



Automated Dehydration Assessment in Cannabis via YOLOv8 Localization and Multi-Modal Feature Classification

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ABSTRACT

Water management is a fundamental aspect of plant physiology, directly influencing photosynthesis and nutrient intake. The objective of this study is to develop and validate a non-invasive, automated pipeline for quantifying water stress in *Cannabis sativa* L. using computer vision and physiological ground-truth measurements. The study utilized a dataset of 988 original outdoor images, which were expanded to 4,940 images through data augmentation to ensure model robustness. The process integrates the state-of-the-art YOLOv8 model for leaf localization, achieving a mean Average Precision (mAP) of 98.3 percent. A multi-modal feature set was constructed by combining color statistics derived from four color space transformations (RGB, HSV, LAB, and YCrCb) and Gray-Level Co-occurrence Matrix (GLCM) texture descriptors. The features were used to train a classifier to categorize dehydration into six severity levels (Normal, Mild, Moderate, Distinct, Severe, and Extreme), and the classifier was verified against ground-truth leaf water potential (Ψ_{leaf}) measurements. The findings show that a Cubic Support Vector Machine (SVM) outperformed Artificial Neural Networks, achieving an overall accuracy of 86.2%. The research provides a scalable, high-precision solution for real-time monitoring in precision agriculture.

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1. INTRODUCTION

Effective water management promotes global crop development, but maintaining control over agricultural variables remains a challenge. Agriculture consumes approximately 70 percent of global freshwater, and inefficient practices lead to significant waste and limited yields [1]. Furthermore, climate change compels producers to manage unpredictable rainfall, prolonged droughts, and sudden flash floods [2]. Water stress is defined by moisture conditions that influence agricultural productivity. A reduction in water availability triggers stomatal closure, which subsequently restricts gas exchange and inhibits photosynthetic activity [3]. Conversely, excess water restricts oxygen transmission to the roots and promotes the spread of

plant diseases, ultimately leading to widespread crop failure [4].

Precision agriculture methodologies offer the essential accuracy required for the cultivation of *Cannabis sativa* L. The pharmaceutical and industrial sectors possess significant economic value that depends on optimizing the extraction of THC and CBD cannabinoids [5]. Environmental stress heavily influences these yields. Traditional monitoring approaches, such as visual inspections and soil sensors, often prove insufficient, being either labor-intensive or unable to address the specific biological requirements of the plants [6]. Conventional water status monitoring relies on soil-based or plant-based methodologies. However, soil sensors provide indirect data that often fail to reflect specific plant reactions

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or field variations [7]. Although the pressure chamber method is widely considered the gold standard for measuring leaf water potential, its destructive nature and high labor demands make it impractical for large-scale, frequent monitoring in precision agriculture [8]. Other methods, such as thermal imaging, provide precision; however, their application is often limited by weather conditions or high operational costs [9].

Consequently, there is an increasing demand for automated, non-invasive solutions. Precision agriculture utilizes computer vision and deep learning to address these challenges [10]. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in disease detection and yield estimation [11], while the YOLOv8 architecture has established new benchmarks for real-time object detection in agricultural contexts [12]. However, current research has primarily concentrated on nutrient deficiency and disease identification, resulting in a relative lack of exploration into automated water stress assessment, particularly when validated against quantitative physiological measurements.

The novelty of this study lies in the implementation of a specialized hybrid pipeline that bridges the gap between advanced deep learning architectures and rigorous plant physiology. Recognizing that outdoor cannabis canopies present challenges like overlapping leaves and complex backgrounds, our approach decouples the task into two distinct stages. First, we employ the YOLOv8 architecture specifically to robustly localized individual leaf Regions of Interest (ROIs) within the canopy. Secondly, we extract a multi-modal set of handcrafted features encompassing color statistics from four color spaces (RGB, HSV, LAB, and YCrCb) and five texture descriptors from the Gray-Level Co-occurrence Matrix (GLCM). These features are subsequently fed into a Cubic Support Vector Machine (SVM) classifier, which was selected for its high precision in high-dimensional feature spaces.

Critically, every classification level in this system is validated against empirical ground-truth measurements obtained via pressure chamber analysis. This study provides a scalable, non-invasive solution for real-time water stress monitoring in precision agriculture by combining the high-dimensional classification strength of the Cubic SVM with the rapid leaf localization capability of YOLOv8. Additionally, all severity level is rigorously validated against pressure chamber measurements.

The manuscript is organized as follows. Section 2 reviews the relevant literature. Section 3 details the methodological framework, data collection, and model development. Section 4 reports the experimental results. Section 5 evaluates the findings and discusses limitations, and Section 6 summarizes the key contributions and practical implications.

2. LITERATURE REVIEW

2.1 Plant Water Stress: Physiological Foundations

The soil-plant-atmosphere continuum (SPAC) regulates water status by facilitating the movement of moisture from regions of higher to lower potential through various resistances [13]. The total water potential, expressed in megapascals (MPa), characterizes the thermodynamic state of this water. This metric represents the aggregate of solute, pressure, matric, and gravitational potentials [14]. The interaction between solute and pressure potentials determines the hydration status of leaves. Healthy plants maintain leaf potential within the range of -0.5 and -3.0 MPa, although these values decline during periods of water deficiency [15]. Crops respond to moisture deficiencies by a coordinated series of the molecular and cellular mechanisms, encompassing stomatal regulation, osmotic adjustment, and the synthesis of stress-responsive proteins. Initial physiological alterations involve the reduction of guard cell turgor, thereby initiating stomatal closure [16].

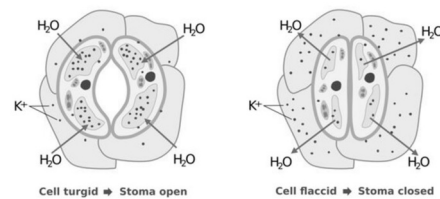


Fig.1: Stomatal Opening and Closing.

Reducing water loss through transpiration restricts carbon dioxide absorption and photosynthesis. Plants also initiate osmotic adjustment by accumulating solutes to maintain internal pressure stability [17] and elevate abscisic acid (ABA) concentrations to modulate the expression of stress-responsive genes. These internal modifications manifest as observable phenotypes: a reduction in pressure results in wilting and leaf curling, while alterations in chlorophyll content cause leaves to develop yellow or purple coloration [18].

The pressure chamber continues to serve as the primary instrument for assessing water levels in plants, as established by Rodriguez-Dominguez et al. [19]. This procedure involves applying pressure on a cut leaf until fluid appears on the stem surface. Figure 1 indicates the water potential of the plant. Although this technique demonstrates high accuracy, its destructive and time-intensive nature renders it unsuitable for the high-frequency, spatial mapping demands of contemporary precision agriculture [20], thereby highlighting the necessity of non-invasive alternatives.

2.2 Computer Vision Approaches for Plant Stress Detection

Computer vision offers a non-destructive path for stress assessment, largely relying on color and texture analysis. Color features are sensitive to the pigment changes associated with physiological disorders [21]. While studies have successfully used RGB, HSV, and LAB color spaces to detect nitrogen deficiency and water stress, these methods are highly sensitive to illumination variability and often struggle to distinguish water stress from other biotic or abiotic factors before visible symptoms appear [22].

Complementing color analysis, texture features capture spatial patterns and surface properties using methods like the Gray-Level Co-occurrence Matrix (GLCM). GLCM descriptors, such as contrast, energy, and homogeneity, have proven effective in plant disease detection [23]. In the context of water stress, texture analysis can quantify surface changes associated with wilting, such as wrinkling and altered reflectance. Shape-based morphological features provide further discrimination by quantifying leaf curling and area reduction, though these are often dependent on precise segmentation and camera orientation [24]. While multispectral and hyperspectral imaging offer deeper insights into biochemical properties via infrared wavelengths, their high cost and data complexity currently limit their widespread commercial deployment [25].

2.3 Machine Learning for Agricultural Applications

Researchers have widely utilized conventional machine learning algorithms to classify these extracted features. SVMs are particularly favored for high-dimensional classification tasks by leveraging kernel functions to map input features into higher-dimensional spaces. Other algorithms, including Random Forests, k-Nearest Neighbors (k-NN), and Naive Bayes, have also demonstrated high accuracy in disease and stress classification tasks [26].

However, the field is increasingly shifting toward Artificial Neural Networks (ANNs), which approximate complex non-linear mappings through layers of interconnected neurons.

Modern ANN architectures employ Rectified Linear Units (ReLU) as activation functions. ReLU introduces non-linearity while preserving computational efficiency and preventing the vanishing gradient problem. This problem commonly hinders training in deeper networks. Deep learning approaches, specifically Convolutional Neural Networks (CNNs), have revolutionized this domain by automatically extracting hierarchical features, eliminating the need for manual feature engineering [27].

2.4 Deep Learning in Precision Agriculture: From Architectures to Application

Object detection has undergone a transformation from computationally expensive region-based methods, such as R-CNN and Faster R-CNN [28], to efficient single-stage detectors. This enables the implementation of real-time automated monitoring in precision agriculture. The YOLO family transformed object detection by enabling real-time processing through a single regression approach. Its latest version, YOLOv8, features new architectural enhancements ideal for agricultural applications. YOLOv8 utilizes C2f backbone modules for enhanced gradient flow and a decoupled head that separately manages classification and localization, facilitating accurate detection in complex and overlapping canopy environments. Significantly, it is anchor-free, indicating that it does not rely on pre-defined anchor boxes. Rather, it directly predicts the object centers, hence improving generalization across the diverse array of leaf forms present in outdoor Cannabis canopies. [29].

These deep learning architectures have achieved remarkable success in various agricultural domains. Convolutional Neural Networks (CNNs) have been extensively deployed for crop disease detection, achieving near-perfect accuracy on controlled datasets like PlantVillage, and for real-time weed identification to facilitate targeted herbicide application [30]. However, while disease and pest identification have matured, automated water stress detection remains comparatively underexplored. Existing studies often rely on thermal or multispectral imaging [31], and few systems integrate robust object detection with quantitative physiological validation to map stress severity spatially.

Cannabis sativa L. represents a critical case study for closing this technological gap. As a high-value crop in pharmaceutical and industrial sectors [32], it requires precise water management to balance yield with secondary metabolite production. While mild water stress (-1.5 to -2.5 MPa) can stimulate cannabinoid synthesis as a defense mechanism, severe stress (< -3.5 MPa) causes irreversible yield loss [33]. The plant exhibits distinct morphological responses to dehydration, including leaf drooping, chlorosis, and margin curling, which provide strong visual cues for computer vision analysis.

This study addresses the intersection of these domains by developing a comprehensive end-to-end pipeline. It represents the first application of YOLOv8 for Cannabis stress assessment, leveraging the model's anchor-free detection to handle complex canopy structures. Classification is based on multi-modal color and texture features fused and all outputs are validated against quantitative leaf water potential measurements obtained with pressure chamber analysis. This work provides a validated solution for real time water stress monitoring by bridging deep learn-

ing and plant physiology through systematic comparison of classification architectures.

Despite the proliferation of deep learning applications in agriculture, a significant research gap remains at the intersection of high-precision object detection and physiological plant science. Most current studies utilizing Convolutional Neural Networks (CNNs) for stress detection treat the entire plant image as a single input, which introduces noise from the soil, background, and non-leaf structures, particularly in complex, outdoor cannabis canopies. In addition, most existing models rely only on visual heuristics for labelling, not validated by direct physiological indicators such as leaf water potential (Ψ_{leaf}).

YOLOv8 has set new benchmarks for real-time localization, nonetheless, existing studies have concentrated elementary application such as fruit counting and disease identification. This study addresses that gap by employing a two-stage approach. YOLOv8 anchor-free detection isolates individual leaf ROIs from dense canopies. The extracted features are then classified using machine learning models calibrated against quantitative pressure chamber data. This dual-stage approach ensures both environmental robustness and physiological accuracy, which are missing in current descriptive literature.

3. METHODOLOGY

This section describes the five-phase methodology developed for automated water stress detection in *Cannabis sativa* L., illustrated in Figure 2, the end-to-end processing pipeline for automated water stress detection in outdoor *Cannabis sativa* L.

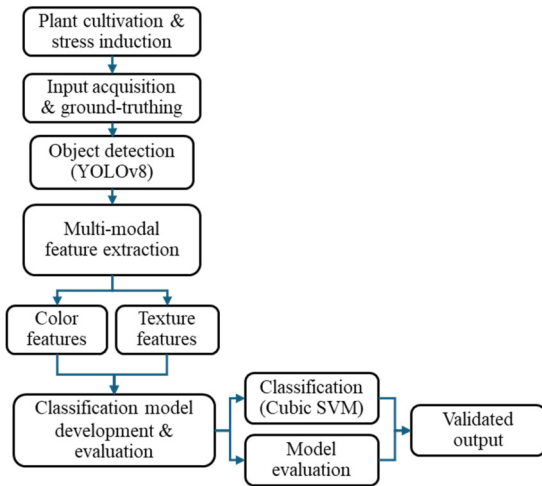


Fig.2: A system pipeline flowchart.

The system begins by acquiring raw plant images under natural lighting, which are then preprocessed through resizing to 640×640 pixels and normalization to ensure input consistency. A YOLOv8 object detection model then localizes individual leaves by generating bounding boxes, achieving 98.3% mAP.

The detected regions are cropped from the original high-resolution image as regions of interest (ROIs). From each ROI, two complementary feature sets are extracted in parallel: color statistics across four color spaces (RGB, HSV, LAB, and YCrCb) and texture descriptors derived from the Gray-Level Co-occurrence Matrix (GLCM), including contrast, correlation, energy, homogeneity, and dissimilarity. These combined features are then fed into a Cubic Support Vector Machine (SVM) classifier, which maps the input to one of six water stress severity levels. Finally, the classification outputs are validated against ground truth leaf water potential (Ψ_{leaf}) measurements obtained using a pressure chamber, ensuring the system's predictions are grounded in established physiological data.

3.1 Data Collection and Preprocessing

Plant Material and Cultivation. The dataset for this study was collected from an outdoor *Cannabis sativa* L. cultivation site at the Kasetsart University research facility in Sakon Nakhon, Thailand, during the 2023–2024 growing season. The *Cannabis sativa* L. cultivar 'Hang Kra Rog Phu Phan,' a locally adapted Thai landrace, was selected for experimentation, noted for its agricultural relevance and sensitivity to water deficit [34]. A total of 120 plants were cultivated in a controlled greenhouse environment.

Controlled Stress Induction and Ground Truth Measurement. To induce varying degrees of physiological dehydration, plants were divided into six experimental groups (n=20 per group). Following a two-week baseline period of optimal irrigation, water was withheld according to a staggered schedule ranging from 0 hours (Control) to 120 hours. Physiological ground truth was established using leaf water potential (Ψ_{leaf}) measurements, the standard metric for plant water status [35], conducted at pre-dawn (04:00–06:00). Based on the measured Ψ_{leaf} values, dehydration levels were classified into six distinct stages based on water potential measurements as shown in Table 1.

Table 1: Comparative Summary of Related Studies.

Level	Hydration stress (MPa)
Level 0 (Normal)	-0.1 and -1.9
Level 1 (Mild)	-2.0 to -2.9
Level 2 (Moderate)	-3.0 to -3.9
Level 3 (Distinct)	-4.0 to -4.9
Level 4 (Severe)	-5.0 to -5.9
Level 5 (Extreme)	-6.0 MPa or lower

Image Acquisition Protocol. High-resolution images were captured concurrently with physiological measurements using a Camera C922 PRO HD STREAM WEBCAM. To ensure radiometric consistency, imaging was conducted in a light-controlled

environment using 5500K LED panels against a uniform white background. The acquisition of the image dataset is illustrated in Figure 3.

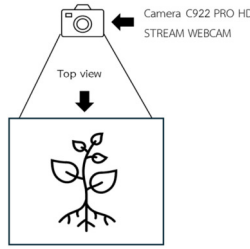


Fig.3: A photobooth setting.

A total of 988 high-resolution original images were acquired and split into a training set (85%, $n = 840$) and an independent testing set (15%, $n = 148$). To enhance model generalization, the training dataset was augmented (rotation, flipping, brightness variation, and Gaussian noise), resulting in a final dataset of 4,940 images. Figure 4 represents cropped leaf images corresponding to each of the six water stress severity levels defined in this study. At Level 0 (Normal), leaves exhibit full turgidity, a vibrant, deep green color, and flat, firm leaflet edges, indicative of well-hydrated plant tissue. As stress progresses to Level 1 (Mild) and Level 2 (Moderate), subtle visual changes emerge, including a gradual loss of surface luster, initial tip drooping, and slight curling of the leaf serrations. By Level 3 (Distinct), wilting becomes visually distinct, accompanied by a noticeable color shift toward duller green and early yellowing as chlorophyll degradation begins. At Level 4 (Severe), leaves display pronounced inward curling, heavy drooping across all leaflets, and significant tissue dehydration, reflecting substantial loss of turgor pressure. Finally, Level 5 (Extreme) is characterized by a fully desiccated appearance, brittle leaf texture, and widespread brown-to-yellow chlorosis, indicating near-complete cellular water loss and irreversible tissue damage. This visual progression demonstrates the feasibility of using morphological and chromatic leaf features as reliable indicators for automated water stress classification.

All images were resized to 640×640 pixels to align with the YOLO8 input requirements. Ground-truth labels for dehydration severity were established using the pressure chamber to measure leaf water potential (Ψ_{leaf}), ensuring that the visual classifications were anchored in physical plant physiology.

3.2 Leaf Localization: YOLOv8 Implementation

Architecture and Configuration. To isolate leaf regions of interest (ROIs) from complex backgrounds, the YOLOv8m (medium) architecture was implemented. This model employs a CSPDarknet53 backbone with C2f modules for feature extraction and

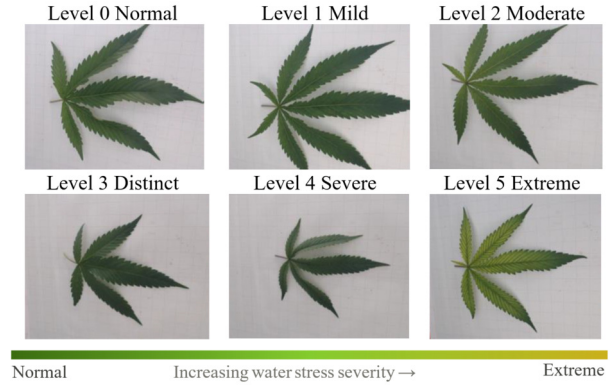


Fig.4: Representative cropped leaf images corresponding to each of the six water stress severity levels, progressing from Level 0 (Normal) to Level 5 (Extreme). Visual changes include progressive color shift from deep green to yellow-brown.

a Path Aggregation Network (PAN-FPN) for multi-scale feature fusion. Unlike its predecessors, YOLOv8 utilizes an anchor-free detection strategy with a decoupled head, separating classification and regression tasks.

The object detection phase was implemented using the YOLOv8 (You Only Look Once version 8) framework. Within this architecture family, the YOLOv8m (medium) variant was specifically selected to serve as the backbone for leaf localization. While YOLOv8 offers a range of model scales from Nano (n) to Extra-large (x), the medium (m) variant was chosen because it provides an optimal trade-off between computational efficiency and detection precision. In our experimental setup, YOLOv8m achieved a mean Average Precision (mAP) of 98.3% with an inference latency of 23.4 ms. This balance ensures that the model is deep enough to extract complex spatial features from dense cannabis canopies while remaining lightweight enough for the real-time agricultural deployment discussed in later sections.

In this study, each input image typically contains multiple leaves within the canopy. The YOLOv8m model is configured to detect and generate individual bounding boxes for every identifiable leaf in the frame. Following localization, each detected leaf is treated as an independent Region of Interest (ROI). The subsequent feature extraction and classification steps are performed on these individual leaf ROIs rather than the full image. This granular approach allows the system to account for variations in water stress across different parts of the plant canopy. For this study, performance metrics are reported based on individual leaf predictions. However, this framework establishes a foundation for whole-plant assessment; in a production environment, individual leaf scores could be aggregated (e.g., via majority voting or mean stress indexing) to provide a holistic dehydration status for the entire plant.

Training and Loss Functions. The model was initialized with COCO-pretrained weights and fine-tuned for 150 epochs using an SGD optimizer with momentum (0.937) and weight decay (0.0005). The loss function (L_{total}) combines three components:

$$L_{total} = \lambda_{box} L_{box} + \lambda_{cls} L_{cls} + \lambda_{dfl} L_{dfl} \quad (1)$$

where L_{cls} is the Binary Cross-Entropy loss for classification, bounding box regression accuracy is optimized using Complete IoU L_{box} or L_{CIoU} and Distribution Focal Loss (L_{dfl}). The $CIoU$ loss minimizes the normalized distance between predicted and ground-truth box centers while enforcing aspect ratio consistency:

$$L_{CIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \quad (2)$$

where ρ is the Euclidean distance between b and b^{gt} (the central points of the predicted and ground truth bounding boxes, respectively), c is the diagonal length of the smallest enclosing box, and αv is an aspect ratio penalty term [36].

3.3 Multi-Modal Feature Extraction

Following ROI extraction, a comprehensive feature vector was constructed to capture physiological changes associated with water stress.

Color Space Transformations. Color features were extracted to quantify pigment degradation (chlorosis) and darkening associated with necrosis. To account for varying illumination and human perception, four color spaces were analyzed: RGB, HSV (separating chromaticity from intensity), LAB (perceptually uniform), and YCrCb (luma-chroma separation). For each channel in these spaces, four statistical moments were computed: mean (μ), standard deviation (σ), skewness (γ), and kurtosis (κ), yielding 48 distinct color features.

Texture Analysis (GLCM). Texture features were utilized to detect morphological changes such as wilting, wrinkling, and surface deformation. To strictly quantify the textural changes associated with dehydration, we calculated five key metrics based on the Gray-Level Co-occurrence Matrix (GLCM), where represents the probability of occurring pixel pairs. We measured Contrast ($\sum_{i,j} (i-j)^2 p(i,j)$) to capture local intensity variations, effectively identifying the sharp edges formed by wilting. Correlation ($\sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_j}$) was utilized to determine the linear dependency of gray levels between pixels. Energy ($\sum_{i,j} P(i,j)^2$) served as a metric for textural uniformity, where higher values indicate a smoother leaf surface. Conversely, Homogeneity ($\sum_{i,j} \frac{P(i,j)}{1+|i-j|}$) assessed the closeness of the distribution to the diagonal, indicating how similar neigh-

boring pixels are to one another. Finally, Dissimilarity ($\sum_{i,j} |i-j| P(i,j)$) provided a linear measure of local intensity differences, complementing the contrast metric by highlighting variations in surface texture. For GLCM, we used a distance $d = 1$, angles $\theta \in \{0^\circ, 45^\circ, 90^\circ, 135^\circ\}$, and 64 quantization levels. The final feature vector x comprised 53 dimensions (48 colors and 5 textures), standardized via z-score normalization.

3.4 Classification Models

To map the extracted features to the six dehydration severity levels, two machine learning paradigms were evaluated.

Support Vector Machines (SVM). SVMs were employed to construct optimal hyperplanes maximizing the margin between classes. A One-vs-One (OvO) strategy was implemented to handle the multi-class problem. We evaluated Linear, Quadratic, Cubic, and Radial Basis Function (RBF) kernels. The optimization objective included a regularization parameter C that was optimized at 1.0 using a heuristic procedure for the tuning method, and slack variables ξ_i to manage non-linearly separable data:

$$\min_{w,b,\xi} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \xi_i \quad (3)$$

Artificial Neural Networks (ANN). Feedforward neural networks were designed with varying topologies to assess the trade-off between model capacity and generalization. Three architectures were tested: Narrow (1 hidden layer, 10 neurons), Medium (2 hidden layers, 25/15 neurons), and Wide (2 hidden layers, 50/30 neurons). The architecture is shown in Figure 5. Networks utilized ReLU activation for hidden layers and Softmax for the output layer. Training was performed using the Scaled Conjugate Gradient (SCG) algorithm to minimize the Cross-Entropy Loss:

$$L = - \sum_{i=1}^N \sum_{k=1}^K y_{ik} \log(\hat{y}_{ik}) \quad (4)$$

Regularization was applied via weight decay ($\lambda = 0.001$) and early stopping to prevent overfitting.

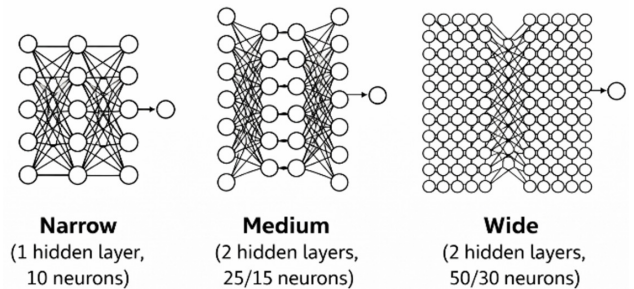


Fig.5: Three ANN Architectures.

The Artificial Neural Network (ANN) baseline was developed using a multilayer perceptron architecture. To ensure optimal performance, hyperparameters were tuned via a grid search cross-validation. We evaluated hidden layer sizes ranging from a single layer of 10 neurons to dual layers of 100 neurons each. The final architecture selected featured a 50-neuron hidden layer with a Rectified Linear Unit (ReLU) activation function and an Adam optimizer. Despite this optimization, the ANN struggled with the non-linear distribution of handcrafted features compared to the SVM, likely due to the limited number of training samples, which hindered the network's ability to generalize complex leaf textures without overfitting.

4. RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed automated water stress detection pipeline. The analysis is structured into four components: (1) the efficacy of the YOLOv8 model in leaf localization, (2) the physiological relevance of extracted visual features, (3) the comparative performance of classification architectures, and (4) the system's computational efficiency and validation against ground-truth water potential measurements.

4.1 Performance Evaluation

Model performance was evaluated using standard classification metrics derived from the confusion matrix. Primary metrics included Accuracy, Precision (Positive Predictive Value), Recall (Sensitivity), and the F1-Score (harmonic mean of precision and recall). To provide a comprehensive assessment of classifier separation capability, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was computed using a One-vs-Rest strategy. All models were validated using a stratified test set comprising 15% of the total data, ensuring balanced representation of all stress severity levels.

Training Dynamics and Convergence. The YOLOv8m architecture demonstrated robust convergence characteristics over the 150-epoch training period. As shown in Table 2, the total loss exhibited decrease monotonically, stabilizing around epoch 142. The Box Loss, which quantifies localization error, was reduced by 73.2%, indicating the model's increasing precision in delineating leaf boundaries despite complex canopy overlaps. Concurrently, the Class Loss decreased by 81.2%, reflecting high confidence in object categorization. The convergence of training and validation losses suggests that the applied augmentation strategies effectively mitigated overfitting.

Detection Accuracy on Test Set. It is crucial to mention that despite 148 original images being assigned for testing (Section 3.1), each image has multiple leaves; the YOLOv8m model detected a total of 741 distinct leaf instances across these images, and all

Table 2: YOLOv8 Training Loss Evolution.

Epoch	Box Loss	Class Loss	DFL Loss	Total Loss
10	1.245	0.823	1.156	3.224
30	0.687	0.412	0.789	1.888
50	0.523	0.298	0.634	1.455
110	0.367	0.176	0.489	1.032
142*	0.334	0.155	0.465	0.954
150	0.336	0.157	0.467	0.960

*Best model checkpoint selected based on validation mAP.

localization metrics are indicated at the leaf-instance level. Evaluated on the independent test set ($n=741$ leaf ROIs automatically detected across the 148 held-out images), the model achieved near-perfect precision and high recall, confirming its suitability for automated phenotyping. The mean Average Precision (mAP@0.5) of 98.3% indicates consistent detection across varying leaf orientations and sizes. The YOLOv8 model demonstrated exceptional detection capabilities, achieving a Precision of 99.0%, which indicates the system effectively eliminated false positives by distinguishing leaves from background noise. This was complemented by a Recall of 96.9%, ensuring that nearly every leaf in the frame was successfully identified with minimal missed detections. The resulting F1-Score of 97.9% highlights the model's ability to maintain a harmonic balance between these two critical metrics. In terms of overall robustness, the system attained a mean Average Precision (mAP@0.5) of 98.3% at standard thresholds. In comparison, the mAP@0.5:0.95 of 87.6% confirms its high localization precision, proving that the model draws accurate, tight bounding boxes around the target leaves.

Error analysis revealed that the 3.1% false negative rate was primarily driven by physiological deformation; 58% of missed detections occurred in leaves exhibiting severe wilting or curling, which significantly altered the standard leaf morphology. Conversely, false positives were rare (1.0%) and mostly attributed to cast shadows mimicking leaf margins.

4.2 Feature Analysis and Physiological Correlation

Statistical analysis of color features confirmed distinct spectral shifts corresponding to dehydration severity. As detailed in Table 3, the RGB space showed a significant reduction in the green channel (112.5 ± 15.7 to 78.5 ± 24.3) and a rise in the red channel, consistent with chlorophyll degradation and the onset of necrosis.

More critically, the HSV space revealed a substantial hue shift from green (118.7°) toward yellow (74.2°) and a marked reduction in saturation (0.68 to 0.35). These quantitative changes correlate strongly with the visual symptoms of chlorosis and loss of turgor pressure.

GLCM texture analysis quantified the surface morphological changes associated with water deficit. Contrast increased by a factor of 3.2 (12.4 to 39.7) from Level 0 to Level 5, while Energy decreased (0.31 to 0.13). This inverse relationship captures the transition from the smooth, uniform surface of turgid leaves to the wrinkled, irregular texture of wilted tissue.

Table 3: RGB and HSV Feature Distribution by Severity.

Severity Level	R (mean)	G (mean)	H (deg)	S (mean)
0 (Normal)	68.3	112.5	118.7	0.68
1 (Mild)	72.1	108.3	114.2	0.64
2 (Moderate)	78.5	102.7	107.5	0.58
3 (Distinct)	86.2	95.4	98.3	0.51
4 (Severe)	94.8	87.2	87.6	0.43
5 (Extreme)	103.7	78.5	74.2	0.35

To evaluate the contribution of different feature sets to the classification of water stress, an ablation study was performed. We compared the classification accuracy using individual color spaces, texture features (GLCM) alone, and the proposed multi-modal combination.

Table 4: Performance Comparison of Different Feature Subsets using Cubic SVM.

Feature Subset	Accuracy (%)	Precision (%)	Recall (%)
RGB Color Space	74.5	73.2	74.0
HSV Color Space	77.8	76.5	77.2
LAB Color Space	76.1	75	75.8
YCrCb Color Space	79.2	78.4	78.9
Combined Color Features	81.3	80.5	81
GLCM Texture Only	72.4	71	71.8
Multi-modal (Color + GLCM)	86.2	85.4	85.9

As shown in Table 4, while the YCrCb color space provided the highest individual accuracy among color models (79.2%), and the combined color features reached 81.3%, the integration of GLCM texture features significantly enhanced the model’s ability to distinguish between intermediate stress levels. The multi-modal approach achieved the highest overall accuracy of 86.2%, confirming that the structural changes in leaf texture during dehydration provide critical complementary information to color-based indicators.

Pearson correlation analysis demonstrated highly significant relationships ($p < 0.001$) between these features and the ground-truth water potential (Ψ_{leaf}). The strongest correlations were observed for HSV Hue ($r = -0.847$) and GLCM Contrast ($r = 0.798$), validating the selection of these features as robust physiological indicators.

Table 5 presents the comparative performance of

Table 5: Overall Model Performance Ranking.

Model	Mean Accuracy $\pm$ SD	F1-Score	Total Cost (Misses)
Cubic SVM	86.2% $\pm$ 1.4%	86.4%	181
RBF SVM	84.5% $\pm$ 1.6%	84.6%	203
Quadratic SVM	83.7% $\pm$ 1.8%	83.8%	213
Wide Neural Network	82.8% $\pm$ 2.3%	83.0%	225
Medium Neural Network	81.3% $\pm$ 2.5%	81.5%	245
Linear SVM	78.3% $\pm$ 2.1%	78.5%	284
Narrow Neural Network	76.8% $\pm$ 2.9%	77.0%	304

all models using 10-fold cross-validation with Mean Accuracy $\pm$ Standard Deviation. The Cubic SVM achieved the highest stability with a mean accuracy of 86.2% $\pm$ 1.4%, followed by RBF SVM (84.5% $\pm$ 1.6%) and Quadratic SVM (83.7% $\pm$ 1.8%). ANN architectures showed higher variance, with the Wide Neural Network at 82.8% $\pm$ 2.3% and the Narrow Neural Network at 76.8% $\pm$ 2.9%, indicating greater sensitivity to fold composition in smaller-sample contexts. The low standard deviation of the Cubic SVM across folds indicates that the multi-modal feature extraction pipeline is resilient to different subsets of the data.

Statistical significance: McNemar’s test confirmed that the Cubic SVM significantly outperformed the Wide Neural Network ($\chi^2=8.15$, $p=0.004$) and the RBF SVM ($\chi^2=4.82$, $p=0.028$).

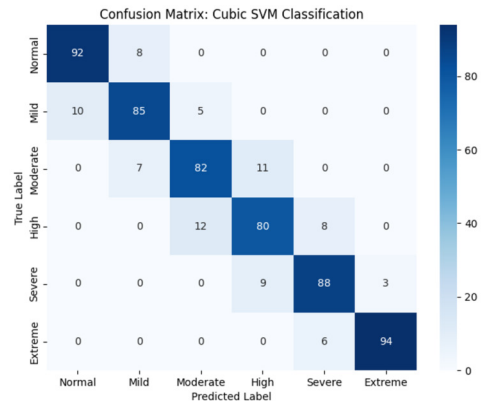


Fig. 6: Confusion Matrix for Cubic SVM Classification.

The confusion matrix for the Cubic SVM in Figure 6 highlights specific patterns in classification error. The model demonstrated excellent separation for extreme states, Level 0 (Normal) and Level 5 (Extreme), achieving F1-scores above 90%.

Table 6 represents the per-class performance on Cubic SVM. Classification errors were concentrated in the intermediate stages (Level 2 and 3), where

Table 6: Per-Class Performance (Cubic SVM).

Severity Level	Precision	Recall	F1-Score
Level 0 (Normal)	94.3%	91.7%	92.9%
Level 1 (Mild)	85.1%	84.6%	84.8%
Level 2 (Moderate)	81.2%	82.1%	81.6%
Level 3 (Distinct)	81.0%	81.5%	81.2%
Level 4 (Severe)	84.2%	82.6%	83.4%
Level 5 (Extreme)	88.4%	92.6%	90.5%

physiological symptoms are transitional. Crucially, 98.2% of all predictions fell within ± 1 severity level of the ground truth. Large errors (≥ 3 levels) were non-existent, indicating that the system reliably tracks the trajectory of dehydration even when exact boundary classification is ambiguous.

4.3 Computational Efficiency

To assess the feasibility of real-time deployment, the end-to-end processing latency was evaluated on an NVIDIA RTX 3060 GPU. The total processing time per image was 260 ms, equating to a throughput of approximately 3.85 images per second.

The entire diagnostic pipeline operates with impressive speed, completing the analysis of a single image in just 260.0 ms, making it highly suitable for real-time applications. A breakdown of the processing time reveals that Color Feature Extraction is the most computationally intensive phase, consuming 142.5 ms (54.8% of the total time), followed by Texture Feature Extraction at 68.2 ms (26.2%). Together, these feature engineering steps account for over 80% of the workload. In contrast, the advanced model inference steps are remarkably efficient: the YOLOv8 Detection requires only 23.4 ms (9.0%), and the final Cubic SVM Classification is executed in a mere 9.8 ms (3.8%). The remaining time is distributed among minor administrative tasks, including Image Loading (8.3 ms, 3.2%), ROI Extraction (5.7 ms, 2.2%), and Feature Normalization (2.1 ms, 0.8%).

Notably, the feature extraction stage dominates the computational cost (81% of total time), particularly color statistics and GLCM computation. While the YOLOv8 inference is highly efficient (23.4 ms), future optimization efforts should focus on parallelizing the feature extraction to enhance throughput further.

These benchmarks confirm that the hybrid framework achieves a processing rate of approximately 3.8 frames per second (FPS), which is sufficient for high-throughput autonomous scouting or drone-based monitoring, and is suitable for real-time water stress assessment in field environments.

4.4 Validation Against Physiological Ground Truth

A critical contribution of this study is the rigorous validation of the computer vision output against physiological measurements. The predicted severity

levels showed a strong Spearman's rank correlation ($\rho = 0.892$, $p < 0.001$) with the measured water potential.

When the ordinal severity predictions were mapped back to water potential values, the system achieved a Mean Absolute Error (MAE) of 0.43 MPa and a Root Mean Square Error (RMSE) of 0.58 MPa. With 96.7% of samples estimated within ± 1.0 MPa of the actual Ψ_{leaf} , the system demonstrates sufficient accuracy to serve as a non-invasive decision support tool for irrigation management in precision agriculture.

4.5 Discussion

The YOLOv8m model demonstrated superior leaf localization capabilities (mAP@0.5 = 98.3%), surpassing previous agricultural detection benchmarks [37], [38], and [39] shown in Table 7. This performance is attributed to the model's anchor-free architecture and C2f modules, which effectively handle the morphological variability of Cannabis leaves.

Physiologically, the extracted features validated the biological basis of the vision system. The strong negative correlation between HSV Hue and water potential ($r = -0.847$) aligns with established chlorophyll degradation pathways under stress. Concurrently, the sharp increase in GLCM Contrast quantitatively captured the loss of turgor pressure and subsequent surface wrinkling. The fusion of chromatic and textural data proved essential, as color features alone (81.3% accuracy) failed to capture structural deformations in early-stage stress.

Table 7: Comparison with Previous Agricultural Object Detection Studies.

Study	Crop	Model	mAP@0.5	Application
Proposed Study	Cannabis	YOLOv8m	98.3%	Stress Assessment
Jiang <i>et al.</i> [37]	Soybean	YOLOv4	92.1%	Weed detection
Ghosal <i>et al.</i> [38]	Sorghum	Faster R-CNN	95.0%	Panicle detection
Liu <i>et al.</i> [39]	Tomato	YOLOv5	94.7%	Disease detection

While the prevailing trend in computer vision favors end-to-end deep learning architectures, our results indicate that for agricultural datasets of moderate size ($n > 1,000$ original images), a hybrid approach remains highly advantageous. The superior performance of the Cubic SVM (86.2%) compared to the shallow ANN configurations evaluated in this study suggests that handcrafted features (color and GLCM texture) capture the physiological nuances of water stress more efficiently when training data is limited. Deep neural networks typically require significantly larger datasets to automatically learn these complex features without overfitting. Therefore, for

real-time agricultural applications where data collection and labeling are labor-intensive, the integration of YOLOv8 for localization and SVM for classification offers an optimal trade-off between computational efficiency and diagnostic accuracy.

Analysis of the confusion matrix revealed that 87.3% of errors occurred between adjacent severity levels (e.g., Mild vs. Moderate). This pattern reflects the continuous nature of physiological dehydration, where discrete classification boundaries are inherently artificial. Crucially, the absence of catastrophic errors (e.g., Normal vs. Severe) confirms the system’s reliability for decision support.

The disparity in performance between the Cubic SVM and the ANN highlights a critical consideration in agricultural vision: the relationship between feature complexity and dataset volume. The Cubic SVM excels in high-dimensional spaces where the number of features is large relative to the number of samples. Because our pipeline utilizes 18 distinct color and texture features, the SVM’s ability to map these into a higher-dimensional kernel space allowed for a clearer separation of the six dehydration classes. In contrast, the ANN, while tuned for optimal learning rates and depth, tended to converge on local minima, resulting in lower recall for intermediate stress stages (Mild and Moderate).

With a processing latency of 260 ms/image, the system enables real-time phenotyping on commodity hardware. While thermal imaging offers superior sensitivity for pre-symptomatic stress detection (detecting stomatal closure before wilting), it remains cost-prohibitive for many growers. Our RGB-based approach offers a favorable trade-off. It provides significantly higher spatial resolution and accessibility than thermal sensors, making it a viable tool for scalable, routine scouting in commercial horticulture. Table 8 gives a comparison of the variation of stress detection technologies.

Table 8: Comparison of Stress Detection Technologies.

Technology	Advantages	Disadvantages	Suitability
RGB Imaging (Ours)	Low cost, high resolution, simple deployment	Indirect measurement, sensitive to lighting	Small-to-medium farms
Thermal Imaging	Early detection (pre-visual), lighting independent	High cost, environmental sensitivity	Research / High-value crops
Multispectral	Quantitative indices (NDVI), water-specific	High cost, data-intensive, complex calibration	Large-scale aerial mapping
Soil Sensors	Continuous monitoring, predictive	Indirect (measures soil, not plant), point-source only	All scales (complementary)

While our current findings are robust, the study is primarily limited by its reliance on controlled greenhouse data derived from a single cultivar. Transitioning to real-world field deployment will inevitably introduce confounding variables, such as shifting light conditions, wind motion, and complex backgrounds, that will likely require advanced domain adaptation techniques to maintain accuracy. To bridge this gap, future research should validate the pipeline across diverse cultivars and open-field environments to ensure broad applicability. Furthermore, we aim to evolve beyond static snapshots by implementing Recurrent Neural Networks (RNNs) to model the temporal dynamics of stress progression, while simultaneously exploring sensor fusion to combine RGB structural data with multispectral indices for superior early detection capabilities.

4.6 Limitations and Future Works

Despite the high accuracy and localization performance achieved by the YOLOv8-SVM pipeline, certain limitations must be acknowledged. First, the dataset used in this study ($n = 988$ original images) focuses on a specific cultivar of *Cannabis sativa* L. grown under consistent environmental conditions. While the results serve as a robust proof-of-concept for automated water stress monitoring, broader generalization to different cultivars or more varied agroclimatic zones requires further validation. Factors such as varied leaf morphology, canopy density, and diverse soil types could influence the feature extraction process. Furthermore, although the 260 ms processing latency supports the potential for real-time deployment, true scalability across large-scale commercial operations would require testing on edge-computing devices and integration with autonomous scouting platforms. Future research will focus on expanding the dataset to include multi-cultivar samples and evaluating the system’s performance across different growth stages to ensure a more comprehensive agricultural solution.

5. CONCLUSION

This study successfully established an automated pipeline for water stress assessment in *Cannabis sativa* L. by integrating YOLOv8 object detection with multi-modal feature extraction. The YOLOv8m model demonstrated exceptional leaf localization capabilities (98.3% mAP), while the Cubic Support Vector Machine (SVM) achieved an overall classification accuracy of 86.2%. The system’s reliability was rigorously validated against physiological ground truth, with 98.2% of predictions falling within ± 1 severity level of measured water potential. With a processing latency of 260 ms, the framework is viable for real-time phenotyping.

From a practical perspective, this research validates the use of low-cost RGB sensors as a non-

invasive alternative to expensive thermal or hyperspectral equipment. The system facilitates scalable precision irrigation, offering potential benefits of water savings without compromising crop yield. However, current limitations include the reliance on controlled greenhouse conditions and a single cultivar.

Future research must address these constraints by validating the model in open-field environments and employing transfer learning for multi-cultivar generalization. Additionally, integrating thermal data for pre-symptomatic detection and temporal modeling (e.g., LSTMs) to track stress dynamics represents a critical next step. Ultimately, this work demonstrates that accessible AI-driven computer vision can effectively approximate physiological measurements, contributing to sustainable, resource-efficient agriculture.

AUTHOR CONTRIBUTIONS

Conceptualization, N.M. and N.T.; methodology, N.M.; software, W.P. and N.C.; validation, N.T. and P.S.; formal analysis, N.M.; investigation, N.M.; data curation, N.C.; writing—original draft preparation, N.M.; writing—review and editing, N.M. and W.P.; visualization, N.M.; supervision, N.M. and N.T.; funding acquisition, N.T. All authors have read and agreed to the published version of the manuscript.

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