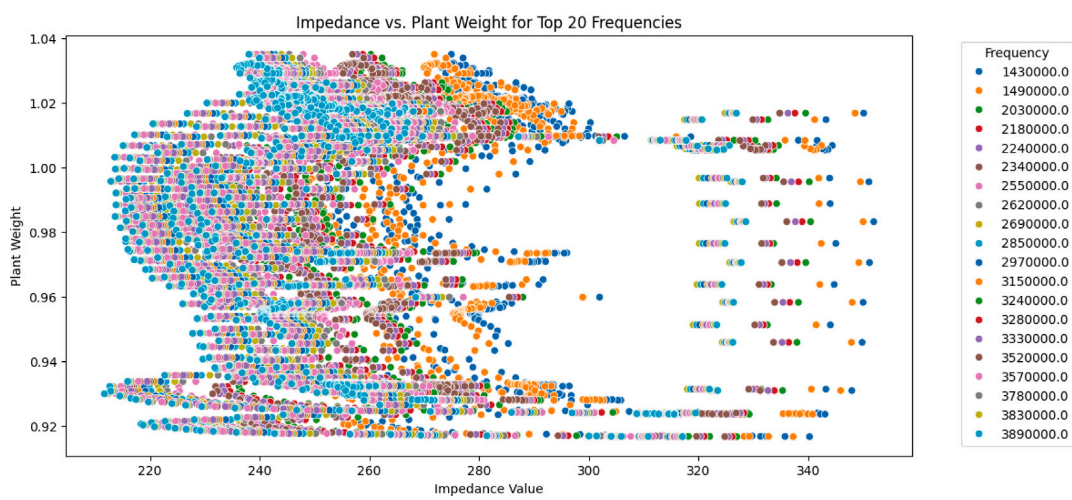

Fig. 13. Impedance vs. Plant weight for top 20 frequencies.

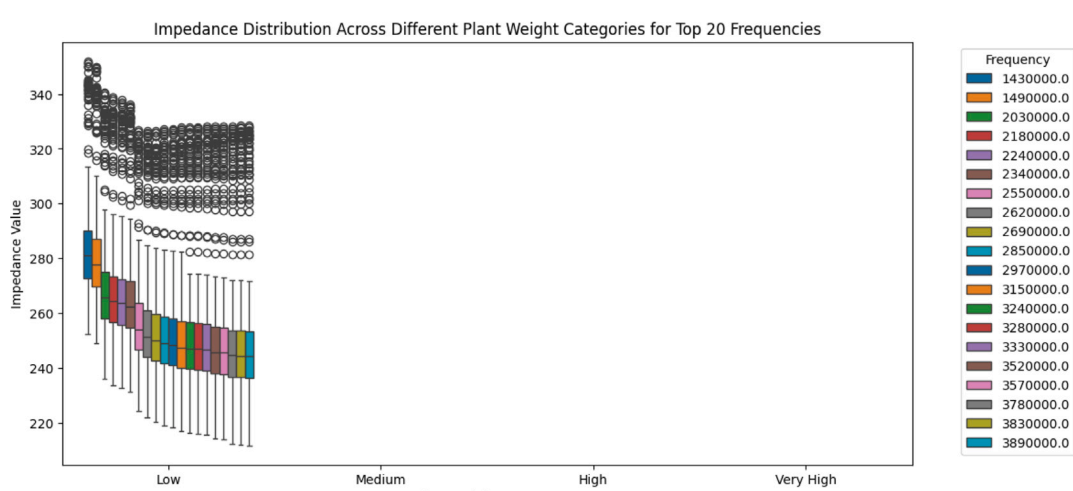

Fig. 14. Impedance distribution across different plant weight categories for top 20 frequencies.

The use of electrical impedance spectroscopy also enables continuous and non-invasive monitoring of plant physiological behavior, making the approach suitable for real-time and field-deployable applications. Unlike conventional gravimetric methods, which require physical measurement, the proposed machine learning framework effectively models complex, non-linear relationships between impedance features and plant weight. The proposed framework demonstrates potential for smart irrigation and plant health monitoring, contributing towards data-driven precision agriculture systems.

Another important strength of the proposed framework is its independence from specific electrode implementations. Recent studies have demonstrated the feasibility of flexible and low-cost electrodes for plant-based electrical impedance measurements (Matuszewski et al., 2025), particularly in wearable sensing applications (Teixeira et al., 2025). The present work does not aim to design or optimize electrode materials or form factors. Instead, the focus of this study is on establishing and modeling the relationship between multi-frequency EIS features and plant gravimetric dynamics using machine learning. The proposed framework is inherently independent of the specific electrode implementation and can be readily integrated with flexible or wearable electrode technologies in future deployments.

3.7. Practical implications and real-world applications

The proposed EIS-based machine learning framework can be directly applied in real-world plant monitoring scenarios, particularly in controlled environments such as greenhouses and vertical farms. In practice, impedance sensors can be non-invasively attached to plant stems or roots to continuously acquire multi-frequency impedance data, while environmental parameters are simultaneously recorded. The trained machine learning model can then be deployed on an edge device or local server to estimate plant weight in real time without requiring repeated manual or destructive measurements.

Such real-time plant weight estimation can support applications including irrigation scheduling, transpiration monitoring, growth assessment, and early stress detection. For example, deviations between predicted and expected weight dynamics may indicate water stress or abnormal growth, enabling timely corrective actions. Therefore, the proposed method provides a scalable and data-driven solution for precision agriculture and automated plant monitoring systems.

4. Conclusion

A rigorous analysis of machine learning models has been offered comparatively on experimental data, allowing direct plant health monitoring. The algorithms of machine learning were used for the analysis and interpretation of the signals. A combination of standard methods is analyzed, followed by a unique approach using ensembles and designated data partitioning. The algorithm's performance is evaluated using multiple parameters, revealing that the proposed method outperforms all other algorithms, achieving an R-squared value of 0.855. The study has shown that a novel ensemble approach can allow for high-accuracy prediction of plant gravimetric changes based on impedance data and environmental parameters.

While this study provides valuable insights, it has several limitations as well. The dataset used in this study is limited to the Tobacco plant, which could impact the generalizability of the findings to other plant types or varied environmental conditions. Future work could include a broader dataset covering different plant species and growth conditions. Also, the proposed method is subject to several sources of uncertainty, including variations in electrode positioning, fluctuations in illumination due to shadowing or cloud cover, electromagnetic interference from nearby radiation sources, and mechanical disturbances caused by plant movement. Although absolute bias was mitigated through initial calibration, residual noise may still influence measurements. Some noise components were reduced by analyzing relative changes in impedance rather than absolute values. In future work, more advanced noise reduction techniques, such as double correlated sampling, could be implemented to further enhance measurement stability. Nevertheless, the observed noise levels in the present study were sufficiently low to permit reliable analysis. Future improvements in this method will also include standard electrode design with a protective cover, digital signal processing using more sophisticated methods, such as digital filtering methods for fitting to the theoretical model. Learning the results over a few seasons will definitely improve the reliability of the data.

Furthermore, the machine learning ensemble approach used in this study improves predictive performance, but the interpretation of individual feature contributions remains complex. Although Pearson correlation analysis was performed, further exploration using SHAP (Shapley Additive Explanations) could provide deeper insights.

The current study also opens the way for the development of a device and method to improve agricultural crop monitoring in the field using improved informatics decision-making based on data study, prediction, and new sensing methods. The approach suggested here allows for further developments towards embedded systems for ongoing crop monitoring. The proposed work promotes the study of continuous plant impedance monitoring, showing that it can indeed provide reliable predictions for changes in plant gravimetric behavior and serve as a field monitor and predictor for plant health. This data and algorithmic approach provide further reassurance of improved monitoring in the field, which is crucial for promoting new sensor technologies in precision agriculture. Thus, it can be concluded that integrating electrical signals and machine learning algorithms holds tremendous potential in monitoring and predicting plant health, ultimately leading to improved crop yields and enhanced food security.

CRediT authorship contribution statement

Harpreet Singh: Writing, Supervision, Project administration, Methodology, Conceptualization, Validation. **Divisha Garg:** Writing, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Lee Bar-On:** Review & editing, Investigation, Data curation. **Adi Avni:** Data curation. **Yosi Shacham-Diamand:** Supervision, Project administration, Investigation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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