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Ali Ahmad, Vinie Lee Silva-Alvarado, Sandra Sendra & Jaime Lloret

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Edge Computing and RGB Phenotyping Enables Machine Learning-Driven Salinity Monitoring in Peppermint

Ali Ahmad¹, Vinie Lee Silva-Alvarado¹, Sandra Sendra¹, and Jaime Lloret^{1, *}

¹ Instituto de Investigación para la Gestión Integrada de Zonas Costeras, Universitat Politècnica de València, Carrer del Paranimf 1, 46730 Grao de Gandia (Valencia), Spain

aahmad1@upv.es, vlsilalv@doctor.upv.es, sansenco@upv.es, jlloret@dcom.upv.es

* Correspondence: Jaime Lloret (jlloret@dcom.upv.es)

Abstract: Salinity stress severely constrains crop productivity, creating an urgent need for rapid, scalable, and non-destructive diagnostic tools compatible with intelligent farming systems. This study presents an integrated phenotyping and analytics framework that combines RGB imaging, machine learning, and edge enabled wireless sensor network for accurate detection of three levels of salinity stress, 0 mM, 100 mM, and 200 mM of NaCl, in peppermint. Daily lateral and nadir images were acquired over a ten-day period and subjected to robust color space segmentation, after which two complementary feature extraction strategies were applied, namely RGB-based and histogram-based representations, with vegetation indices computed for both feature sets alongside morphological descriptors. Machine learning models were evaluated with emphasis on predictive accuracy, computational efficiency, and suitability for deployment on resource constrained devices. Nadir image features consistently outperformed lateral perspectives, achieving classification accuracies of up to 98.30% using a Fine KNN model with only two features. Under specific compact feature-model configurations, a Wide Neural Network, with a memory footprint of 0.010 MB, achieved a near perfect classification (100%) on the independent test set, while also exhibiting negligible generalization gaps between validation and testing performance, suggesting stable model behavior under the evaluated experimental conditions rather than evident overfitting. Histogram-based feature analysis further achieved 85.26% accuracy under nadir configuration with a compact 7.08 MB model. SHAP interpretability analysis revealed that salinity stress signatures were dominated by reductions in vegetation greenness, increased hue variability, and canopy contraction, possibly reflecting chlorophyll degradation and growth inhibition. This work establishes RGB-based edge intelligence as a practical

and biologically meaningful solution for scalable salinity stress monitoring in smart agriculture.

Keywords: plant phenotyping, coastal stress monitoring, precision agriculture, image analysis, artificial intelligence, digital farming.

1. Introduction

Soil salinization represents a major constraint to agricultural productivity and food security worldwide [1, 2]. Excess salt accumulation disrupts osmotic balance and induces ionic toxicity, thereby limiting crop growth and yield [3]. Mediterranean coastal regions of Spain are particularly vulnerable to salinization as a consequence of seawater intrusion, intensive irrigation practices, and evaporative concentration, with field studies from Valencia and Alicante reporting Na^+ and Cl^- concentrations sufficient to impair plant productivity [4–6]. Aromatic species such as peppermint are moderately sensitive to salt stress and are highly valued for their essential oil yield. They exhibit complex and species-specific physiological responses that require continuous monitoring to avoid irreversible biomass and quality losses [7]. Experimental studies on peppermint have demonstrated the onset of measurable physiological alterations at approximately 50 mM NaCl, with severe stress responses observed beyond 150 to 180 mM NaCl [8–10]. Early responses to salinity include partial stomatal closure, reduced transpiration, increased leaf temperature, chlorophyll degradation, and growth inhibition [11, 12]. Since these physiological alterations precede visible damage, their timely detection is essential for preserving biomass production and crop quality.

Recent advances in precision agriculture have accelerated the adoption of artificial intelligence (AI) approaches for non-destructive crop monitoring [12, 13]. Machine learning (ML) and deep learning (DL) models can exploit image derived information to capture spatial variability in crop vigor and stress response with greater efficiency than conventional destructive assessments [14–16]. Among imaging approaches, RGB sensing has gained particular attention because of its low cost, accessibility, and compatibility with field deployment. RGB derived vegetation indices provide valuable information related to chlorophyll content, canopy structure, and stress induced discoloration [17]. Combined with ML algorithms, these indices enable the detection of subtle physiological alterations associated with salinity and water stress [13, 19]. Previous studies have also demonstrated that integrating image features with predictive models improves the

estimation of biomass, yield, and crop health under variable environmental conditions [19, 20].

Reliable extraction of plant information from RGB imagery depends strongly on accurate segmentation of leaf tissue from soil, shadows, and background artifacts [21]. Conventional RGB thresholding approaches are often sensitive to illumination variability and reflective noise, which can reduce the stability of vegetation indices and ML predictions. Incorporating Hue Saturation Value (HSV) color space provides improved separation between chromatic information and luminance, allowing more robust identification of biologically relevant pixels under heterogeneous lighting conditions [22]. In addition, the use of Boolean filtering and morphological refinement improves canopy delineation and reduces contamination from non-plant regions [12,17, 24]. Such preprocessing steps are particularly important for salinity stress detection, where subtle changes in leaf coloration and canopy structure must be identified with high reliability.

The increasing use of ML in plant phenotyping has enabled the analysis of complex and nonlinear relationships between physiological stress and image derived traits [23]. Traditional statistical models often show limited performance when applied to species such as *Mentha × piperita*, where stress responses vary across developmental and environmental conditions [3]. In contrast, ML algorithms can integrate multiple descriptors simultaneously while maintaining resilience to sensor noise and environmental variability [24]. Ensemble and neural network approaches have further improved predictive robustness and reduced overfitting under heterogeneous conditions [20]. These developments have strengthened the role of image-based AI systems as practical tools for precision agriculture and automated crop monitoring [12, 15, 16, 25].

Despite these advances, limited attention has been given to salinity monitoring in aromatic and medicinal crops such as peppermint. Existing RGB based phenotyping studies frequently rely on raw color information without advanced preprocessing, which increases sensitivity to background interference and illumination variability. Furthermore, few studies have examined the integration of HSV based segmentation, multi view RGB phenotyping, and lightweight ML models suitable for edge deployment in Wireless Sensor Networks (WSNs). Therefore, this study evaluates an integrated framework for non-destructive salinity stress detection in peppermint using RGB imaging, HSV based plant segmentation, vegetation and morphological descriptors, and supervised ML models. The framework

was designed to balance predictive performance, computational efficiency, and interpretability, with the objective of supporting real time salinity monitoring in smart agricultural systems.

The remainder of this article is organized into four sections. Section 2 describes Materials and Methods along with an overview of the experimental workflow and data processing pipeline. Section 3 presents the Results and Discussion, including the study's limitations and future research directions. Finally, Section 4 summarizes the main Conclusions.

2. Materials and Methods

A complete methodological workflow adopted in this study is summarized in **Figure 1**. Briefly, segmented RGB images were used to extract RGB and histogram features and to compute vegetation indices. Preprocessed features were used to train ML models. All selected ML were evaluated in terms of their performance, computational metrics along with feature importance analysis.

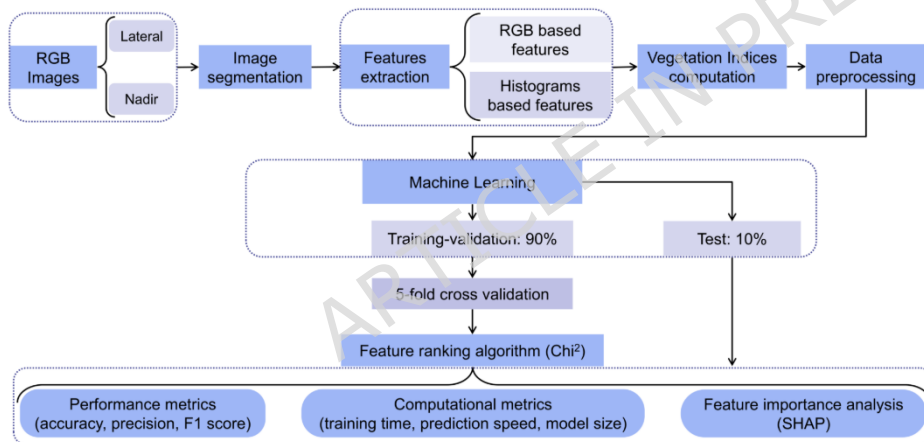


Figure 1. Methodological workflow for RGB based plant stress analysis.

2.1. Plant materials and experimental conditions

Peppermint plants (*Mentha × piperita*) were obtained as uniform plantlets from a local commercial nursery in Valencia, Spain (Naturae; 38.9622° N, 0.1639° W). Prior to treatment imposition, plants underwent a seven-day pre acclimation period during which irrigation with a complete nutrient solution was applied every other day.

Plants were cultivated individually in plastic pots with a top diameter of 13.5 cm, bottom diameter of 7.5 cm, and height of 10 cm. Pots were filled with a commercial peat-based substrate formulated for ornamental cultivation [26]. According to the manufacturer specifications, the substrate consisted of composted bark and/or organic amendments, vegetal compost, wood fiber, and sphagnum peat as primary components. The substrate exhibited a dry bulk density of approximately 500 kg m^{-3} , organic matter content of 70% on a dry matter basis, electrical conductivity below 0.5 mS cm^{-1} , and pH of 7.0.

Fertigation was performed using a liquid organic fertilizer (VITHAL Fertilizante Plantas Verdes BIOSPHERE PLUS; Vithal Garden, Spain) formulated with amino acids and a proprietary biostimulant complex [27]. According to the manufacturer composition, the fertilizer contained total nitrogen at 2.5% (w/w), potassium oxide at 4.0% (w/w), and organic carbon at 29.0 % (w/w), resulting in a carbon to nitrogen ratio (C:N) of 12.6. The formulation exhibited a density of 1.30 kg L^{-1} and pH of 6.5.

The experiment followed a randomized complete block design with three salinity treatments based on sodium chloride concentration: control (T0) at 0 mM, moderate stress (T1) at 100 mM, and severe stress (T2) at 200 mM. All treatments received identical fertigation volumes. Salinity stress was imposed by dissolving sodium chloride in distilled water prior to mixing with the fertilizer solution according to manufacturer recommendations. Control plants received no sodium chloride addition. Plants were maintained under controlled environmental conditions with daytime temperature of $24 \pm 2 \text{ }^{\circ}\text{C}$, nighttime temperature of $20 \pm 2 \text{ }^{\circ}\text{C}$, and relative humidity between 50 and 60%.

2.2. RGB Image acquisition

Digital images of individual plants were acquired daily using a high resolution RGB camera mounted on a fixed tripod to maintain consistent imaging geometry, following the procedure reported previously [28]. Image acquisition was performed using a Pi Camera Module 3 equipped with a 5 MP OV5642 sensor and autofocus capability. Images were captured under natural daylight conditions without artificial illumination.

Lateral images were acquired with plants positioned on a gray tabletop against a white background wall, while nadir images were captured against a uniform white background. Lateral views included front, back, left, and right orientations. The distance between the camera and plant canopy during lateral imaging was approximately 25 to 30 cm (**Figure 2**). Nadir images

were acquired from a vertical position at approximately 35 to 40 cm above ground level. Image acquisition continued throughout the 11-day salinity stress period. Images were captured daily over an 11-day period. Each treatment included three plants, with five images captured per plant per day, resulting in a total of 495 images used for analysis.

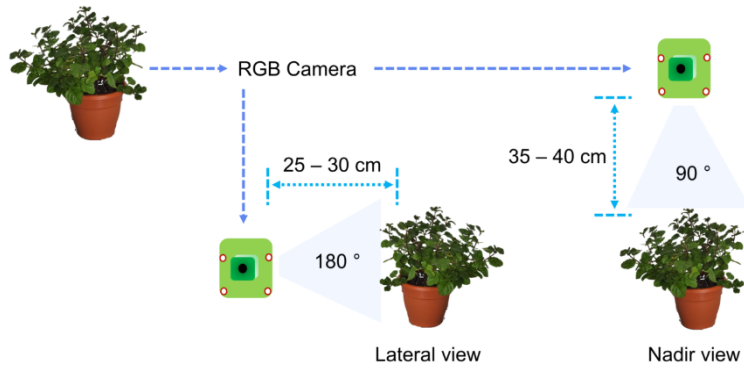


Figure 2. Illustration of imaging setup used for capturing lateral and nadir images.

2.3. Image processing

All images were standardized in the RGB coordinate system prior to analysis using Python version 3.10. Plant regions were isolated through a digital filtering pipeline implemented in the Hue Saturation Value color space. Raw JPG images were transformed into high precision PNG segmentation masks following threshold-based classification.

Images were converted from RGB to HSV space as described previously [29, 30]. A Boolean filtering operation was applied simultaneously across hue, saturation, and value channels. A pixel $P(h, s, v)$ was classified as leaf tissue when satisfying the following membership condition (Equation 1):

$$\Omega_{\text{Bio}} = \{P(h,s,v) | 15 \leq h \leq 100 \wedge 86 \leq s \leq 255 \wedge 25 \leq v \leq 255\} \quad (1)$$

Where $h \in [15,100]$ delimited the biological spectrum ranging from early chlorosis to green foliage. Saturation, $s \geq 86$, thresholds excluded achromatic components and specular reflections, while value, $v \geq 25$, thresholds eliminated shadows and dark substrate residues.

2.3.1. Morphological refinement and noise removal

Binary masks were subjected to connected component analysis under an eight-connectivity criterion to remove spatial artifacts. A cleaning function $L(M)$ was applied based on component area (Equation 2). Connected components with surface area below 100 pixels were discarded by assigning null opacity in the alpha channel, reducing impulsive noise and preventing statistical bias during feature extraction.

$$L(M) = \{C_i \in M | A(C_i) \geq 100 \text{ px}\} \quad (2)$$

where C_i represents the i -th connected component identified under the 8-connectivity criterion. Similarly, $A(C_i)$ denotes the area of the component, defined as the total number of pixels belonging to C_i .

2.3.2. Quantitative validation of segmentation

In order to assess the accuracy of the segmentation pipeline, two widely adopted overlap-based metrics were employed: the Dice coefficient and the Intersection over Union (IoU). Although these metrics are frequently associated with deep learning-based segmentation, they are equally applicable to classical image segmentation approaches, as they rely solely on the spatial overlap between predicted and ground truth binary masks [31, 32].

For two binary masks A (generated segmentation) and B (manual ground truth), the Dice coefficient measures the degree of similarity between the masks, while IoU quantifies their relative overlap. These metrics are defined in Equations 3 and 4.

$$\text{Dice} = \frac{2|A \cap B|}{|A| + |B|} \quad (3)$$

$$\text{IoU} = \frac{|A \cap B|}{|A \cup B|} \quad (4)$$

where $|A \cap B|$ is the number of pixels classified as plant in both masks, $|A|$ and $|B|$ are the total plant pixels in each mask, and $|A \cup B|$ is the total number of pixels belonging to at least one mask. Both metrics range from 0 (no overlap) to 1 (perfect agreement).

2.3.3. RGB-based image feature engineering

Image analysis employed a structured RGB processing pipeline designed for plant segmentation and chlorosis quantification. Illumination variability was reduced through linear stretching of the lightness channel in the CIELAB color space. Morphological closing operations improved structural continuity within segmented plant regions.

Adaptive estimation of hue intervals associated with leaf yellowing was performed daily. Hue values extracted from segmented nadir masks were aggregated, and mean values guided selection of lower and upper thresholds for chlorosis detection. Yellow pixel detection operated within an empirically defined hue range (Equation 5).

$$H \in [H_{low}, H_{high}] \quad (5)$$

where H denotes the hue value of a pixel, and H_{low} represents the adaptive threshold range corresponding to yellow coloration associated with chlorosis. Pixels satisfying the condition ($H_{low} \leq H \leq H_{high}$) were classified as chlorotic.

Chlorosis quantification followed three complementary color-based approaches as reported previously [30, 33]. The first approach relied on HSV-based yellow interval detection. The second approach employed K means clustering of HSV pixels within plant masks, assigning each pixel vector x to the nearest cluster centroid μ_k by minimizing the Euclidean distance (Equation 6).

$$\arg\min_k ||x - \mu_k||^2 \quad (6)$$

where x represents the feature vector of an individual pixel in HSV space, and μ_k denotes the centroid of the k -th cluster. Each pixel was assigned to the cluster for which the squared Euclidean distance was minimized.

Clusters exhibiting reduced saturation and increased lightness were classified as chlorotic tissue. The third approach applied the green minus red difference index ($G - R$), which decreases under chlorophyll degradation and is suitable for color-based stress detection.

Agreement among methods was summarized using a confidence score defined as the fraction of pixels identified as chlorotic by at least two approaches. Structural traits were extracted from segmented masks using connected component analysis. Projected area A , perimeter P , and compactness were calculated following Equation 7 [34]:

$$C = \frac{P^2}{(4\pi A)} \quad (7)$$

where P represents the perimeter of the segmented plant region and A denotes the corresponding projected area. This metric corresponds to the isoperimetric quotient and describes the geometric compactness of the plant canopy.

This metric represents the isoperimetric quotient of a two-dimensional shape. Horizontal and vertical spans derived from nadir and lateral views captured plant width and height, respectively.

2.3.4. Histogram based RGB feature extraction

Frequency based feature extraction was applied to construct datasets for comparison purposes with RGB based engineered features [28]. For each segmented image, probability density distributions of pixel intensities were calculated using colour histograms for red, green, and blue channels. Analysis was restricted to foliar regions defined by alpha channel values greater than zero. Weighted RGB intensity values were calculated to represent the global chromatic state of each experimental unit (Equation 8).

$$C_{val} = \sum_{i=0}^{255} (i \cdot f_{C,i}) \quad (8)$$

where C represents the respective R, G, or B channel, i denotes pixel intensity, and f represents the corresponding frequency. These weighted values served as primary descriptors for subsequent vegetation index computation.

2.3.5. Vegetation Indices

For improving the sensitivity of RGB based phenotyping to salinity-induced physiological alterations, a set of RGB VIs was computed, each designed to capture complementary information related to pigment composition, canopy colour dynamics, and early stress expression (**Table 1**). These indices were used as input features for the ML model development. These indices transform pixel level spectral information into quantitative descriptors of plant physiological status, enabling non-destructive assessment of chlorophyll degradation, pigment redistribution, and overall canopy vigour [35, 36].

Table 1. List of vegetation indices (VIs) computed from nadir and lateral images of peppermint cultivated under different regimes of salinity.

Vegetation Indices	Equation	Reference
Excess Green (ExG)	$ExG = 2G - R - B$	[37]
Excess Red (ExR)	$ExR = 1.4R - G$	[38]
Excess Blue (ExB)	$ExB = 1.4B - G$	[39]
Normalized Difference Index (NDI)	$NDI = \frac{G - R}{G + R}$	[40]
Green Leaf Index (GLI)	$GLI = \frac{2G - R - B}{2G + R + B}$	[41]
Visible Atmospherically Resistant Index (VARI)	$VARI = \frac{G - R}{G + R - B}$	[42, 43]
Color Index of Vegetation (CIVE)	$CIVE = 0.441R - 0.811G + 0.385B + 18.787$	[44]
Triangular Greenness Index (TGI)	$TGI = -0.5[190(R - G) - 120(R - B)]$	[45, 46]
Vegetative Index (VI green)	$VI_{green} = \frac{G}{R}$	[47]
Red-Green-Blue Vegetation Index (RGBVI)	$RGBVI = \frac{G^2 - RB}{G^2 + RB}$	[48]
Kawashima Index (IKAW)	$IKAW = \frac{R - B}{R + B}$	[49]
Modified Green Red Vegetation Index (MGRVI)	$MGRVI = \frac{G^2 - R^2}{G^2 + R^2}$	[48]

Indices emphasizing the green spectral component, such as Excess Green (ExG), Green Leaf Index (GLI), VI green, Triangular Greenness Index (TGI), and RGB Vegetation Index (RGBVI), are particularly sensitive to early reductions in chlorophyll content and the onset of leaf yellowing commonly associated with salinity stress. Conversely, indices that enhance red reflectance, including Excess Red (ExR), IKAW, Colour Index of Vegetation Extraction (CIVE), and Modified Green Red Vegetation Index (MGRVI), respond to the weakening of chlorophyll absorption, serving as indicators of pigment loss, accelerated senescence, and the development of necrotic tissues. Additional indices such as Excess Blue (ExB) and the Visible Atmospherically Resistant Index (VARI) capture secondary spectral shifts influenced by changes in epidermal reflectance properties, pigment ratios, and illumination variability, thereby improving robustness under natural lighting conditions. The Normalized Difference Index (NDI) provides a normalized measure of contrast between red and green reflectance, making it particularly effective for detecting progressive declines in canopy greenness as salinity severity increases.

Collectively, these vegetation indices provide complementary insights into both early and advanced stages of physiological deterioration. Accordingly, all indices were incorporated as input features for machine learning model development. [Their combined use increases the diversity of extracted](#)

features. This improved feature richness enhances the model's ability to detect subtle phenotypic changes associated with osmotic stress, pigment degradation, and structural canopy alterations. As a result, it supports more reliable salinity stress monitoring within an RGB-based edge computing framework.

2.4. Machine learning based stress classification

Feature sets derived from RGB-based and histogram-based analysis were systematically organized into three input configurations, namely lateral, nadir, and combined datasets, to evaluate the influence of acquisition perspective on classification performance.

A 90:10 train-test split was adopted, where 90% of the data were used for model training and internal validation, while the remaining 10% were strictly reserved as an independent test set to assess final model generalization. Within the training subset, a 5-fold cross-validation (CV) strategy was implemented across all feature sets. This approach ensures that the training data are iteratively partitioned into five subsets, where four folds are used for model training and one-fold for validation, thereby allowing robust estimation of model performance while reducing variance associated with a single data split.

The choice of combining a hold-out test set with k-fold cross-validation follows well-established practices in machine learning, where cross-validation is used for model selection and hyperparameter optimization, and an independent test set is retained for unbiased performance evaluation. This hybrid strategy has been widely recommended in the literature to improve reproducibility and to mitigate optimistic bias during model development [50, 51].

More specifically, the 90:10 split was selected to maximize the amount of data available for training, particularly important in moderate-sized experimental datasets, while still preserving a sufficiently representative test subset for independent validation. The use of 5-fold cross-validation further provides a balanced trade-off between computational efficiency and robustness of performance estimates, as increasing the number of folds may not significantly improve stability but would increase computational cost.

This partitioning strategy is particularly important in the context of subsequent analyses, such as model ranking and performance comparison, where consistent data splits ensure fair and reproducible evaluation across all tested machine learning algorithms. Additionally, maintaining a strict separation between training/validation and testing phases minimizes the

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Tao, H., Al-Sulttani, A. O., Salih Ameen, A. M., Ali, Z. H., Al-Ansari, N., Salih, S. Q., & Mostafa, R. R. (2020). Training and testing data division influence on hybrid machine learning model process: application of river flow forecasting. *Complexity*, 2020(1), 8844367.

likelihood of data leakage, thereby supporting a more reliable assessment of model generalization. Overall, this experimental protocol was designed to provide a rigorous, unbiased, and statistically stable evaluation framework, ensuring that the reported performance metrics reflect the true predictive capability of the models rather than artifacts of data partitioning.

In order to ensure a comprehensive comparison and identify the most suitable models for resource-constrained edge deployment, a wide range of machine learning algorithms spanning different families—including discriminant analysis, ensemble methods (Bagged, Boosted, RUSBoost, Subspace), kernel methods, k-nearest neighbors, naive Bayes, neural networks (shallow architectures), support vector machines, and decision trees—was evaluated. Furthermore, ML modelling and analysis were conducted using MATLAB version 2025b. Model performance was evaluated using accuracy, precision, F1 score, training time, model size, and optimized hyperparameters. Feature contribution and interpretability were assessed using Shapley Additive Explanations (SHAP) analysis, and dominant contributing features were reported for best performing models. ML models evaluated along with their corresponding hyperparameters for histogram- and RGB-based image features for classifying salinity groups are listed in **Table 2**.

Table 2. Nomenclature and hyperparameters of machine learning models employed for image-based salinity stress classification.

Model Type	Preset	Hyperparameters	Model Type	Preset	Hyperparameters
DD	Linear Discriminant	Covariance structure: Full	NB	Gaussian Naive Bayes	Distribution for numeric predictors: Gaussian
DD	Quadratic Discriminant	Covariance structure: Full	NB	Kernel Naive Bayes	Distribution for numeric predictors: Kernel
ESB	Bagged Trees	Learners: 30	NN	Bilayered Neural Network	Fully connected layers: 2
ESB	Boosted Trees	Learners: 30	NN	Medium Neural Network	Fully connected layers: 1
ESB	RUSBoosted Trees	Learners: 30	NN	Narrow Neural Network	Fully connected layers: 1
ESB	Subspace Discriminant	Learners: 30	NN	Trilayered Neural Network	Fully connected layers: 3
ESB	Subspace KNN	Learners: 30	NN	Wide Neural Network	Fully connected layers: 1
ETL	Efficient Linear SVM	Relative coefficient tolerance: 0.0001	SVM	Coarse Gaussian SVM	Kernel function: Gaussian
ETL	Efficient Logistic Regression	Relative coefficient tolerance: 0.0001	SVM	Cubic SVM	Kernel function: Cubic

KN	Logistic Regression Kernel	Iteration limit: 1000	SVM	Fine Gaussian SVM	Kernel function: Gaussian
KN	SVM Kernel	Iteration limit: 1000	SVM	Linear SVM	Kernel function: Linear
KNN	Coarse KNN	Neighbors: 100	SVM	Medium Gaussian SVM	Kernel function: Gaussian
KNN	Cosine KNN	Neighbors: 10	SVM	Quadratic SVM	Kernel function: Quadratic
KNN	Cubic KNN	Neighbors: 10	Tree	Coarse Tree	Maximum number of splits: 4
KNN	Fine KNN	Neighbors: 1	Tree	Fine Tree	Maximum number of splits: 100
KNN	Medium KNN	Neighbors: 10	Tree	Medium Tree	Maximum number of splits: 20
KNN	Weighted KNN	Neighbors: 10			

A comprehensive inventory of all engineered features derived from the RGB-based and histogram-based feature extraction pipelines is presented in **Table 3**, respectively. These features were evaluated independently for the lateral, nadir, and combined (lateral + nadir) image configurations across the two computer-vision workflows implemented in this study.

Table 3. Consolidated list of engineered features derived from RGB- and histogram-based descriptors across lateral, nadir, and combined image viewpoints employed for machine learning.

ID	Name	Description	ID	Name	Description	ID	Name	Description
RGB-based image features			RGB-based image features			Histogram-based image features		
1	area_px	Plant area (pixels)	22	G_div_R_mean	Mean ratio G/R	1	ICR	Intensity contribution Red
2	perimeter_px	Boundary length (pixels)	23	R_div_B_mean	Mean ratio R/B	2	ICG	Intensity contribution Green
3	compactness	$4\pi A/P^2$ (shape roundness)	24	G_div_B_mean	Mean ratio G/B	3	ICB	Intensity contribution Blue
4	width_px	Bounding width (pixels)	25	NGRDI_mean	Normalized Green-Red Difference	4	Pixel_value	Overall pixel intensity metric
5	height_px	Bounding height (pixels)	26	NDI	Normalized difference of channels	5	R_f	Red bin frequency / proportion
6	kmeans_yellow_fraction	Yellow fraction (k-means segmentation)	27	VIgreen	Green index	6	G_f	Green bin frequency / proportion
7	gr_yellow_fraction	Yellow fraction (G-R rule)	28	MGRVI	Modified Green-Red Vegetation Index	7	B_f	Blue bin frequency / proportion
8	chlorosis_confidence	Chlorosis score (0-1)	29	VARI	Visible Atmospherically Resistant Index	8	NDI	Normalized difference
9	mean_r	Mean red channel intensity	30	RGBVI	RGB-based Vegetation Index	9	GLI	Green Leaf Index

10	mean_g	Mean green channel intensity	31	GLI	Green Leaf Index	10	VARI	Visible Atmospherically Resistant Index
11	mean_b	Mean blue channel intensity	32	GLI_mean	Mean Green Leaf Index	11	VI_green	Green index
12	std_r	Std. dev. red channel	33	ExG	Excess Green	12	MGRVI	Modified Green-Red Vegetation Index
13	std_g	Std. dev. green channel	34	ExG_mean	Mean Excess Green	13	ExR	Excess Red
14	std_b	Std. dev. blue channel	35	ExR	Excess Red	14	ExB	Excess Blue
15	mean_h	Mean hue (HSV)	36	ExR_mean	Mean Excess Red	15	ExG	Excess Green
16	mean_s	Mean saturation (HSV)	37	ExB	Excess Blue (2B-R-G)	16	CIVE	Color Index of Vegetation Extraction
17	mean_v	Mean value/brightness (HSV)	38	ExGR_mean	ExG - ExR (mean)	17	RGBVI	RGB Vegetation Index
18	std_h	Std. dev. hue (HSV)	39	CIVE	Color Index of Vegetation Extraction	18	IKAW	Kawashima index variant
19	std_s	Std. dev. saturation (HSV)	40	IKAW	Kawashima index variant (VIS-based)	19	TGI	Triangular Greenness Index
20	std_v	Std. dev. value (HSV)	41	TGI	Triangular Greenness Index	20	Day	Day of experiment
21	R_div_G_mean	Mean ratio R/G	42	Day	Days since start	21	Position	Imaging angle (nadir or lateral)

The detailed separation of feature sources and viewpoints was intentionally designed to (i) identify the most suitable image-feature development strategy, and (ii) determine the minimal yet most informative subset of features required to achieve optimal ML performance. Such an approach is particularly relevant for enabling lightweight inference and real-time deployment of ML models on edge devices for precision agriculture applications.

2.4.1. Data leakage prevention and model generalization assessment

For minimizing the possibility of data leakage during model development, the dataset was initially partitioned into independent training and testing. All preprocessing operations associated with feature ranking and model fitting were performed exclusively on the training subset. Specifically, feature selection using the Chi square (χ^2) ranking algorithm was applied only to the training data, and the resulting selected feature subsets were subsequently transferred to the unseen testing dataset. This procedure ensured that no statistical information from the testing subset influenced feature ranking or model training.

In addition to conventional performance metrics, model robustness and potential overfitting were evaluated through indirect generalization gap analysis by comparing validation and testing performance across all optimized ML models as reported previously [52–54]. Three complementary gap metrics were calculated to quantify the consistency between validation and independent test performance.

The prediction error gap was further estimated using Equation 9.

$$Gap_{acc} = Accuracy_{val} - Accuracy_{test} \quad (9)$$

The weighted F1 score gap was calculated according to Equation 10.

$$Gap_{F1} = WeightedF1_{val} - WeightedF1_{test} \quad (10)$$

Whereas the prediction error gap was further estimated using Equation 11.

$$Gap_{err} = Error_{test} - Error_{val} \quad (11)$$

where $Accuracy_{val}$, $F1_{val}$, and $Error_{val}$ correspond to validation metrics obtained during model optimization, whereas $Accuracy_{test}$, $F1_{test}$, and $Error_{test}$ represent performance metrics derived from the independent testing subset.

Generalization gaps approaching zero were interpreted as indicators of stable model transferability and reduced overfitting, reflecting close agreement between validation and testing performance. Positive gap values indicated that validation performance exceeded testing performance, suggesting potential overfitting or optimistic validation estimates. Conversely, negative gap values indicated slightly improved performance on the testing subset, which may occur because of sample variability, conservative validation estimates, or increased class separability within the independent testing partition.

In order to facilitate comparative interpretation, the relationship between accuracy gap and weighted F1 score gap was additionally visualized through a two-dimensional generalization map. Models positioned close to the origin and near the ($y=x$) reference line were interpreted as exhibiting balanced and stable generalization behavior, whereas increasing displacement from the origin indicated progressively larger discrepancies between validation and testing performance.

2.5. Salinity monitoring using wireless sensor network

Salinity stress monitoring system was implemented through a distributed WSN architecture, as illustrated in **Figure 3**, designed to support real-time phenotypic inference under constrained energy and bandwidth conditions. The system followed a hierarchical topology that integrated edge intelligence, low power communication, and cloud-based coordination for scalable agricultural deployment.

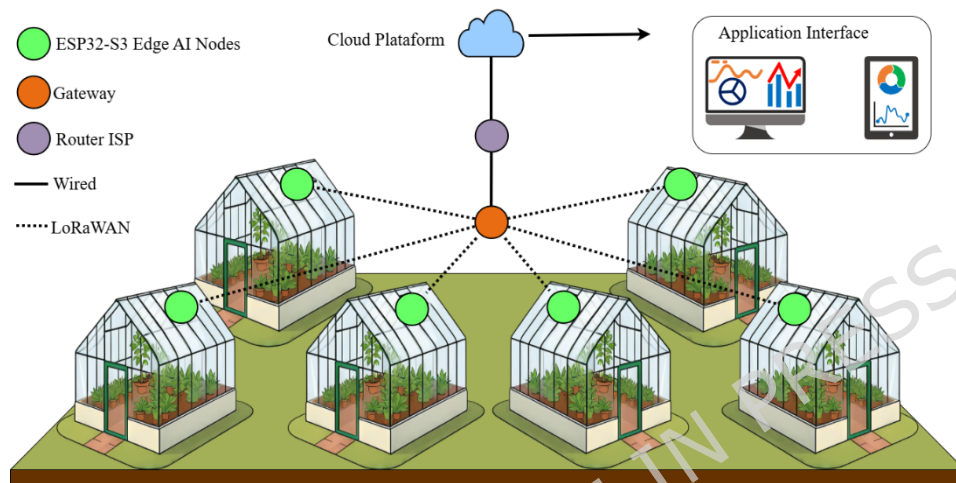


Figure 3. Illustration of the distributed wireless sensing architecture for salinity-stress monitoring. ESP32-S3 edge nodes acquire and locally process RGB phenotypic data before transmitting compacted information to a central gateway via LoRaWAN. The gateway forwards aggregated data through a wired connection to an Internet Service Provider router, enabling cloud-based storage, analysis, and real-time visualization through the application interface.

At the sensing tier, multiple ESP32-S3 based edge AI nodes were deployed within individual greenhouse compartments. Each node functioned as an autonomous phenotyping unit equipped with an RGB imaging module and onboard processing resource, enabling local feature extraction and data reduction prior to transmission to minimize bandwidth demand. Communication between the edge nodes and the central gateway was established through a LoRaWAN link, providing energy-efficient, long-range connectivity suitable for spatially distributed agricultural environments. These nodes enabling high speed, low latency data exchange through LoRaWAN communication.

A Raspberry Pi 5 unit functioned as the gateway and intermediate aggregation layer. The gateway received LoRaWAN packets from all sensing nodes, synchronized incoming data streams, and performed temporary buffering and validation prior to forwarding information to the cloud platform through a wired connection to an Internet Service Provider (ISP) router. The cloud platform handled long term data storage, centralized monitoring, and visualization through an application dashboard that displayed stress predictions, historical trends, and network status in real time. This hybrid architecture combined local edge inference with lightweight communication and centralized management to improve scalability, reduce communication overhead, and support stable operation under field conditions.

The operational logic of the proposed system is illustrated in **Figure 4** and follows an event driven, energy aware sensing paradigm. Each sensing cycle commenced with node activation from deep sleep mode, minimizing idle power consumption during non-operational periods. Upon activation, the ESP32-S3 module acquired high resolution RGB images of the crop canopy and executed machine learning based visual inference directly at the edge.

Several computational and communication efficiency metrics were quantified to evaluate the suitability of the proposed framework for edge deployment. Inference latency was estimated from the measured prediction throughput of each ML model according to Equation 12 [55].

$$\text{Latency (ms)} = \frac{1000}{\text{Throughput}(\text{obs}\cdot\text{s}^{-1})} \quad (12)$$

where Throughput represents the number of processed observations per second during model inference. This metric quantified the real time responsiveness of each model under edge computing conditions.

Communication efficiency was evaluated through transmission reduction analysis by comparing the size of raw RGB images with processed representations and extracted feature vectors. Percentage reduction in transmitted data was calculated using Equation 13 [56, 57].

$$\text{Data Reduction (\%)} = \frac{S_{\text{raw}} - S_{\text{processed}}}{S_{\text{raw}}} \times 100 \quad (13)$$

where S_{raw} denotes the size of the original RGB image and $S_{\text{processed}}$ represents the size of the processed image or transmitted feature representation after local edge processing. Transmission efficiency

throughput capability was defined as the maximum number of image samples processed per second during inference execution. These metrics collectively provided an estimate of the operational feasibility of deploying the proposed salinity monitoring framework on resource constrained embedded hardware platforms.

3. Results and Discussion

This section synthesizes the performance of the proposed RGB-based phenotyping and edge intelligence framework for salinity stress monitoring in peppermint, with emphasis on image segmentation fidelity, ML classification outcomes, and biological interpretability of the derived features. Results are structured to progressively evaluate segmentation quality, predictive performance of RGB- and histogram-based feature sets, and the explanatory power of model driven feature attribution, followed by a critical appraisal of methodological constraints and future research directions.

3.1. Image segmentation

Image segmentation consistently produced accurate and clean delineation of plant tissue from background across all salinity treatments and viewing geometries. Both nadir and lateral images produced well-defined binary masks. However, nadir views showed more uniform boundaries and fewer segmentation artifacts due to reduced self-shading and more homogeneous canopy exposure. Lateral images occasionally exhibited minor edge irregularities under severe salinity stress, reflecting physiological responses such as leaf curling, tissue dehydration, and structural collapse that altered canopy geometry and reflectance. Removal of small connected components below 100 pixels effectively eliminated background noise and substrate interference, preserving contiguous plant regions and preventing artificial inflation of color and structural variability. Representative segmented images in **Figure 5**, and Figures S1 and S2, illustrate reliable preservation of chlorotic and necrotic areas under increasing stress severity, providing a robust basis for subsequent extraction of morphological and spectral features used in ML based salinity classification.

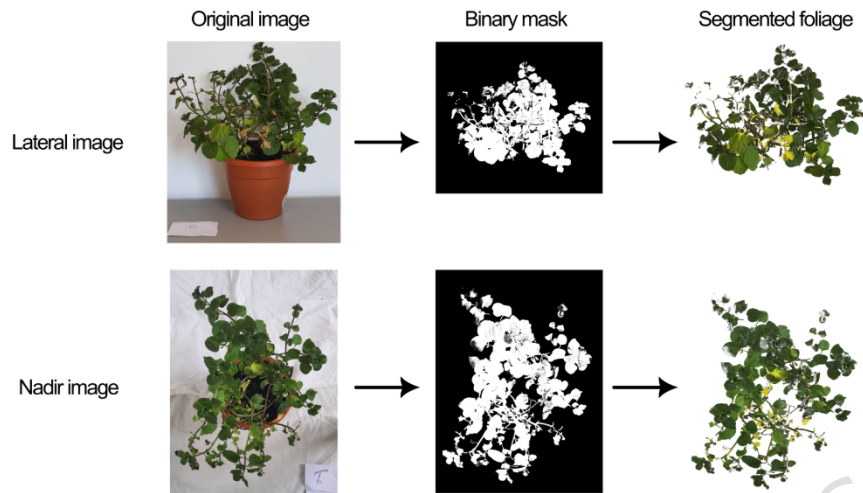


Figure 5. Foliage segmentation results and corresponding binary mask outputs generated from original RGB images of peppermint plants on day 10 of salinity exposure, shown for both lateral and nadir imaging perspectives under 200 mM NaCl stress (T2). The figure illustrates the performance of the segmentation pipeline in isolating leaf area across contrasting viewpoints under high salinity conditions.

Some representative histograms based on mean R, G, and B frequency values from the segmented images are presented in **Figure 6**, and **Figures S3-S5**. A systematic reduction in the amplitude of pixel intensity for the three color channels (red, green, and blue) is evident when transitioning from T0 to T1 and, finally, to T2. This attenuation pattern, present in both the lateral (**Figure 6a-c**) and nadir (**Figure 6d-f**) perspectives, reflects a profound alteration in the reflectance properties of the leaf canopy.

In the control group (T0), probably the high chlorophyll concentration and cellular turgor generated narrow, elevated frequency peaks, indicating saturated and uniform pigmentation. As salinity increases in T1 and T2, the decrease in the average frequency of these peaks and their broadening suggest a transition toward more opaque and heterogeneous tones. Physically, this generalized reduction in RGB channel intensity probably corresponds to the degradation of photosynthetic pigments and the appearance of necrotic areas, which absorb or scatter light differently than healthy tissue. This downward trend in the frequency distribution is precisely the factor that allows histogram descriptors to act as sensitive indicators for

the automatic classification of salt stress, as reflected in the precision results of the models presented in Section 3.3.

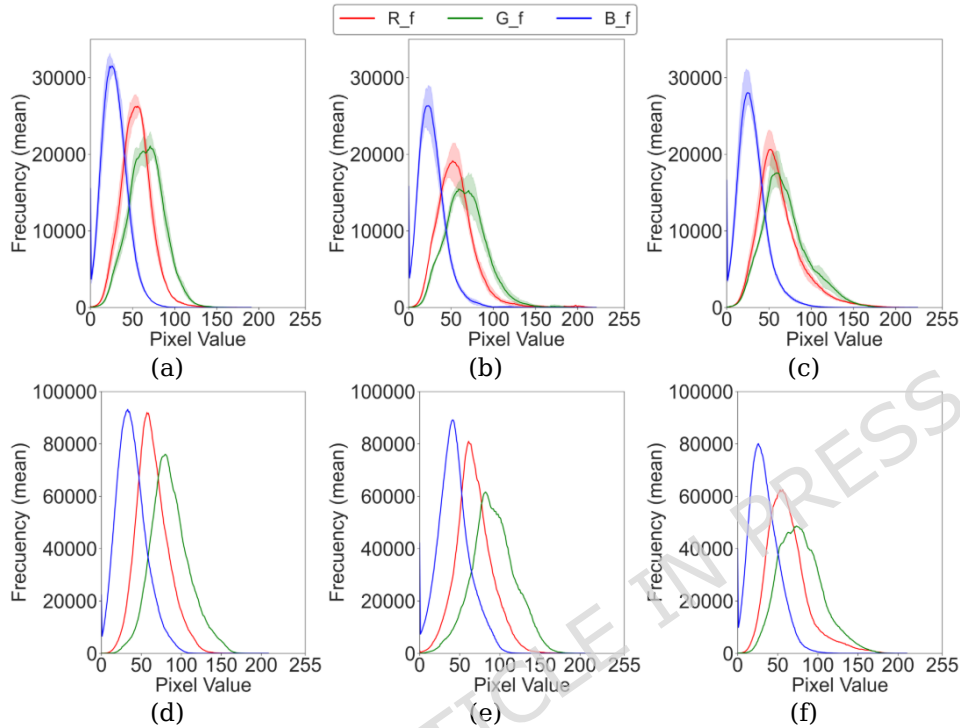


Figure 6. RGB channel histogram profiles for plants exposed to increasing salinity levels on day 10 post stress initiation. Panels (a-c) present the Lateral view for treatments T0, T1, and T2, respectively, while panels (d-f) show the corresponding Nadir view histogram profiles for T0, T1, and T2.

3.1.1. Quantitative validation of the segmentation results

Quantitative validation (Table 4) demonstrated near-perfect agreement between the HSV-based segmentation and the manually refined ground truth across the entire dataset. The segmentation pipeline achieved exceptionally high accuracy for both imaging perspectives. For the nadir view, the mean Dice coefficient reached 0.9995 (95% CI: 0.9994–0.9996), with a corresponding IoU of 0.9989 (± 0.0007). Similarly, the lateral view yielded a Dice coefficient of 0.9984 (95% CI: 0.9983–0.9985) and an IoU of 0.9968 (± 0.0018).

Although both configurations demonstrated consistently high performance, the nadir-based segmentation exhibited slightly superior agreement with the ground truth. This improvement is likely due to more uniform canopy exposure and reduced geometric distortion. In contrast, the marginally lower performance observed in lateral images can be attributed to increased complexity introduced by oblique viewing angles, including less distinct leaf boundaries, self-occlusion, and heterogeneous illumination conditions.

Table 4. Quantitative segmentation performance for nadir and lateral views. Values indicate means $\pm$ confidence interval (CI).

Imaging angle	Dice coefficient (95% CI)	IoU (95% CI)
Nadir	0.9995 $\pm$ 0.0004	0.9989 $\pm$ 0.0007
Lateral	0.9984 $\pm$ 0.0009	0.9968 $\pm$ 0.0018

3.2. ML results for RGB-based image features

Across the three RGB derived feature configurations, classification performance varied substantially as a function of viewing geometry and feature dimensionality, revealing a consistent balance between predictive accuracy and suitability for edge deployment (Table 5). Feature ranking based on Chi² algorithm are provided in Supplementary Information (Figure S6 and S7).

Using lateral image features, overall classification accuracy remained moderate, ranging between approximately 64% and 66%. Among evaluated models, the Quadratic SVM emerged as the most appropriate under these conditions. This model achieved the highest accuracy of 66.33% while relying on only 11 features, resulting in rapid training time of 1.77 s, fast inference, and a compact memory footprint of 0.032 MB. The corresponding confusion matrix is presented in Figure 7a. However, misclassifications were most frequent between adjacent salinity levels, particularly confusing moderate stress (100 mM) with control (0 mM) and severe stress (200 mM). This pattern reflects the gradual nature of salinity-induced phenotypic changes and the lower discriminative power of lateral views, where leaf occlusion, variable lighting, and heterogeneous stress expression along stems reduce feature reliability. Although Wide NN and logistic regression yielded comparable accuracy, both approaches required a substantially larger feature space of 38 features without providing meaningful gains in predictive

performance. Further reduction of feature dimensionality did not result in improved accuracy or computational efficiency.

Table 5. Summary of performance and computational metrics of best performing machine learning models for classifying salinity from RGB-derived image features.

ML Model	No. of features	Accuracy %	Macro Precision %	Macro Recall %	Macro F1 Score %	Prediction Speed (obs/sec)	Training Time (sec)	Code r Model Size (MB)
Lateral image features								
Wide Neural Network	38	66.33	66.21	65.92	66.02	12414.18	4.13	0.052
Efficient Logistic Regression	38	65.99	65.00	65.14	64.94	9751.41	2.36	0.028
Quadratic SVM	11	66.33	65.76	66.33	65.75	9870.31	1.77	0.032
Linear Discriminant	11	64.29	64.17	64.29	63.41	11499.06	2.09	0.004
Nadir image features								
Bagged Trees	38	100	100	100	100	1404.23	10.82	0.318
Cubic SVM	38	99.320	99.267	99.359	99.306	5522.361	5.430	0.072
Fine KNN	2	98.299	98.410	98.127	98.231	9120.974	8.809	0.009
Weighted KNN	2	98.299	98.410	98.127	98.231	9250.432	12.202	0.009
Bagged Trees	2	98.299	98.410	98.127	98.231	1953.151	25.490	0.131
Combined feature set (lateral and nadir)								
Bagged Trees	82	98.30	98.22	98.26	98.24	1090.46	28.18	0.466
Cubic SVM	82	91.50	91.28	91.25	91.27	5491.38	15.54	0.270
Subspace KNN	6	100	100	100	100	622.85	6.18	0.324
Wide Neural Network	6	100	100	100	100	19585.25	4.00	0.010

Nadir image features markedly enhanced discrimination among salinity treatments. Using the complete 38 feature set, Bagged Trees achieved perfect classification accuracy; however, this performance was accompanied by increased computational complexity and memory requirements. Considering constraints related to energy consumption and deployment in agricultural field environments, the Fine KNN model provided the most favorable compromise. This model relied on only two features and achieved an accuracy of 98.30%, strong macro averaged performance metrics, an exceptionally small model size of 0.009 MB, and high prediction speed. These

attributes establish it as the most efficient nadir-based model for embedded applications. The confusion matrix for the Fine KNN model is shown in **Figure 7b**. Nevertheless, only approximately 1.87% of samples were misclassified, with errors occurring exclusively between the moderate and severe stress classes. These rare misclassifications likely correspond to individual plants exhibiting atypical stress responses or to image acquisition artifacts such as slight variations in lighting or leaf orientation.

The combined lateral and nadir feature set further demonstrated that near complete classification performance can be achieved with minimal input information. Both Subspace K Nearest Neighbors and Wide Neural Networks reached 100% accuracy using only six features. Among these, the Wide Neural Network exhibited superior computational efficiency, achieving a throughput of 19,585 observations per second, a training time of approximately 4 s, and a compact model size of 0.010 MB. These characteristics position the Wide NN as the most suitable model under combined imaging conditions. The corresponding confusion matrix is presented in **Figure 7c**.

Collectively, these results demonstrate that high fidelity salinity stress monitoring in peppermint can be achieved using extremely lightweight ML models. Nadir or combined imaging configurations, coupled with Fine KNN or Wide NN, provide an optimal balance between predictive performance and deployability within real world edge-based sensor networks.

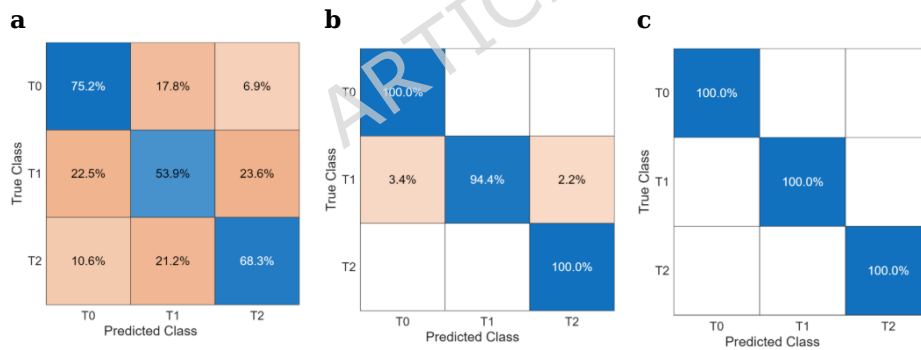


Figure 7. Classification performance of the top models, illustrated through confusion matrices for (a) Quadratic SVM, (b) Fine KNN, and (c) Wide Neural Network.

3.2.1. SHAP feature importance analysis results

SHAP analysis revealed statistical associations between spectral and morphological features and salinity stress classification across lateral, nadir, and combined feature sets. Nevertheless, the interpretations are grounded in literature-supported physiological associations and should be considered indicative rather than direct evidence of causal physiological mechanisms.

In the lateral view model (**Figure 8a**), the most influential features included the variance of red and blue channel intensities and the projected canopy area. High SHAP contributions associated with control and severe stress classes suggest that spatial heterogeneity in coloration and reductions in plant size are statistically linked to salinity exposure. Increased variability in red and blue reflectance is consistent with possible patchy chlorosis, pigment redistribution, and tissue desiccation, which may generate non-uniform optical patterns along leaf surfaces and stems under salt stress [36]. Concurrently, reductions in lateral canopy area align with well documented growth inhibition responses driven by osmotic stress and restricted leaf expansion [59]. Although lateral features provided moderate predictive power, their importance correlates with visible structural degradation accompanying increasing salinity levels.

The nadir view model (**Figure 8b**) produced a more compact feature signature dominated by hue variability and the NDI. Strong contributions from hue variability across treatments suggest a possible sensitivity of canopy top reflectance to chlorophyll degradation, loss of turgor, or the emergence of necrotic tissue, all of which may disrupt pigment uniformity [60]. The declining influence of the NDI from control to severe stress classes probably corresponds to progressive reductions in vegetation greenness, a pattern commonly reported under saline conditions and often associated with decreased chlorophyll content [35]. These two nadir derived features thus serve as statistical indicators of stress related optical changes while enabling near perfect classification with minimal feature input.

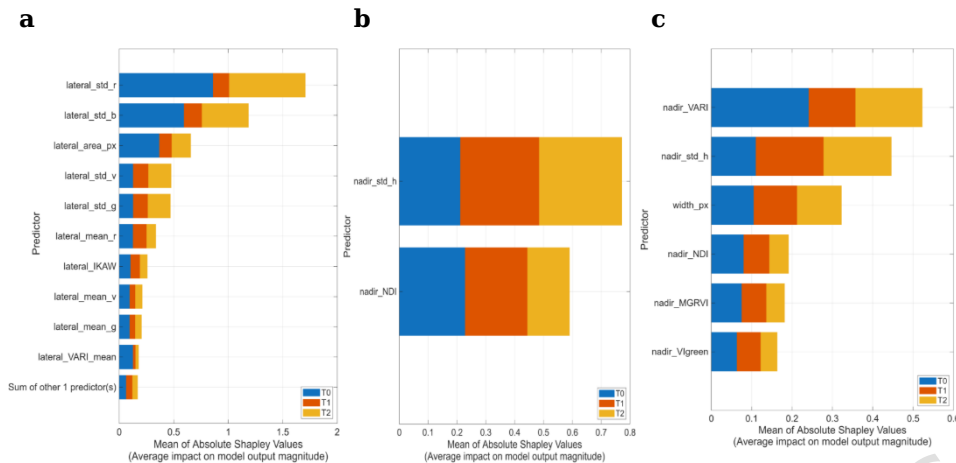


Figure 8. SHAP-based feature importance summaries for the best performing models, showing contributions of lateral (a), nadir (b), and combined (c) feature sets for Quadratic SVM, Fine KNN, and Wide Neural Network.

The combined feature SHAP profile (**Figure 8c**) reinforced the dominance of nadir based spectral indices, particularly the VARI derived from nadir images. This index exhibited the strongest influence across all stress classes, which is consistent with its known sensitivity to subtle changes in green reflectance and pigment composition reported in earlier studies [61]. Additional contributions from nadir hue variability, nadir NDI, and structural attributes such as canopy width suggest that the combined model integrates both spectral and morphometric information. This integration may reflect concurrent effects of ionic toxicity and osmotic imbalance on pigment stability and canopy architecture, although independent physiological confirmation would be required.

Overall, SHAP analysis supports a statistical interpretation in which salinity stress in peppermint is primarily associated with changes in canopy pigmentation, spectral variability, and plant size. These responses are most consistently captured from the nadir perspective. The dominance of a limited number of features in the best performing models highlights the presence of a strong optical fingerprint linked to salinity stress, enabling accurate on device monitoring using compact and computationally efficient ML models for precision agriculture applications. However, as with all SHAP-based interpretations, these findings reflect associations rather than direct causal physiological mechanisms.

3.3. ML results for histogram-based image features

ML performance based on histogram derived RGB features revealed a distinct dependence on viewing geometry and feature dimensionality, highlighting differences in how global color distributions capture salinity induced physiological changes (**Table 6**).

For the lateral histogram-based image features, the Bagged Trees model emerged as the top algorithm, achieving a maximum accuracy of 71.04% with 20 features configuration (**Figure 9a**). The confusion matrix shows that misclassifications were distributed across all three stress levels, with the moderate stress class (100 mM) most frequently confused with both control and severe classes. This indicates that lateral histogram features, while capturing some discriminatory information, lack sufficient resolution to reliably separate overlapping color intensity distributions caused by partial shading, leaf curling, and non-uniform chlorosis along the stem. This model demonstrated a prediction speed of 20,349 obs/sec and a training time of 400.18 s. Furthermore, the model maintained a memory footprint of 30.53 MB, suggesting that the full features set is essential for balancing predictive power and computational efficiency in lateral perspectives. These results indicate that lateral histograms encode moderate discriminatory information related primarily to heterogeneous color distributions along leaf margins and stems. Such patterns are consistent with non-uniform pigment degradation, localized chlorosis, and tissue dehydration commonly induced by salt stress [62–64]. However, effective classification from lateral perspectives required the full feature set, reflecting the spatial complexity and variability of stress symptoms when observed from oblique angles.

When utilizing nadir features, the Bagged Trees model again demonstrated superior predictive performance, reaching its peak accuracy of 85.26% with 20 features set (**Figure 9b**). The errors occurred when the model assigned moderate stress (100 mM) plants to either the control or severe stress categories. This confusion arises from the progressive and continuous nature of pigment degradation under salinity: plants at early stages of moderate stress may still exhibit color distributions similar to controls, while those at later stages may resemble severe stress, creating a zone of spectral overlap that histogram-based features cannot fully resolve. This configuration proved to be the most efficient for stress detection, maintaining a high prediction speed of 28,829 obs/sec and a training time of 436.97 s. The model also featured a remarkably compact memory footprint of 7.08 MB, making it the most suitable candidate for real-time monitoring applications. The improved

performance observed under nadir imaging may reflect the ability of canopy top views to capture integrated color distributions associated with chlorophyll degradation, reductions in green intensity, and shifts toward yellow and brown pigmentation. These changes correspond to well established physiological responses to salinity, including impaired photosynthetic efficiency, ionic toxicity, and accelerated senescence [65, 66]. The reduced memory requirement further supports the suitability of nadir histogram features for real time stress monitoring in embedded systems.

Table 6. Summary of performance and computational metrics of best performing machine learning models for classifying salinity from [histogram](#)-derived image features.

ML Model	No. of features	Accuracy %	Macro Precision %	Macro Recall %	Macro F1 Score %	Prediction Speed (obs/sec)	Training Time (sec)	Coder Model Size (MB)
Lateral image features								
Bagged Trees	20	71.04	70.86	70.96	70.88	20349.17	400.18	30.53
Fine KNN	20	66.85	68.75	68.73	68.73	3362.05	74.07	9.55
Bagged Trees	19	61.24	61.1	61.22	61.1	20114.03	379.99	35.68
Fine KNN	19	55.25	56.4	56.38	56.39	2604.9	482.46	9.10
Nadir image features								
Bagged Trees	20	85.26	85.24	85.28	85.24	28829.51	436.97	7.08
Fine KNN	20	82.65	86.22	86.18	86.2	9953.71	261.95	3.05
Bagged Trees	19	74.08	74.1	74.08	74.06	26361.25	572.25	9.06
Fine KNN	19	68.72	71.28	71.21	71.24	7927.17	311.92	2.91
Combined feature set (lateral and nadir)								
Bagged Trees	21	74.22	74.09	74.18	74.1	51109.07	337.05	37.97
Fine KNN	21	71.1	73.42	73.41	73.41	2228.49	153.1	13.18
Bagged Trees	19	61.41	61.34	61.45	61.33	47782.94	344.32	45.86
Fine KNN	19	55.85	57.14	57.12	57.13	2275.87	160.37	12.01

The combined use of nadir and lateral features resulted in a maximum accuracy of 74.22% using 21 features configuration (**Figure 9c**). [The result of this model demonstrates that combining lateral and nadir histograms did not reduce misclassification rates compared to using nadir features alone. Errors remained concentrated in the moderate stress class, with additional confusion introduced between control and severe stress, suggesting that lateral histogram features add noise rather than complementary information](#)

under heterogeneous illumination conditions. While this represents an improvement over the lateral only feature set, classification performance remained inferior to the nadir only approach. The combined configuration achieved the highest processing efficiency observed in this study, with a prediction speed of 51,109 observations per second and a training time of 337.05 s, albeit at the expense of increased memory usage of 37.97 MB. These results suggest that integrating lateral information introduces additional variability without proportionally increasing discriminatory power, likely due to redundancy and noise in lateral color distributions under heterogeneous lighting and shading conditions [62, 66, 67].

Feature reduction strategies applied to Bagged Trees models consistently resulted in pronounced losses in predictive performance across all acquisition perspectives. Removal of even a single feature produced a precision decline exceeding 11% (**Figure 9**), demonstrating that histogram-based classification relies on the complete feature set to capture subtle shifts in global color intensity distributions. From a physiological standpoint, salinity stress induces gradual and overlapping changes in pigment composition, water status, and tissue integrity. Histogram features collectively encode these cumulative effects across the full intensity spectrum, making dimensionality reduction detrimental to reliable stress discrimination.

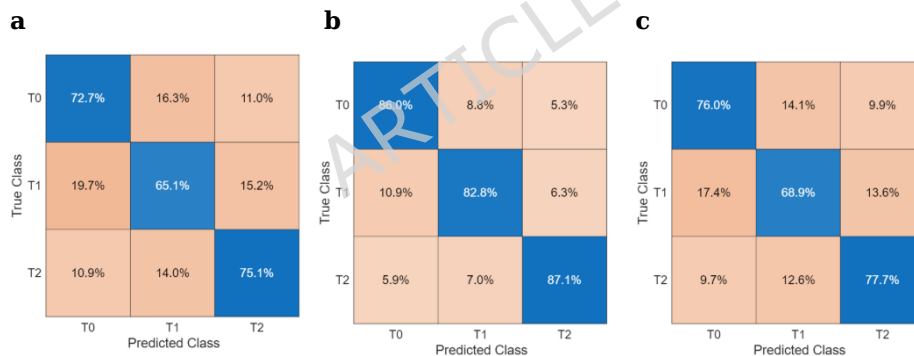


Figure 9. Confusion matrices derived from histogram-based features using the Bagged Trees model under (a) lateral, (b) nadir, and (c) combined configurations.

Overall, histogram-based ML analysis confirms that high fidelity salinity stress monitoring in peppermint can be achieved using global RGB intensity distributions, particularly under nadir imaging conditions. The nadir oriented

Bagged Trees model delivered the best balance between predictive accuracy, computational efficiency, and memory footprint, achieving robust performance with only 7.08 MB of model size. This configuration offers a practical and biologically grounded solution for deployment in edge based WSN aimed at real time crop stress monitoring.

3.3.1. SHAP feature importance analysis results

The SHAP analysis revealed distinct spectral and temporal drivers underlying salinity stress classification across the lateral, nadir, and combined feature sets (Figure 10). However, the interpretations provided are based on plausible explanations derived from existing literature and reflect associated physiological trends, rather than establishing direct causal physiological mechanisms.

In the lateral view model (Figure 10a), the most influential features included the Pixel Value and the Intensity contribution Red. High SHAP contributions associated with control and severe stress classes may indicate that spatial heterogeneity in pixel intensity and red reflectance constitute dominant lateral manifestations of salinity exposure. Increased variability in these parameters could be associated with possible patchy chlorosis and tissue desiccation, which collectively generate non-uniform optical patterns along leaf surfaces and stems under salt stress [66]. Concurrently, the importance of the Day variable and the IKAW index could be associated to the cumulative impact of osmotic stress and restricted water uptake over time as reported previously in salt affected plant [62]. Although lateral features provided moderate predictive power, their importance may align closely with possible structural and pigment degradation accompanying increasing salinity levels.

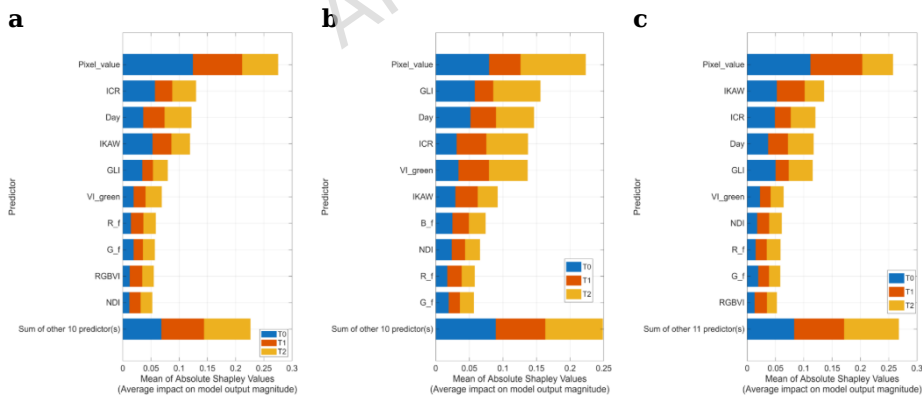


Figure 10. SHAP interpretation results for the Bagged Trees model, highlighting feature contributions across (a) lateral, (b) nadir, and (c) combined feature sets.

In nadir view model (**Figure 10b**), a more compact and physiologically coherent feature signature dominated by the Pixel Value and the GLI index were found to be major contributors to ML model. Strong contributions from GLI across treatments likely indicate high sensitivity of the canopy top reflectance to pigments, i.e., chlorophyll, degradation and the emergence of necrotic tissue, both of which could disrupt pigment uniformity [67]. The ranking of the Day variable and Intensity contribution Red possibly correspond to the progressive reductions in vegetation greenness and the redistribution of pigments commonly reported under saline conditions [2]. Overall, these nadir-derived features, including VI Green, likely encapsulate key optical indicators of stress physiology while enabling superior classification accuracy with minimal feature input.

The combined feature SHAP profile (**Figure 10c**) reinforced the dominance of nadir-based spectral information, led again by Pixel Value and the IKAW index. The high significance of the IKAW index in this configuration might suggest that the combined model effectively integrated surrogates of leaf hydration status with general intensity distributions. This possibly reflects the physiological response of the plant to the osmotic stress caused by salinity, where reduced water uptake leads to slight changes in leaf turgor and, consequently, in surface reflectance [24]. Additional contributions from Intensity contribution Red, Day, and GLI indicate that the model likely leveraged both chromaticity changes and the temporal progression of the experiment. This integration might indicate the concurrent effects of ionic toxicity and osmotic imbalance on pigment stability and canopy architecture under salinity stress [1]. Overall, SHAP analysis possibly supports a likely physiological interpretation in which salinity stress in peppermint is primarily expressed through changes in canopy pigmentation and pixel intensity distributions. These responses are most consistently captured from the nadir perspective. The dominance of a limited number of features in the best-performing Bagged Trees models highlights the presence of a strong optical fingerprint associated with salinity stress, enabling accurate on-device monitoring using compact and computationally efficient ML models for precision agriculture applications.

3.4. Data leakage and model generalization analysis

Given the near perfect classification performance achieved in some RGB-based imaging pipeline, an additional assessment of model robustness and potential overfitting was conducted using indirect generalization gap analysis (**Table 7**). The analysis compared validation and independent testing performance to evaluate the stability and transferability of the optimized classifiers beyond conventional accuracy metrics.

Table 7. Summary of metrics estimated for generalization assessment.

Model	Features	Accuracy Gap	F1 Gap	Error Gap
Lateral feature set				
Wide Neural Network	38	17.27	17.58	17.27
Efficient Logistic Regression	38	7.5	7.21	7.5
Quadratic SVM	11	2.18	2.51	2.18
Linear Discriminant	11	13.34	13.88	13.34
Nadir feature set				
Cubic SVM	38	-0.68	-0.68	-0.68
Bagged Trees	38	0	0	0
Weighted KNN	2	-1.7	-1.71	-1.7
Fine KNN	2	-1.7	-1.71	-1.7
Bagged Trees	2	-1.7	-1.71	-1.7
Combined feature set				
Cubic SVM	82	0.93	1	0.93
Bagged Trees	82	-1.7	-1.7	-1.7
Wide Neural Network	6	0	0	0
Subspace KNN	6	0	0	0

Several factors may explain the reduced stability observed for lateral image configurations. Lateral perspectives capture increased background variability, leaf overlap, shadowing effects, and heterogeneous illumination across canopy depth. These factors can reduce the consistency of extracted color and morphological descriptors and increase sensitivity to minor dataset variations. In addition, lateral images may contain a larger proportion of redundant or less discriminative features, particularly when high dimensional feature subsets are used in combination with flexible nonlinear classifiers such as neural networks.

In contrast, nadir-based feature set ML models demonstrated substantially improved generalization behavior. The Bagged Trees model trained using 38 nadir features achieved identical validation and testing performance, producing zero accuracy, F1, and error gaps. Similarly, Fine KNN, Weighted KNN, and Bagged Trees models using only two nadir features exhibited

slightly negative gaps of approximately -1.7% , indicating marginally improved performance on the independent testing subset. The Cubic SVM model also showed near zero discrepancies with gap values below 1% .

The combined lateral and nadir feature configuration further reinforced model stability when compact feature subsets were used. Both the Wide Neural Network and Subspace KNN models achieved zero generalization gaps while maintaining 100% classification accuracy using only six features. These results indicate that the selected combined feature subset captured highly stable and discriminative stress related information without introducing excessive model complexity. The absence of measurable validation testing discrepancies strongly suggests that the selected features generalized effectively across unseen samples under the experimental conditions evaluated in this study.

The relationship between accuracy and weighted F1 score gaps across all evaluated models is further illustrated in **Figure 11**. Models positioned close to the origin exhibited minimal discrepancy between validation and testing performance and therefore demonstrated stronger generalization capacity. Most nadir and combined feature models clustered tightly around the origin, indicating stable transferability and limited evidence of overfitting. In contrast, several lateral feature models were displaced further along both axes, reflecting larger discrepancies between validation and testing metrics.

The close alignment between accuracy and weighted F1 score gaps across most classifiers also indicates balanced multiclass behavior without substantial class specific instability. Importantly, the models achieving the highest predictive performance also maintained very small or zero generalization gaps, suggesting that the observed near perfect accuracies were not solely attributable to memorization of training patterns. Instead, the results indicate that nadir oriented RGB phenotyping produced highly separable and biologically consistent salinity stress signatures under the evaluated conditions.

Nevertheless, these findings should be interpreted within the scope of the current experimental design. Although the indirect overfitting assessment suggests strong internal robustness, the dataset was acquired under controlled greenhouse conditions with limited environmental variability per se. Additional validation using independent field datasets, broader genotype diversity, and mixed stress conditions will therefore remain essential for fully

assessing large scale model generalization under practical agricultural deployment scenarios.

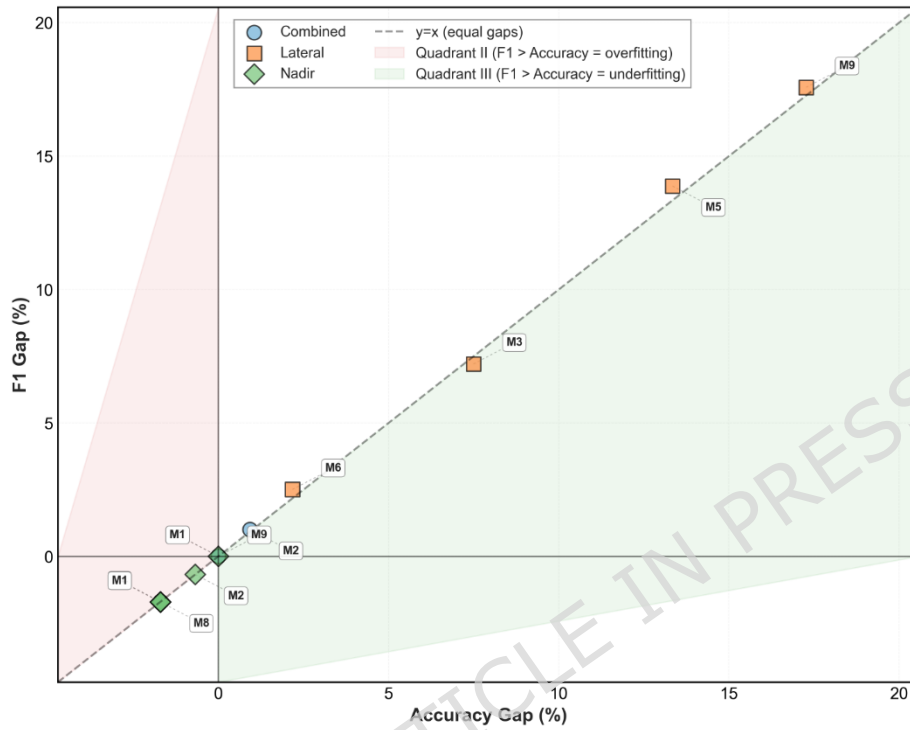


Figure 11. The relationship between accuracy and weighted F1 score gaps across all evaluated models. Where M1: Bagged Trees; M2: Cubic SVM; M3: Efficient Logistic Regression; M4: Fine KNN; M5: Linear Discriminant; M6: Quadratic SVM; M7: Subspace KNN; M8: Weighted KNN; and M9: Wide Neural Network.

3.5. Edge computing and WSN performance results

The practical applicability of image-based salinity monitoring depends not only on predictive accuracy but also on computational efficiency, communication cost, and suitability for deployment in resource constrained agricultural environments. In this study, the computational behavior of both RGB based and histogram-based pipelines was therefore evaluated from an edge computing and WSN perspective using inference latency, model size, throughput capability, and transmission efficiency metrics.

3.5.1. Edge inference performance and computational efficiency

The evaluated ML models demonstrated very high inference efficiency across all feature extraction strategies (**Table 8**). Prediction throughput ranged from approximately 1,400 to 19,585 observations per second, corresponding to inference latencies between 0.71 and 0.05 ms per sample. Among all evaluated models, the Wide Neural Network trained on combined RGB features achieved the highest throughput at 19,585 observations per second while maintaining 100% classification accuracy with an exceptionally compact model size of only 0.010 MB. This result highlights the strong compatibility of the proposed framework with low power embedded hardware and edge AI architectures.

Table 8. Computational performance and edge deployment suitability of representative machine learning models.

Feature set	Angle	Model	Features	Accuracy (%)	Model size (MB)	Throughput (obs s ⁻¹)	Latency (ms)	Edge suitability
RGB	Lateral	Wide NN	38	66.33	0.052	12414.18	0.081	Excellent
RGB	Lateral	Quadratic SVM	11	66.33	0.032	9870.31	0.101	Excellent
RGB	Nadir	Bagged Trees	38	100	0.318	1404.23	0.712	Moderate
RGB	Nadir	Cubic SVM	38	99.32	0.072	5522.36	0.181	Excellent
RGB	Combined	Wide NN	6	100	0.01	19585.25	0.051	Excellent
RGB	Combined	Subspace KNN	6	100	0.324	622.85	1.606	Moderate
Histogram	Lateral	Bagged Trees	20	71.04	30.53	20349.17	0.049	Limited
Histogram	Lateral	Fine KNN	20	66.85	9.55	3362.05	0.297	Limited
Histogram	Nadir	Bagged Trees	20	85.26	7.08	28829.51	0.035	Moderate
Histogram	Nadir	Fine KNN	20	82.65	3.05	9953.71	0.1	Moderate
Histogram	Combined	Bagged Trees	21	74.22	37.97	51109.07	0.02	Limited
Histogram	Combined	Fine KNN	21	71.1	13.18	2228.49	0.449	Limited

Linear and shallow nonlinear models also demonstrated strong computational efficiency. Most RGB based models achieved inference speeds between 9,700 and 12,400 observations per second, corresponding to approximately 0.08 to 0.10 ms latency per sample. Even computationally heavier ensemble models such as Bagged Trees maintained sub millisecond response times below 0.71 ms, indicating that real time stress classification can be achieved without imposing significant computational burden on edge devices.

The compact model sizes observed for RGB based pipelines further reinforce deployment feasibility. Several models with moderate to high classification

accuracy required less than 0.05 MB of memory, including Linear Discriminant Analysis, Efficient Logistic Regression, and Quadratic SVM models. The Wide Neural Network provided the best balance between predictive performance and deployment efficiency by combining perfect classification accuracy with minimal memory requirements. Such characteristics are highly advantageous for deployment on microcontroller-based systems including ESP32-S3 platforms integrated within distributed agricultural sensor networks.

In contrast, histogram-based models generally required substantially larger memory allocations and longer computational times while producing lower classification performance. Some histogram models exceeded 45 MB in size, which considerably limits their practicality for lightweight embedded systems. Although histogram descriptors retained biologically relevant stress information, their reduced deployment efficiency suggests that RGB derived feature engineering offers a more suitable compromise between predictive accuracy and edge compatibility.

3.5.2. Transmission efficiency and communication load reduction

Edge-based feature extraction produced substantial reductions in communication load relative to raw image transmission (**Table 9**). Raw RGB images acquired from lateral and nadir perspectives occupied approximately 3.71 MB and 3.92 MB, respectively. Following RGB feature extraction and preprocessing, the effective transmission size decreased to 354 KB for lateral images and 395 KB for nadir images, corresponding to communication reductions of 90.45% and 89.92%, respectively.

Table 9. Communication efficiency and data reduction achieved through edge-based image processing.

Processing stage	Lateral image size	Nadir image size	Reduction (%)	Transmission improvement
Raw RGB image	3.71 MB	3.92 MB	—	—
RGB processed image	354 KB	395 KB	90.45 / 89.92	~10×
Histogram processed image	90 KB	132.3 KB	97.57 / 96.63	~29-41×
Extracted feature vectors	152-328 bytes	152-328 bytes	>99.99	>10,000×

Even greater reductions were achieved using histogram-based representations. Histogram feature encoding reduced lateral image transmission requirements from 3.71 MB to 90 KB and nadir image requirements from 3.92 MB to 132.3 KB, yielding transmission reductions of

97.57% and 96.63%, respectively. These results indicate that local edge processing could substantially reduce bandwidth requirements before data transmission through WSN infrastructure.

The most substantial reduction was achieved when only extracted feature vectors were transmitted instead of processed images. Assuming 32-bit floating-point representation, feature vectors containing 38 to 82 descriptors required only 152 to 328 bytes for transmission. Relative to the original image size, this corresponds to an effective reduction exceeding 99.99%. From a WSN perspective, such compression significantly decreases communication overhead, energy consumption, and transmission latency while improving scalability for large sensor deployments.

Furthermore, transmission efficiency gains were particularly evident for histogram pipelines, where communication load was reduced by approximately 29 to 41 times relative to raw image transfer. These reductions are highly relevant for LoRaWAN and other low bandwidth agricultural communication systems, where network capacity and power consumption remain critical operational constraints.

3.5.3. Implications for real-time agricultural deployment

The combination of high throughput, low inference latency, and substantial communication reduction demonstrates the feasibility of integrating the proposed framework within edge enabled WSN architectures for real time salinity monitoring. Even the fastest image acquisition scenarios in agricultural environments typically require processing frequencies well below one image per second per node. Given the maximum observed throughput of 19,585 observations per second, the proposed framework provides a considerable computational safety margin for continuous operation under field conditions.

These findings also emphasize the broader significance of lightweight RGB phenotyping for smart agriculture applications. Unlike computationally intensive hyperspectral or cloud dependent approaches, the proposed framework enables local inference directly at the sensor node while minimizing communication requirements. This architecture supports scalable deployment across distributed agricultural environments where energy efficiency, network stability, and low latency operation are essential. In addition, the integration of explainable ML with compact edge compatible models strengthens the interpretability and operational reliability of automated salinity monitoring systems for high value horticultural crops.

3.6. Comparative analysis with literature

A comparative evaluation of the present study against existing literature highlights both methodological advances and application specific contributions in the context of crop stress phenotyping ([Table 10](#)).

Previous studies addressing salinity or related abiotic stresses have largely focused on major field crops and have relied on hyperspectral or multispectral sensing platforms combined with complex modeling strategies. [These sensing platforms provide rich spectral information and often achieve strong predictive performance because they capture narrow band reflectance responses associated with physiological and biochemical alterations.](#)

For example, hyperspectral imaging coupled with a Ridge Classifier achieved an accuracy of approximately 83% for salinity stress classification in canola across a wide gradient of sodium chloride concentrations [1]. Similarly, ensemble learning applied to UAV based multispectral data produced a strong relationship with normalized difference water index in sorghum, reporting an R^2 value of approximately 0.95 [12]. High predictive performance has also been reported for structural and physiological traits, including leaf area index estimation in cotton using convolutional neural networks and multispectral imagery with R^2 values near 0.92 [16], and canopy water content prediction in sorghum using Random Forest models with R^2 values around 0.90 [24]. [These approaches benefit from enhanced spectral sensitivity and broader physiological characterization, particularly for detecting subtle biochemical variations that may not be fully represented within the visible spectrum alone.](#)

Despite these advantages, hyperspectral and multispectral systems frequently require specialized optical hardware, radiometric calibration procedures, large data storage capacity, and higher computational resources for image processing and model inference. Such requirements may limit their scalability for continuous field deployment within low-power WSN or resource constrained edge environments. In addition, the high dimensionality of hyperspectral datasets often increases computational complexity, memory allocation, and communication overhead, particularly when cloud dependent processing pipelines are employed.

RGB based approaches remain [comparatively](#) less explored for salinity stress detection, [although they offer important advantages in terms of affordability, simplicity, and deployment flexibility.](#) DL applied to RGB imagery achieved an accuracy of approximately 97.7% for nitrogen stress classification in

wheat [21], although such models required substantial computational resources and extensive training data. Yield estimation studies in millet combining multisource satellite imagery and Random Forest modeling reported moderate performance with R^2 values near 0.83 [3]. However, many RGB-based studies rely on computationally intensive deep neural architectures or large-scale datasets, which can reduce their suitability for lightweight edge deployment.

Table 10. Comparative summary situating the findings of this study relative to previously published work on crop stress phenotyping. The table highlights methodological distinctions, imaging perspectives, feature-engineering strategies, and machine-learning performance outcomes to contextualize the advances achieved in the present research.

Ref.	Crop	Analyses Approach	Camera/Sensor	Target trait/variable	Performance
[1]	Canola	Ridge Classifier + Hyperspectral	PikaL	Salinity stress (0, 20, 40, 60, 80, and 100 mM NaCl)	Accuracy ~ 83%
[12]	Sorghum	Ensemble model+ UAV multispectral	Sentinel-2 + MicaSense Altum+ DLS-2	NDWI	R^2 0.95
[16]	Cotton	CNN + UAV multispectral	LAI-2200C	Leaf area index	R^2 0.92
[21]	Wheat	AlexNet DL + RGB	Ravtron RAV17/02	Nitrogen stress (0 and 25% RD, 50 and 75% RD, 100 and 125% RD)	Accuracy ~97.7%
[3]	Millet	Random Forest + Teledetection	Sentinel-2 + ZY-1 02D	Yield	R^2 0.83
[24]	Sorghum	Random Forest + UAV multispectral	ASD Field Spec Pro	Canopy Content Water	R^2 0.90
This Work	Peppermint	Subspace KNN + RGB	OV5642	Salinity stress (0, 100 and 200 mM NaCl)	Accuracy 85~100%

Nevertheless, the proposed RGB framework also presents certain limitations relative to hyperspectral and multispectral approaches. RGB imaging captures information only within the visible spectrum and therefore may show reduced sensitivity to subtle biochemical responses associated with early-stage stress development compared with narrow band spectral systems. Hyperspectral platforms can provide finer characterization of

pigment composition, water absorption features, and cellular level physiological changes that may remain partially unresolved in RGB imagery.

Within this context, the proposed framework should not be interpreted as a replacement for hyperspectral or multispectral sensing, but rather as a complementary and deployment-oriented alternative that prioritizes accessibility, computational efficiency, and scalability. The results indicate that carefully optimized RGB phenotyping combined with lightweight ML models could provide reliable salinity stress monitoring for aromatic crops while substantially reducing hardware complexity, communication overhead, and energy consumption. Such characteristics are particularly advantageous for distributed edge computing systems and real-time precision agriculture applications where low-cost and operational scalability remain essential considerations.

3.7. Limitations and future perspectives

The present study demonstrates the potential of RGB-based imaging combined with lightweight ML models for salinity stress detection in peppermint under controlled greenhouse conditions; however, several limitations should be acknowledged. The experimental evaluation was conducted using a single species and a limited range of salinity levels, which may restrict direct extrapolation to open field conditions characterized by heterogeneous lighting, variable backgrounds, and fluctuating microclimates. Additionally, RGB imaging captures indirect optical manifestations of stress. It does not directly measure physiological parameters such as ion accumulation, osmotic adjustment, or stomatal conductance. These internal processes may influence stress responses without showing immediate visual symptoms. Although nadir imaging and histogram-based features achieved high classification accuracy, model robustness under extreme canopy overlap, mixed stress scenarios, and different growth stages remains to be established. Likewise, present study lacks cross-dataset validation to evaluate the trained model performance and generalization gap for reproducibility.

The robustness of the developed models also remains dependent on the representativeness of the training dataset. While high accuracies were achieved for the evaluated salinity levels, model performance may decline under mixed stress conditions where salinity co-occurs with drought, nutrient imbalance, heat stress, or pathogen related damage. Several of these stressors produce overlapping visual symptoms, including chlorosis, canopy reduction, and pigment alteration, which may complicate stress

discrimination using RGB information alone. In addition, the present dataset did not include large temporal variability across developmental stages, seasonal transitions, or multiple peppermint cultivars, which may affect model generalization capacity.

Another important limitation relates to the sensing modality itself. RGB imaging captures visible phenotypic responses associated with stress exposure but does not directly quantify physiological or biochemical processes such as ion accumulation, osmotic regulation, stomatal conductance, or photosynthetic efficiency. Consequently, subtle physiological disturbances that precede visible canopy alterations may remain partially undetected compared with hyperspectral, thermal, or fluorescence-based sensing systems. Although the HSV segmentation framework improved robustness against background variability and illumination effects, segmentation accuracy may still decrease under severe canopy overlap, partial occlusion, or highly reflective environmental conditions.

From an edge computing perspective, scalability across large, distributed deployments also requires further validation. Communication efficiency and inference latency demonstrated strong suitability for resource constrained operation; however, long term performance under continuous field conditions remains uncertain. Factors such as packet loss, node synchronization, environmental interference, battery degradation, and fluctuating network density may influence operational reliability in large scale WSN deployments. In addition, some histogram-based models exhibited relatively large memory footprints despite moderate classification accuracy, indicating that computational efficiency may vary considerably depending on feature representation and model architecture.

Future research should extend this framework to multi-species and multi-cultivar datasets and validate performance under open field conditions using natural illumination variability. Integration of RGB imaging with complementary sensing modalities, including thermal, multispectral, or soil electrical conductivity measurements, would enhance physiological interpretability and stress specificity. Longitudinal analysis across full growth cycles and progressive salinity gradients would further improve model generalization. Finally, deployment of the proposed edge-based architecture in real agricultural settings will allow evaluation of long-term system stability, energy efficiency, and scalability, advancing practical adoption of smart sensing technologies for precision salinity management.

4. Conclusion

This study presents an integrated framework for salinity stress detection in peppermint through the combination of RGB phenotyping, ML, and edge-enabled sensing architectures. The results demonstrated that carefully optimized RGB imaging, coupled with robust HSV based canopy segmentation, can capture physiologically relevant stress responses associated with salinity exposure. Across all evaluated configurations, nadir imaging provided the most consistent representation of stress induced changes in canopy color and morphology, enabling highly accurate classification with computationally lightweight models suitable for deployment in resource constrained environments.

Beyond predictive performance, the study highlights the importance of combining biologically interpretable image descriptors with efficient ML architecture for practical agricultural applications. SHAP based interpretation linked the dominant predictive features with possible physiological reductions in canopy greenness, pigment alterations, and structural contraction, supporting the physiological relevance of the extracted traits under saline conditions. The strong performance achieved using compact feature sets further indicates that reliable stress detection does not necessarily require computationally intensive imaging systems or large-scale models.

The proposed framework contributes to the growing development of accessible and scalable phenotyping tools for specialty crops that remain comparatively underrepresented in precision agriculture research. By integrating explainable ML with edge compatible image analysis, the study supports the transition toward real-time and field deployable crop monitoring systems capable of assisting salinity management decisions at early stress stages. These findings provide a foundation for future extension of RGB-based edge intelligence to other aromatic and medicinal crops exposed to abiotic stress conditions.

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