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Determination of Water Stress in Okra Plants Using Canopy Temperature Measurement by Infrared Thermometer

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Abstract: Water scarcity represents one of the most severe constraints on agricultural productivity in semi-arid and water-stressed cultivation zones. In traditional vegetable cultivation, farmers predominantly rely on visual symptoms of wilting to detect water deficit stress, which typically manifest only after substantial physiological damage, cellular dehydration, and irreversible yield loss have occurred. This study presents a non-destructive, precision agriculture framework for the early detection and classification of water stress in okra (Abelmoschus esculentus) using handheld infrared thermometry coupled with an ensemble Random Forest machine learning classifier. A primary field dataset comprising 100 observations was acquired under variable diurnal meteorological conditions in Jammu, India. The recorded and derived parameters encompassed canopy surface temperature (Tc), wet-bulb reference temperature (Twet), dry-bulb reference temperature (Tdry), ambient air temperature (Ta), relative humidity (RH), air saturation vapor pressure (SVPair), actual vapor pressure (AVP), leaf saturation vapor pressure (SVPleaf), leaf vapor pressure deficit (VPDleaf), canopy-air thermal differential (Tc – Ta), and the Crop Water Stress Index (CWSI). Using an empirical CWSI threshold of 0.30, samples were categorized into non-stressed (CWSI ≤ 0.30) and stressed (CWSI > 0.30) physiological states. The dataset was partitioned into an 80:20 training and testing split (80 training samples, 20 testing samples). The trained Random Forest classifier achieved an overall classification accuracy of 95.0% (19/20 correct classifications) on the unseen test set. For the non-stressed class, the model demonstrated a precision of 1.00, recall of 0.92, and an F1-score of 0.96 (support = 12). For the water-stressed class, the model yielded a precision of 0.89, recall of 1.00, and an F1-score of 0.94 (support = 8), with zero false negatives (FN = 0), ensuring that no stressed crops were missed. Gini feature importance analysis revealed that dry-bulb reference temperature (Tdry, score = 0.187), leaf saturation vapor pressure (SVPleaf, score = 0.172), wet-bulb reference temperature (Twet, score = 0.160), leaf vapor pressure deficit (VPDleaf, score = 0.112), and Tc – Ta (score = 0.101) were the primary drivers governing classification. The findings confirm that coupling thermal radiometry with psychrometric feature engineering and ensemble learning provides a reliable, non-contact diagnostic mechanism for precision irrigation scheduling in smallholder horticulture.
Keywords: Precision Agriculture, Crop Water Stress Index (CWSI), Canopy Temperature, Infrared Thermometry, Okra (Abelmoschus esculentus), Random Forest Classifier, Vapor Pressure Deficit (VPD).

I. INTRODUCTION

Agriculture serves as the economic backbone of developing nations, supporting over 58% of the rural population in countries like India. However, contemporary agronomic systems face unprecedented threats from freshwater scarcity, climate extremes, and expanding demographic demands. Worldwide, irrigated agriculture accounts for approximately 70% of total freshwater withdrawals [14], [18]. Projections by the Food and Agriculture Organization (FAO) indicate that global agricultural water demand will rise by 20% to 55% by 2050 [14]. Concurrently, per capita freshwater availability has dropped precipitously from ~13,000 m^3/person/year in 1960 to ~5,000 m^3/person/year in 2025, with projections indicating a further decline to 3,500 m^3/person/year by 2050 (TABLE I). Under conventional flood and furrow irrigation systems, application efficiency rarely exceeds 45%, leading to substantial losses via percolation and non-productive evaporation. Precision irrigation resolves this challenge by dynamically applying water in the exact volume, location, and timing required by the crop [1], [18]. Documented field implementations demonstrate water savings of 30% to 70%, yield boosts of 15% to 25%, and pumping energy cuts of 25% to 40% (TABLE II).

TABLE I
GLOBAL POPULATION GROWTH AND FRESHWATER AVAILABILITY TRENDS (1960–2050)

Year	Global Population (billions)	Freshwater Available (m^3/person/yr)
1960	3.0	~13,000
2025	8.0	~5,000
2050*	9.7	~3,500

Okra (Abelmoschus esculentus (L.) Moench) is an economically essential vegetable crop widely cultivated in tropical and subtropical regions. However, okra is exquisitely sensitive to soil moisture deficits during vegetative elongation and flowering. Soil moisture stress induces flower drop, stunted fruit pod elongation, fiber toughening, and severe yield reductions. Traditional farming relies on visual indicators like wilting or foliar drooping; however, these symptoms manifest only after profound internal cellular dehydration and metabolic damage have occurred.

Direct plant physiological measures, such as leaf water potential (Ψleaf) or stomatal conductance (gc), require destructive sampling and specialized instrumentation [2], [11]. Conversely, canopy surface temperature (Tc) measured via non-contact infrared thermometry offers an instantaneous, non-invasive reflection of plant water status [2], [3], [15]. Under well-watered conditions, open stomata facilitate transpirational cooling, maintaining canopy temperature below ambient air (Tc < Ta). Under water stress, stomatal closure suppresses transpiration, elevating sensible heat accumulation (Tc > Ta) [8], [15].

Translating raw thermal readings into reliable irrigation scheduling requires accounting for atmospheric vapor pressure deficit (VPD), dry-bulb temperature, and micrometeorological noise [7], [10]. This study combines handheld infrared thermometry with psychrometric environmental sensing and ensemble Random Forest machine learning to construct a high-precision, non-invasive water stress classification framework for okra crops.

II. LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

The biophysical foundation of thermal remote sensing was established by Aston and van Bavel (1972), who demonstrated that soil water depletion directly triggers leaf temperature elevation [3]. Idso et al. (1981) introduced the Non-Water-Stressed Baseline (NWSB) relating canopy-air temperature differences (Tc – Ta) to atmospheric VPD [14]. Concurrently, Jackson et al. (1981) developed the theoretical energy balance formulation of the Crop Water Stress Index (CWSI) [15]:

$$CWSI = 1 - (ET\_actual / ET\_potential) = [(Tc - Ta) - (Tc - Ta)\_lower] / [(Tc - Ta)\_upper - (Tc - Ta)\_lower]$$

O'Toole and Hatfield (1983) demonstrated that low wind speeds inflate boundary-layer resistance, causing CWSI overestimation, whereas high wind speeds suppress temperature differentials [7]. Fuchs (1990) revealed that water stress initially affects sunlit leaf subsets rather than the canopy uniformly, demonstrating that leaf temperature distribution is more sensitive than simple spatial means [8].

To eliminate aerodynamic resistance modeling in variable climates, Jones (1999) and Jones et al. (2002) introduced artificial wet (Twet) and dry (Tdry) canopy reference surfaces [2], [9]. Gardner (1992) standardized infrared thermometry viewing angles (30°–45°) and solar noon observation windows [10]. Van Zyl (1986) demonstrated in grapevines that a 1°C–3°C canopy temperature elevation reliably signaled the onset of moisture stress [5]. Scott and Gallagher (1985) confirmed Crop Temperature Difference (CTD) as an optimal scheduling metric in bean crops [6]. Parry (2014) formulated the Stomatal Conductance Ratio (SCR) to isolate canopy from soil background flux [11], and Akhtar et al. (2018) established infrared thermometry for high-throughput drought screening in wheat [12].

Recent advances focus on automated pivot-mounted thermal arrays [1], [18] and orchard UAV imagery [17], [20]. However, low-cost ML-assisted infrared thermometry tailored for smallholder vegetable crops like okra remains unexplored. This work addresses this gap through an empirical, multi-parameter classification pipeline.

III. METHODOLOGY

A. *Experimental Design and Target Crop*

The field experiment was conducted on okra (Abelmoschus esculentus (L.) Moench) in experimental plots located in Jammu (32.7266° N, 74.8570° E), Jammu & Kashmir, India. The site features a subtropical semi-arid climate with high summer daytime temperatures. Plants were cultivated in rows spaced 45 cm apart with 30 cm intra-row spacing. Differential watering regimes (well-watered control vs. progressive deficit irrigation) were imposed during peak vegetative and flowering stages to induce a representative range of crop water statuses.

B. *Primary Data Acquisition*

Field observations were recorded diurnally between 12:40 and 15:25 IST under clear-sky conditions. A calibrated handheld infrared thermometer (optical FOV 12:1, emissivity ε = 0.98, spectral range 8–14 μm) was positioned at an oblique angle (30°–45° to horizontal) 0.5 m above the canopy to capture foliar emissions while avoiding background soil [10]. Simultaneously, microclimatic reference parameters were acquired: (1) Twet via an artificial continuously wetted leaf target; (2) Tdry via a petroleum-jelly-coated non-transpiring leaf; (3) Ta via a radiation-shielded digital thermistor; and (4) RH via a calibrated psychrometric hygrometer.

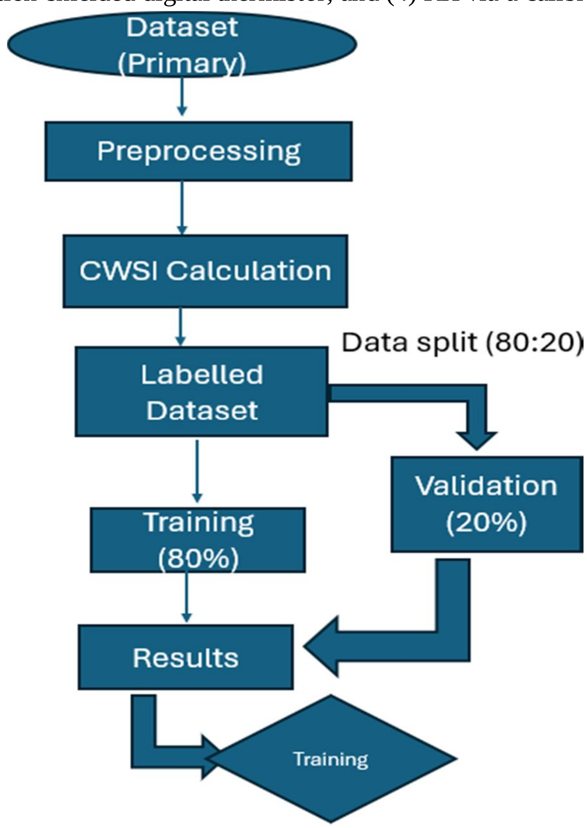

Fig. 1. Methodological flowchart of the proposed okra water stress detection and Random Forest classification pipeline.

C. *Psychrometric Computations*

Atmospheric and foliar vapor pressures were computed via standard psychrometric formulas [14], [15]:

$$SVP\_air = 0.61078 \times \exp[(17.27 \times Ta) / (Ta + 237.3)]$$
$$AVP = (RH \times SVP\_air) / 100$$
$$SVP\_leaf = 0.61078 \times \exp[(17.27 \times Tc) / (Tc + 237.3)]$$
$$VPD\_leaf = SVP\_leaf – AVP$$
$$\Delta T = Tc - Ta$$

TABLE III
REPRESENTATIVE DIURNAL SUBSET OF EXPERIMENTAL PRIMARY FIELD DATASET

Time	Tc (°C)	Twet (°C)	Tdry (°C)	Ta (°C)	RH (%)
12:40	31.4	29.4	36.4	36.0	34
13:05	30.5	26.7	34.2	34.0	33
13:20	29.7	28.0	35.5	34.0	34
13:35	29.9	27.7	35.0	34.0	33
13:45	30.3	28.9	35.9	35.0	33
13:55	31.4	28.5	36.3	35.0	34
14:05	31.6	29.6	36.6	35.0	34
14:20	30.7	29.1	35.8	35.0	34
14:55	27.3	24.7	32.7	36.0	35
15:15	33.0	30.4	37.2	36.0	30
15:25	33.2	30.9	37.8	37.0	30

D. *CWSI Calculation and Stress Thresholding*

Empirical Crop Water Stress Index was calculated using the canopy reference boundary formula [2], [9]:

$$CWSI = (Tc - Twet) / (Tdry - Twet)$$

A threshold of CWSI = 0.30 was defined based on literature standards [10], [17]: samples with CWSI ≤ 0.30 were labeled as Class 0 (Not Water Stressed), and samples with CWSI > 0.30 were labeled as Class 1 (Water Stressed).

E. *Data Partitioning and Model Implementation*

The primary dataset (N = 100 observations) was partitioned into an 80:20 stratified split: 80 samples for training and 20 samples for independent testing. A Random Forest classifier (100 estimators, Gini impurity splitting criterion, max features = sqrt(M)) was implemented in Python 3.12 via scikit-learn [16]. Decision tree splits minimize Gini impurity: $Gini(t) = 1 - \Sigma (pi)^2$, and ensemble outputs are synthesized via majority voting.

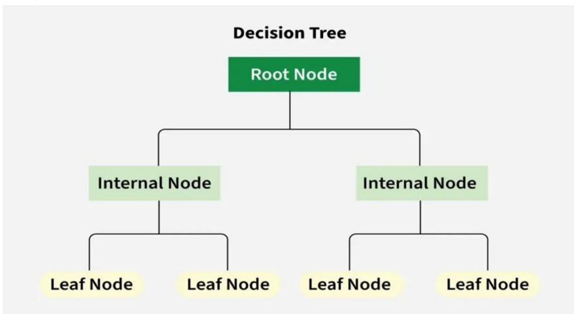

Fig. 2. Schematic representation of decision tree recursive partitioning within the Random Forest ensemble.

IV. RESULTS AND DISCUSSION

A. *Diurnal Variations and CWSI Distribution*

Across the diurnal window, canopy temperature ranged between 27.3°C and 33.2°C, while air temperature ranged from 34.0°C to 37.0°C. The calculated CWSI values displayed a bimodal distribution cleanly separated by the 0.30 threshold (Fig. 4). Non-stressed samples had a median CWSI of 0.17 (IQR: 0.08–0.20, range: 0.05–0.245). In contrast, water-stressed plants exhibited a median CWSI of 0.47 (IQR: 0.43–0.53, max outlier: 0.685). This notable gap between 0.245 and 0.43 confirms the empirical robustness of the 0.30 threshold in discriminating physiological stress.

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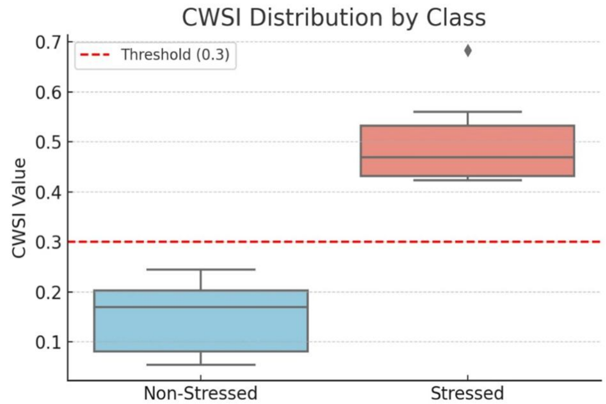

Fig. 4. Boxplot distribution of Crop Water Stress Index (CWSI) values across non-stressed and stressed okra classes.

B. *Model Classification Performance*

Evaluated on the independent test set (N = 20), the Random Forest model achieved 95.0% accuracy (19/20 correct) (TABLE V, Fig. 6). For Class 0 (Non-stressed, support = 12), precision was 1.00, recall was 0.92, and F1-score was 0.96. For Class 1 (Stressed, support = 8), recall reached a perfect 1.00, precision was 0.89, and F1-score was 0.94. The macro-averaged F1-score and weighted-averaged F1-score were both 0.95.

TABLE V
CLASSIFICATION PERFORMANCE METRICS FOR RANDOM FOREST CLASSIFIER (N=20 TEST)

Class	Meaning	Precision	Recall	F1-Score	Support
0	Not Stressed	1.00	0.92	0.96	12
1	Water Stressed	0.89	1.00	0.94	8
Accuracy				0.95	20
Macro Avg		0.94	0.96	0.95	20
Weighted Avg		0.96	0.95	0.95	20

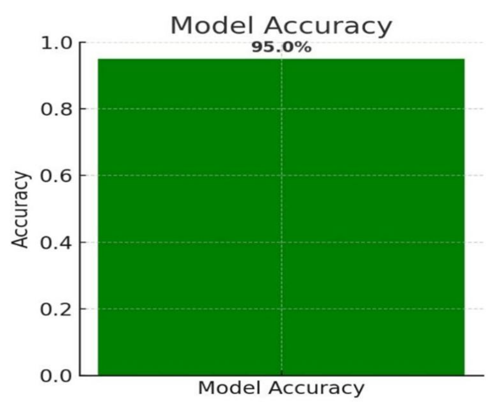

Fig. 6. Overall classification accuracy of the Random Forest model on the independent test dataset.

C. *Confusion Matrix Analysis*

The test confusion matrix recorded 11 True Negatives (TN), 1 False Positive (FP), 0 False Negatives (FN), and 8 True Positives (TP) (Fig. 5). The complete absence of False Negatives (FN = 0) is vital for precision irrigation: no water-stressed okra plants went undetected, preventing irreversible drought damage. The single False Positive (a non-stressed sample classified as stressed) represents a conservative error that would merely prompt an early watering event.

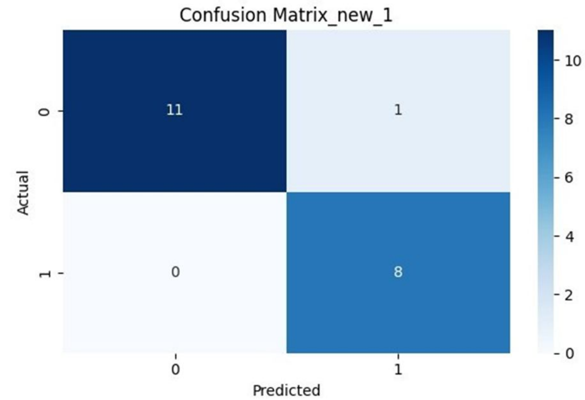

Fig. 5. Confusion matrix of the Random Forest classifier on the independent test dataset.

D. Feature Importance Analysis

Gini feature importance analysis revealed the physiological hierarchy of predictors (Fig. 3): Tdry (0.187), SVPleaf (0.172), Twet (0.160), VPDleaf (0.112), Tc – Ta (0.101), Tc (0.091), AVP (0.075), SVPair (0.057), RH (0.022), and Ta (0.021). Together, reference boundary temperatures (Tdry, Twet) accounted for ~35% of decision weight, confirming that absolute canopy temperature is biologically interpretable only when normalized against dynamic upper and lower boundaries [2], [9]. Leaf-level vapor pressure terms (SVPleaf, VPDleaf) strongly governed classification, while ambient bulk variables (Ta, RH) played secondary roles.

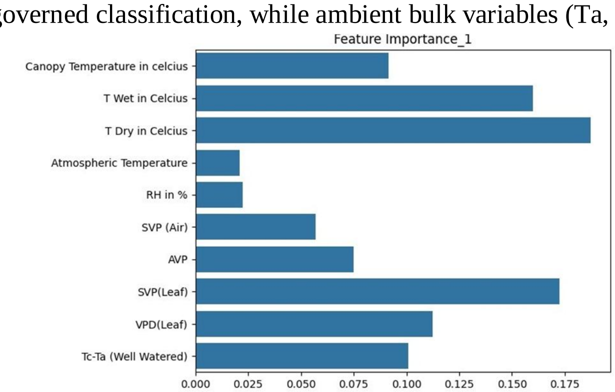

Fig. 3. Relative feature importance ranking derived from the Random Forest model for water stress prediction.

V. LIMITATIONS

Several experimental constraints must be noted: (1) Environmental sensitivity: intermittent clouds and wind gusts alter leaf energy balances and boundary layer resistances [7], [18]. (2) Artificial reference target maintenance: maintaining a clean, continuously saturated wet wick requires regular field servicing [2]. (3) Geographic and cultivar specificity: the current model was evaluated on a single okra cultivar under Jammu subtropical conditions; extrapolating thresholds to disparate climatic zones requires local recalibration [4], [10]. (4) Discrete sampling: observations were gathered during midday windows rather than through continuous automated streaming.

VI. CONCLUSION AND FUTURE SCOPE

This investigation demonstrated that coupling handheld infrared thermometry with psychrometric environmental features and Random Forest ensemble learning provides a highly accurate (95.0%), non-destructive framework for early water stress diagnosis in okra. The complete elimination of false negatives (recall = 1.00 for stressed plants) validates its practical agronomic utility. Future initiatives will: (1) interface long-wave infrared sensors (e.g., MLX90614) with IoT edge microcontrollers for autonomous canopy monitoring; (2) deploy thermal imaging cameras on UAVs for spatial field mapping [17], [20]; (3) incorporate computer vision CNN architectures; and (4) develop smartphone applications to deliver real-time irrigation advisories directly to smallholder farmers.

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