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Early detection of some crops responses to water stress using imaging and artificial intelligence techniques

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Abstract:

The current study was done to evaluate the efficiency of imaging techniques, determine the accuracy and reliability of artificial intelligence models in the early detection of various types of environmental stresses, and study the possibility of combining imaging techniques and artificial intelligence into an integrated system that can be used in agricultural practices, particularly for wheat (*Triticum aestivum* L.) and oat (*Avena sativa* L.) crops. The plants were divided into four groups according to environmental stress factors. The control group included unstressed plants; the second group included plants exposed to water stress (drought). The results of the visual spectrum analysis of water stress images showed that the yellow color intensity of wheat plants was measured at 12.62% on day (10) and a burn rate of 9.71% for the same day. In oat plants, the intensity was 0.91% on day (10) and a burn rate of 10.82% for both plants. The results of the thermal image analysis of water stress in both plants showed an increase in the intensity of red color and the development of leaf reddening. This intensity began to appear in the image (F.bmp) at 0.93% and reached its maximum in the image (J.bmp), recording a color intensity of 10.58% in wheat plants. In oat plants, the intensity began to appear in the image (F.bmp), recording 3.17%, and reached its maximum in the image (J.bmp), recording 10.82%, and indicating deterioration in the physiological condition of the plants. Based on the above, oat plants showed greater sensitivity to the three types of stresses compared to thermal imaging. The study demonstrated that thermal imaging technology was more effective in early detection of stresses in both plants. The results of combining imaging and artificial intelligence techniques using PlantDoc AI and Plantix for both plants and all stresses also showed that both programs provided confidence levels ranging from 70-96% for wheat plants and 60-97% for oat plants, enhancing the accuracy of early detection of stresses to which plants are exposed.

Keywords: *water stress, imaging, artificial intelligence, visible spectrum.*

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الكشف المبكر عن استجابات بعض المحاصيل للإجهاد المائي باستخدام تقنيات التصوير والذكاء الاصطناعي

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الخلاصة

أُجريت هذه الدراسة لتقييم كفاءة تقنيات التصوير، وتحديد دقة وموثوقية نماذج الذكاء الاصطناعي في الكشف المبكر عن أنواع مختلفة من الإجهادات البيئية، ودراسة إمكانية دمج تقنيات التصوير والذكاء الاصطناعي في نظام متكامل يُمكن استخدامه في الممارسات الزراعية، وخاصةً لمحاصيل القمح (*Triticum aestivum*) والشوفان (*Avena sativa*). قُسّمت النباتات إلى أربع مجموعات وفقًا لعوامل الإجهاد البيئي. شملت المجموعة الضابطة نباتات غير مُجهدة، بينما شملت المجموعة الثانية نباتات مُعرّضة للإجهاد المائي (الجفاف). أظهرت نتائج تحليل الطيف المرئي لصور الإجهاد المائي أن شدة اللون الأصفر في نباتات القمح بلغت 12.62% في اليوم العاشر، ومعدل احتراق 9.71% في اليوم نفسه. أما في نباتات الشوفان، فكانت الشدة 0.91% في اليوم العاشر، ومعدل الاحتراق 10.82% لكلا النباتين. وأظهرت نتائج تحليل الصور الحرارية للإجهاد المائي في كلا النباتين زيادة في شدة اللون الأحمر وظهور احمرار الأوراق. بدأت هذه الشدة بالظهور في الصورة (F.bmp) عند 0.93%، وبلغت ذروتها في الصورة (J.bmp) مسجلةً شدة لونية قدرها 10.58% في نباتات القمح. أما في نباتات الشوفان، فقد بدأت الشدة بالظهور في الصورة (F.bmp) مسجلةً 3.17%، وبلغت ذروتها في الصورة (J.bmp) مسجلةً 10.82%، مما يشير إلى تدهور الحالة الفسيولوجية للنباتات. وبناءً على ما سبق، أظهرت نباتات الشوفان حساسية أكبر لأنواع الإجهاد الثلاثة مقارنةً بالتصوير الحراري. وقد أثبتت الدراسة أن تقنية التصوير الحراري أكثر فعالية في الكشف المبكر عن الإجهاد في كلا النباتين. كما أظهرت نتائج دمج تقنيات التصوير والذكاء الاصطناعي باستخدام برنامجي PlantDoc AI وPlantix لكلا النباتين ولجميع أنواع الإجهاد، أن كلا البرنامجين وفّرا مستويات ثقة تتراوح بين 70-96% لنباتات القمح، وبين 60-97% لنباتات الشوفان، مما يعزز دقة الكشف المبكر عن الإجهاد الذي تتعرض له النباتات.

الكلمات المفتاحية: الإجهاد المائي، التصوير، الذكاء الاصطناعي، الطيف المرئي

1. Introduction

Drought stress is one of the most important determinants negatively impacting the growth and productivity of agricultural crops worldwide. It is gaining increasing importance with climate change and the increasing frequency of droughts (Hussain et al., 2019). The effects of water shortages on crops appear at all developmental stages, from germination through vegetative growth to flowering and grain filling. It leads to reduced germination rates, inhibited root elongation, reduced leaf surface area, and decreased photosynthesis and water use efficiency, which negatively impacts the final crop (Oguz et al., 2022).

Wheat (*Triticum aestivum* L.) is considered one of the most water-stressed crops due to its cultivation in semi-arid regions. It has been estimated that drought can reduce its yield by up to 64% in some cases (Hussain et al., 2019). Drought affects wheat by reducing chlorophyll content, closing stomata, and decreasing photosynthetic efficiency, in addition to disrupting ionic and water balances, which limits nutrient uptake and transport to the upper parts of the plant (Oguz et al., 2022). The timing of drought is also a critical factor; exposure to drought during the flowering or grain filling stages leads to irreversible losses in yield and grain quality (Toscano et al., 2023).

Oats (*Avena sativa* L.), while relatively more tolerant than some other cereals, are significantly affected by water shortages. Its vegetative growth is reduced and photosynthesis is impaired due to decreased water use efficiency. This manifests itself in the form of premature yellowing of leaves, increased tissue senescence, and a decline in grain formation and quality (Oguz et al., 2022). Studies have shown that oats resort to adaptive mechanisms such as increased accumulation of proline and soluble sugars to maintain osmotic pressure and protect proteins and cell membranes. However, these mechanisms do not necessarily prevent the significant reduction in yield when exposed to severe drought (Hussain et al., 2019; Toscano et al., 2023). In general, water stress interferes with morphological, physiological, and biochemical processes in wheat and oats, ranging from decreased chlorophyll and carbohydrate content to increased production of reactive oxygen species (ROS). This requires the activation of antioxidant defense systems and altered gene expression patterns associated with tolerance.

A comprehensive understanding of these mechanisms provides a scientific basis for developing more drought-tolerant varieties and implementing sustainable agricultural practices that reduce the effects of water stress in these two strategic crops (Hussain et al., 2019; Oguz et al., 2022;

Toscano et al., 2023). With the increasing frequency of droughts due to climate change, early detection of water stress has become essential to reduce damage and enhance agricultural management efficiency. Studies have shown that traditional imaging techniques (visible imaging) provide early indicators of leaf yellowing and color intensity changes, indicating decreased chlorophyll and water content. Thermal imaging, on the other hand, has enabled the detection of increased leaf temperature resulting from stomatal closure and decreased evaporation, a sensitive and rapid indicator of the onset of drought (Toscano et al., 2023). The integration of these techniques with artificial intelligence (AI) has become more effective in accurately predicting water stress. Machine learning algorithms are used to analyze multispectral and thermal images to identify plant stress signatures even before symptoms appear visible to the naked eye, enabling early intervention and the implementation of precise and effective irrigation strategies (Oguz et al., 2022; Hussain et al., 2019).

Recent research has shown that combining hyperspectral imaging with artificial intelligence algorithms enhances diagnostic accuracy and provides practical tools for breeding programs and the development of drought-resistant varieties (Wahab et al., 2022). Thus, combining conventional and thermal imaging with artificial intelligence is a promising approach for the early detection of water stress in strategic crops such as wheat and oats. It contributes to enhancing food security by supporting sustainable water resource management and the development of more drought-tolerant varieties (Hussain et al., 2019; Oguz et al., 2022; Toscano et al., 2023). Thus, the aim of study was to evaluate the efficiency of imaging techniques, determine the accuracy and reliability of artificial intelligence models in the early detection of various types of environmental stresses. As well as, study the possibility of combining imaging techniques and artificial intelligence into an integrated system that can be used in agricultural practices, particularly for wheat (*Triticum aestivum*) and oat (*Avena sativa*) crops.

2. Materials and Methods

Agriculture and Crop Service

The seeds were washed to remove dirt and impurities, then sterilized using a diluted hydrochloride solution for planting. They were planted in previously prepared soil on November 10, 2024, in the Field Research Unit, which was established by us and affiliated with the Department of Biology, College of Science, Department of Botany, Al-Qadisiyah University. The work site was prepared with an area of (6 x 9 m), and the site was covered with (mixed) soil (5 m3) mixed with (250 L) of peat moss of European Union origin and (1 kg) of DAP. Four rows of oats and four rows of wheat were planted. Wheat (Bohth 22 variety). Oats (from local markets).

Planting was carried out on the sides of the rows, with a distance of (4 lines) between seedlings, and the plants were waited for germination.

Preparation and Implementation of Treatments:

The study plants were divided into four groups, each containing four replicates of each studied species, as follows:

1- Control Plants: This group contains four replicates of healthy study plants or control plants.
2- Water-Stressed Plants: This group contains four replicates of study plants treated with water stress.
3- Plants treated with heavy metal stress: This group contains four replicates of the study plants treated with heavy metal stress (cadmium).
4- Bacteria-Treated Plants: This group contains four replicates of study plants infected with *P. aeruginosa*.

Water Stress (Drought) Treatment

Water stress is the damage that a plant suffers as a result of exposure to a lack or excess of water in the plant's environment beyond the optimal level for growth. Normal plant growth depends on a balance between the water it absorbs and the water it loses. Although water is of great importance to plant life, it can be a stressful environmental factor. This type of stress includes irrigation periods as follows:

- The first period (February 15-20, 2025).
- The second period (February 20-25, 2025).
- The third period (March 25-1, 2025).
- The fourth period (March 1-3, 2025).
- On March 3, 2025, the stress was relieved by rainwater.

Visible (RGB) imaging

This type of imaging relies on capturing the visible spectrum (400-600 nm) of reflected light and recording the levels of red, green, and blue light. Visible imaging is commonly used to monitor changes in leaf color or texture, growth rate, and morphological measurements. High-resolution RGB images enable accurate measurements of plant biomass, root structure, growth rate, germination rate, yield, and disease detection. Its advantages include accessibility, practicality, high resolution, and color depth. This technology can be deployed across multiple devices, improving portability and reducing costs. However, visible imaging provides relatively sparse spectral data, making it insufficient for comprehensive analysis of physiological complications. It is also sensitive to changes in illumination and reflectance, resulting in color variations. Stress is often detected only when physical signs are visually evident.

The Artificial Intelligence (AI)

AI and machine learning are critical tools for processing and interpreting the massive data generated by imaging technologies, enabling accurate modeling of plant stress responses. Deep learning (DL) systems are emerging as powerful methods for diagnosing and treating plant stress, offering high accuracy and efficiency in image data analysis.

Imaging Data Analysis

- Pattern Recognition: Machine learning algorithms are used to analyze imaging data to detect plant stress by recognizing complex patterns in images. These models can be trained on labeled datasets to classify images as healthy or symptomatic (such as leaf spots, knots, wilting, leaf yellowing, and leaf scorch).

- Early and Accurate Detection: AI provides rapid and objective analysis of plant images, enabling early detection of stress, even before visible symptoms appear. Trained models can operate at high speed, analyzing sensor readings and images in real time to guide precise interventions.

- Multimodal Data: Handling multimodal inputs (such as images, temperature, and humidity) allows the model to leverage information from a variety of sources, which can improve prediction accuracy. Data Challenges: Despite advances, AI still faces challenges such as variability in environmental conditions, a lack of diverse, high-quality datasets, and the high cost of advanced sensors.

Color Density

Color Density refers to the intensity or concentration of color in a specific part of the leaf. Measuring color density is one of the primary indicators for diagnosing stress in plants through images, especially under the influence of environmental factors such as drought, heavy metals, and biotic stress. In this work, we used color density analysis of images of oat and wheat plants treated with cadmium to detect heavy metal stress, or exposed to drought to detect water stress, and infected with Pseudomonas aeruginosa to detect biotic stress, using conventional (RGB) images and infrared/thermal images.

Methods used to measure color density

Conventional (RGB) image analysis:

- Image type: JPG or BMP

- Processing: The percentage of yellow color was calculated to determine the intensity of yellowing resulting from stress.

Analysis Method

- Extract the R, G, and B color channels for each image.

- Identify yellowing areas using:

Pixel classified as Yellow if: $R>180$ and $G>180$ and $B<100$

Calculate the percentage of yellow pixels to the total number of pixels:

Yellow Percentage = (Number of Yellow Pixels / Total Pixels) × 100

Thermal Image Analysis

- Thermal BMP image type

- Processing: The red color intensity was measured to assess the severity of heat stress.

Analysis Method

- Convert the image to RGB if it is thermal color.

- Extract the red color channel (R channel).

- Calculate the overall average red color intensity:

Red Intensity = $(1/N) \times \sum R\_i$

Use a threshold such as:

Pixel classified as Hot if: $R>200$

- Tools and Software Used:

- With Python libraries:

- To load and convert images (Open CV).

- For mathematical operations (NumPy).

- For plotting graphs (Matplotlib).

Statistical Analysis

The results were analyzed statistically using the GenStat statistical program, applying a one-way ANOVA, and using the least significant difference (LSD) test at a significance level of 0.05 (Al-Asadi, 2019).

3. Results and Discussion

Visible spectrum imaging of wheat plants

The results of the visual spectrum analysis of the images of the study plants exposed to water stress showed a clear response to water stress, which appeared gradually, represented by leaf yellowing and leaf scorch (Figure 1). Table (1) shows the development of yellowing of leaves through an increase in the color intensity of the yellow color, which indicates a deterioration in the physiological condition of the plant, as it began to appear on day (1), recording (0.0%) and gradually increased to reach (0.1%) on day (6), and reached its maximum on day (10), recording a color intensity estimated at (12.62%). It also showed the percentage of burnt areas in the leaf, as it was noted that it increased with the passage of days. It appeared on day (6), recording a burnt percentage of (0.1%), and gradually increased until day (9), where it reached (3.91%). The highest percentage of leaf burnt was (9.71%) on day (10), compared to the image of the plants on the first day, in which the intensity of the yellow color reached (0%) and the percentage of leaf burnt was (0%).

Table (1) Percentage of wheat leaf burning and color intensity under the influence of drought stress

Image sequence	Color intensity	Percentage
1	0%	0%
2	0%	0%
3	0%	0%
4	0%	0%
5	0%	0%
6	0.1%	0.1%
7	0.2%	0.3%
8	0.3%	0.5%
9	0.96%	3.91%
10	12.62%	9.71%

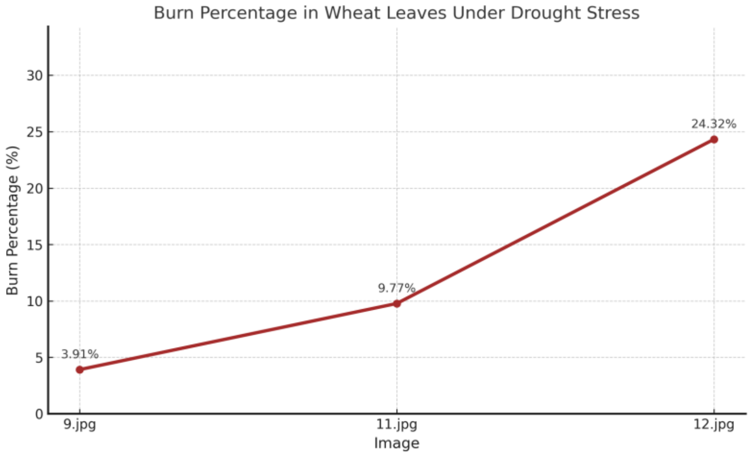


Figure (1) Percentage of wheat leaf burning under the influence of drought stress

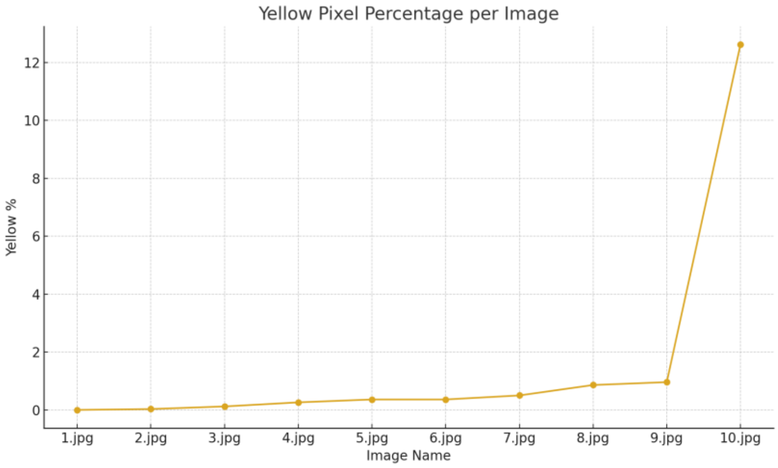


Figure (2) Color density ratio

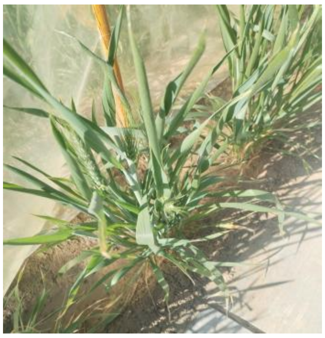


Figure (1) Visible spectrum imaging of wheat plants under drought stress

Visible Spectrum Imaging of Oat Plants

The results of the visual analysis of the images of the study plants exposed to water stress, taken using the visible spectrum, revealed a clear response to water stress, manifesting gradually as leaf yellowing and leaf scorch (Figure 2). Table (2) shows the progression of leaf yellowing through an increase in the color intensity of the yellow color, indicating a deterioration in the plant's physiological condition. This yellowing began to appear on day (1), recording 0.0%, and reached its maximum on day (10), recording a color intensity of 0.91%. Table (4-1) also shows the percentage of scorch areas in the leaf, which increased over time. It appeared on day (9), reaching 6.39%, and the highest percentage of leaf scorch (10.82%) was on day (10). This is compared to the images of the plants on day one, where the yellow color intensity reached 0% and the percentage of leaf scorch reached 0%.

Table (2) Percentage of oat leaf burning and color intensity under the influence of drought stress

Image sequence	Color intensity	Percentage
1	0%	0%
2	0%	0%
3	0%	0%
4	0%	0%
5	0%	0%
6	0.1%	0.1%
7	0.1%	0.2%
8	0.35%	0.7%
9	0.83%	6.39%
10	0.91%	10.82%

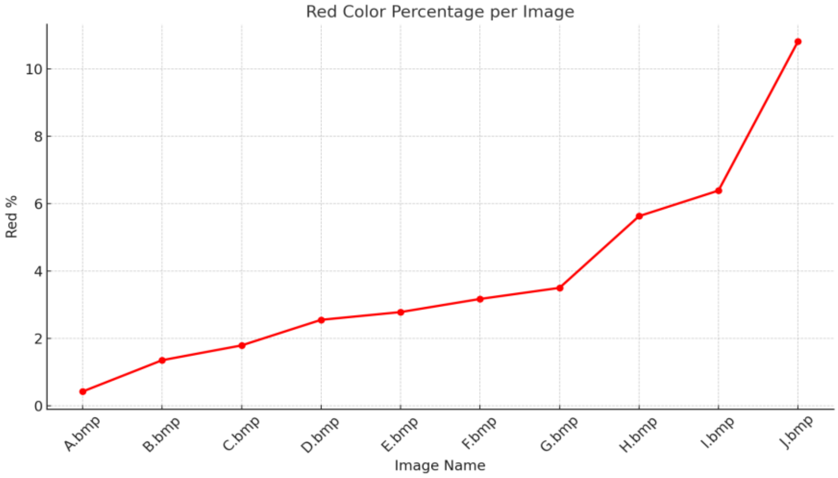


Figure (3) Percentage of oat leaf burning under drought stress

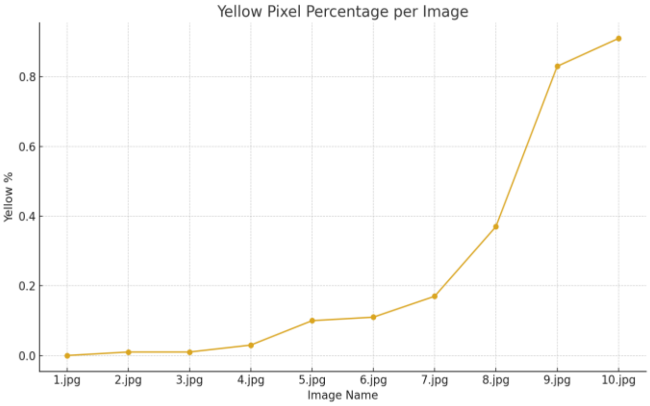


Figure (4) Color density ratio

Figure (2) Visible spectrum imaging of oat plants under drought stress

Thermal Imaging of Wheat Plants

The results of the thermal spectrophotometric analysis of images of the study plants exposed to water stress revealed a clear response to water stress, manifested gradually as leaf scorch (Figure 3). The progression of leaf reddening through an increase in the color intensity of the red color, indicating deterioration in the plant's physiological condition. This reddening began to appear in image F.bmp, recording 0.93%, and reached its maximum in image J.bmp, recording a color intensity of 10.58% (Table 3).

Table (3) Color intensity of thermal images of wheat plants

Image Name	Red Pixel Count	Total Pixels	Red %
A.bmp	369	70320	0.52
B.bmp	431	70320	0.61
C.bmp	467	70560	0.66
D.bmp	511	70080	0.73
E.bmp	527	70320	0.75
F.bmp	656	70320	0.93
G.bmp	671	70080	0.96
H.bmp	893	70266	1.27
I.bmp	1214	70320	1.73
J.bmp	7465	70560	10.58

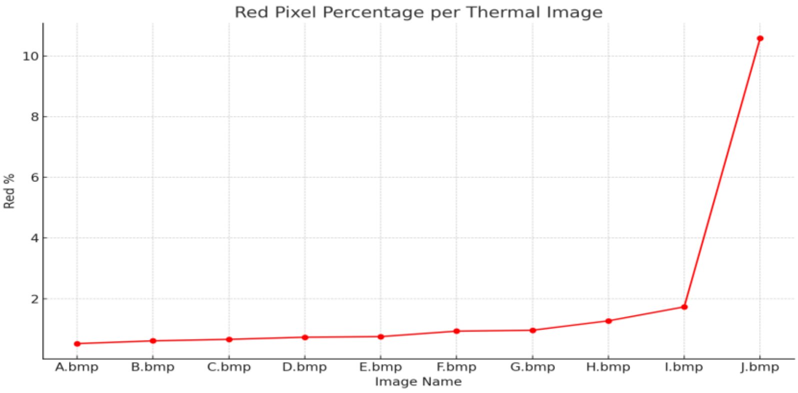
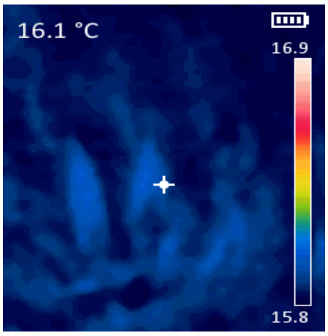
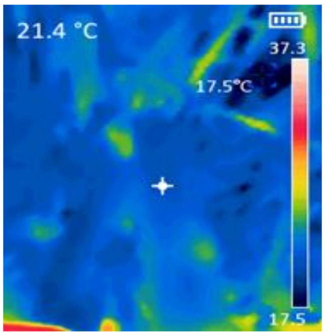


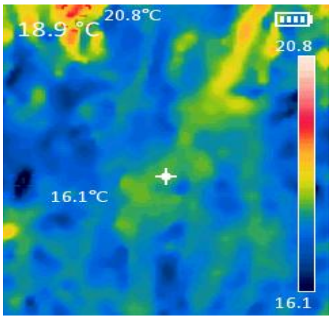
Figure (5) the change in color density of thermal images through a sequence of images of wheat plants



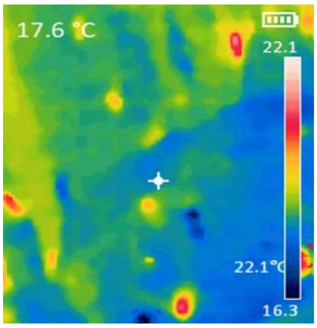
A



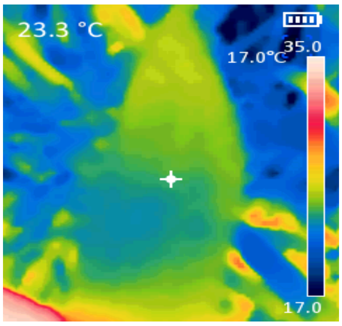
B



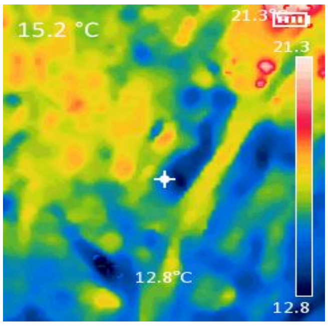
C



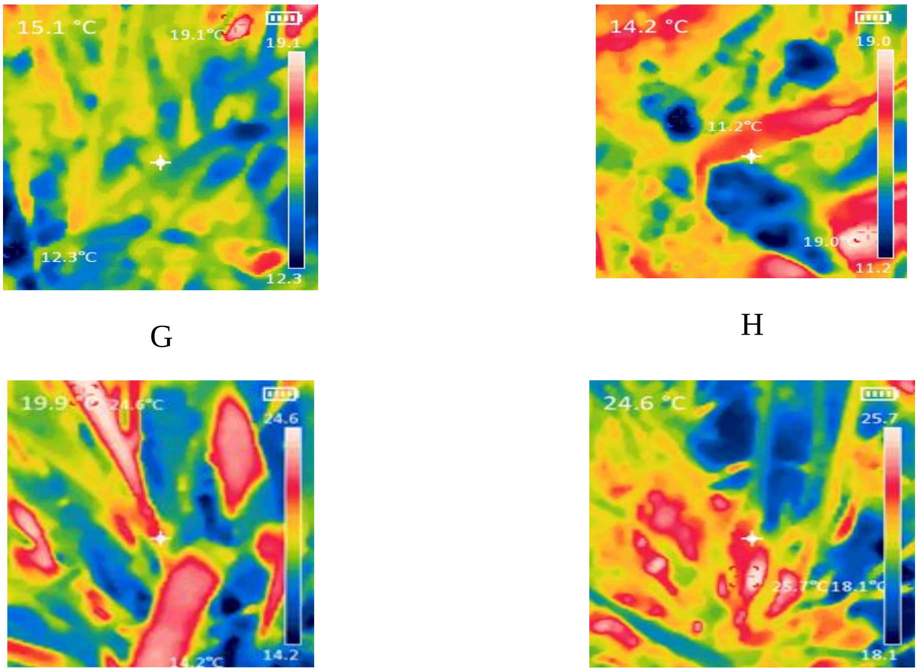
D



E



F



G H

I J

Figure (3) Thermal images of wheat plants under drought stress

Thermal Imaging of Oat Plants under Water Stress

The results of the thermal spectrophotometric analysis of the images of the study plants exposed to water stress revealed a clear response to water stress, manifested gradually as leaf scorch (Figure 4). Table (4) shows the progression of leaf reddening through an increase in the color intensity of the red color, indicating deterioration in the plant's physiological condition. This reddening began to appear in image F.bmp, recording 3.17%, and reached its maximum in image J.bmp, recording a color intensity of 10.82%.

Table (4) Color intensity of thermal images of oat plants

Image Name	Red Pixel Count	Total Pixels	Red %
A.bmp	319	76800	0.42
B.bmp	944	70080	1.35
C.bmp	1252	70080	1.79
D.bmp	1784	70080	2.55
E.bmp	1941	69840	2.78
F.bmp	2231	70320	3.17
G.bmp	2464	70320	3.50
H.bmp	3962	70320	5.63
I.bmp	4495	70320	6.39
J.bmp	7611	70320	10.82

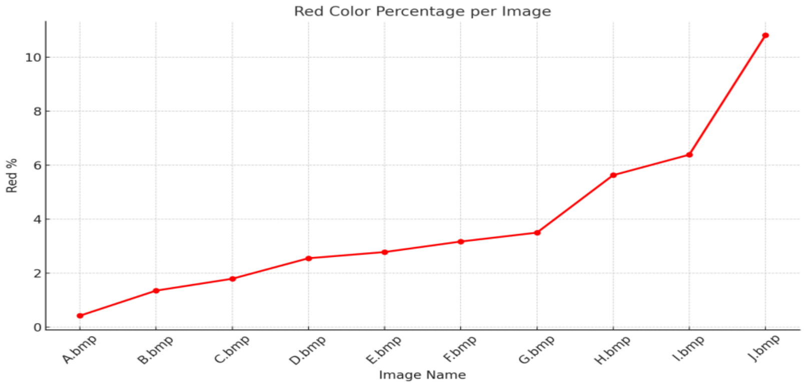
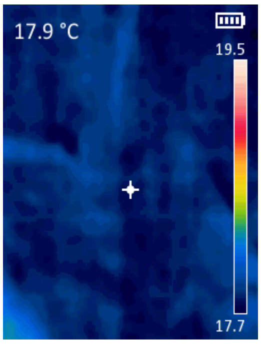
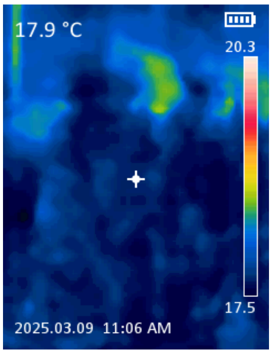


Figure (6) Red color gradation in thermal images of oats



A



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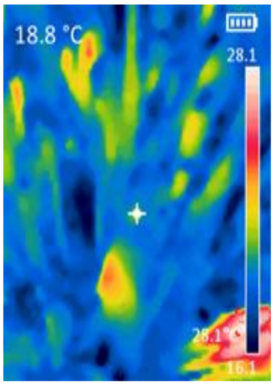

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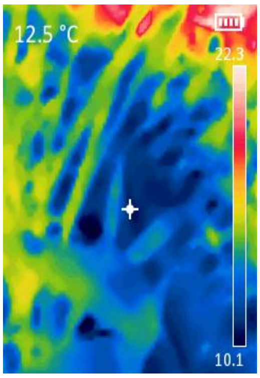

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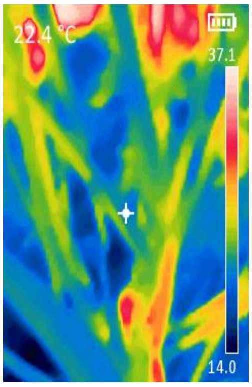

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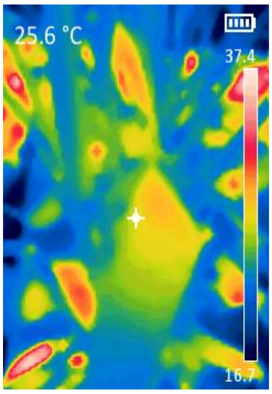
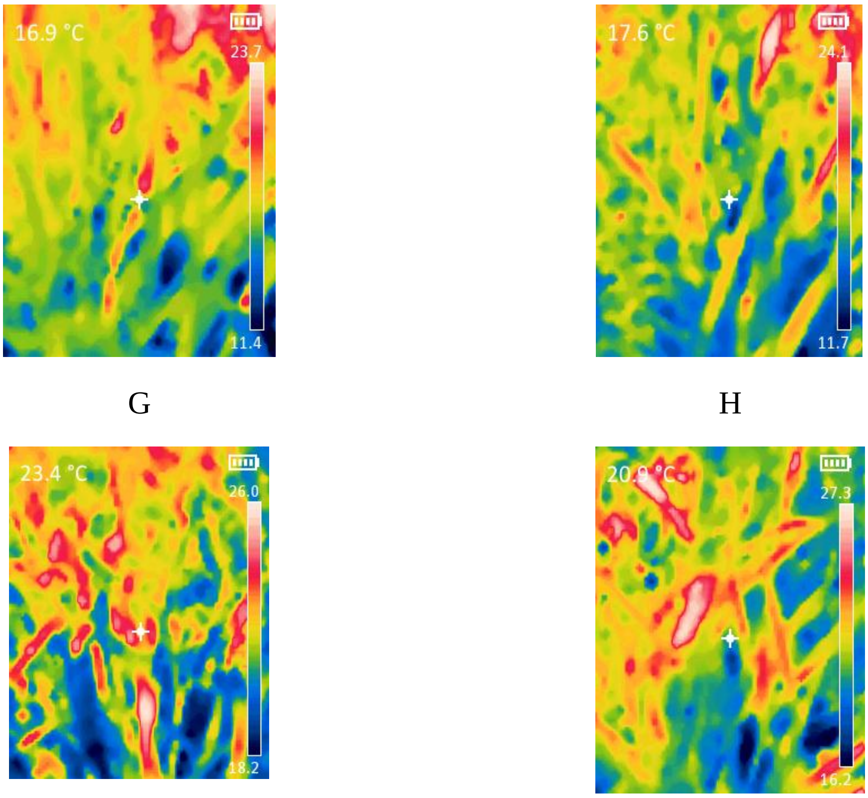


F



G H

I J

Plate (4) Thermal images of oat plants under drought stress

Artificial Intelligence Imaging of Wheat Plants under Water Stress

The artificial intelligence technologies Plantix and PlantDoc AI were used to diagnose wheat plants under drought stress based on conventional images taken from the first to the tenth image. The results show variations in assessment accuracy between the two programs. PlantDoc AI demonstrated a higher ability to detect stress, with a confidence rate ranging between 87% and 96% in the visible spectrum, while the confidence rate ranged between 87% and 96% in thermal imaging (Table 5 and 6).

Table (5) Artificial Intelligence Imaging of Wheat Plants in the visible spectrum

Image Name	Plantix Diagnosis	Plantix Confidence	PlantDoc Diagnosis	PlantDoc Confidence
1.jpg	Healthy	89.78%	Healthy	90.08%
2.jpg	Healthy	92.99%	Healthy	87.71%
3.jpg	Healthy	92.62%	Healthy	91.75%
4.jpg	Healthy	84.48%	Healthy	88.11%
5.jpg	Drought stress	94.3%	Drought stress	89.69%
6.jpg	Drought stress	82.45%	Drought stress	92.01%
7.jpg	Drought stress	83.41%	Drought stress	89.29%
8.jpg	Drought stress	87.73%	Drought stress	94.01%
9.jpg	Drought stress	87.24%	Drought stress	96.04%
10.jpg	Drought stress	81.56%	Drought stress	91.76%

Table (6) Artificial intelligence imaging of wheat plants using thermal images

Thermal Image	Red % (Thermal)	Plantix Diagnosis	Plantix Confidence	PlantDoc Diagnosis	PlantDoc Confidence
A.bmp	0.73	Healthy	89.78%	Healthy	90.08%
B.bmp	0.96	Healthy	92.99%	Healthy	87.71%
C.bmp	0.61	Healthy	92.62%	Healthy	91.75%
D.bmp	0.75	Healthy	84.48%	Healthy	88.11%
E.bmp	0.93	Drought stress	94.3%	Drought stress	89.69%
F.bmp	0.66	Drought stress	82.45%	Drought stress	92.01%
G.bmp	1.73	Drought stress	83.41%	Drought stress	89.29%
H.bmp	1.27	Drought stress	87.73%	Drought stress	94.01%
I.bmp	0.52	Drought stress	87.24%	Drought stress	96.04%
J.bmp	10.58	Drought stress	81.56%	Drought stress	91.76%

Artificial Intelligence Imaging of Oat Plants under Water Stress

Plantix and PlantDoc AI were used to diagnose oat plants under drought stress based on conventional images taken from the first to the tenth image. The results in Table 4-7 show variations in assessment accuracy between the two programs. PlantDoc AI demonstrated a higher ability to detect stress, with a confidence rate ranging from 88% to 95% in the visible spectrum. Confidence rates for thermal imaging ranged from 88% to 95% (Tables 7 and 8).

Table (7) AI imaging of oat plants in the visible spectrum

Image Name	Plantix Diagnosis	Plantix Confidence	PlantDoc Diagnosis	PlantDoc Confidence
1.jpg	Healthy	88.43%	Healthy	89.55%
2.jpg	Healthy	90.74%	Healthy	88.37%
3.jpg	Healthy	94.03%	Healthy	95.51%
4.jpg	Healthy	87.85%	Healthy	93.42%
5.jpg	Drought stress	87.34%	Drought stress	90.27%
6.jpg	Drought stress	88.12%	Drought stress	95.04%
7.jpg	Drought stress	87.68%	Drought stress	91.21%
8.jpg	Drought stress	94.07%	Drought stress	89.19%
9.jpg	Drought stress	84.17%	Drought stress	86.16%
10.jpg	Drought stress	90.32%	Drought stress	88.11%

Table (8) AI imaging of oat plants using thermal imaging

Image Name	Plantix Diagnosis	Plantix Confidence	PlantDoc Diagnosis	PlantDoc Confidence
A.bmp	Healthy	90.97%	Drought stress	94.18%
B.bmp	Healthy	93.35%	Drought stress	90.9%
C.bmp	Healthy	87.27%	Drought stress	89.31%
D.bmp	Drought stress	91.07%	Drought stress	88.37%
E.bmp	Drought stress	91.29%	Drought stress	93.26%
F.bmp	Drought stress	87.33%	Drought stress	89.74%
G.bmp	Drought stress	85.51%	Mild stress	96.64%
H.bmp	Drought stress	85.84%	Drought stress	95.24%
I.bmp	Drought stress	93.47%	Drought stress	95.88%

J.bmp	Drought stress	91.9%	Drought stress	94.79%

Combining Imaging and Artificial Intelligence Technologies

The results of combining optical colorimetric analysis with artificial intelligence diagnostics showed that it enhanced the accuracy of early detection of water stress in the leaves of the two study plants, with confidence levels ranging between 87 and 96% for wheat and 88 and 95% for oats.

Table (9) Effect of water stress (drought) on oats and wheat at the 0.05 probability level

Plants	Control				drought			
Oats *Avena sativa*	Day1	After 1 week	After 2 week	After 3 week	Day1	After 1 week	After 2 week	After 3 week
	17.9 c°	17.9 c°	18.6 c°	18.1	17.9 c°	12.5 c°	16.4 c°	17.8 c°
	18.8 c°	18.2 c°	19.1 c°	18.2	18.8 c°	22.4 c°	16.9 c°	20.9 c°
	19.0 c°	19.2 c°	19.8 c°	18.4	21.9 c°	25.6 c°	17.6 c°	23.4 c°
Wheat *Triticum aestivum*	16.0 c°	16.2 c°	15.5 c°	17.3	16.7 c°	17.6 c°	15.1 c°	14.2 c°
	16.5 c°	17.1 c°	16.1 c°	18.6	18.9 c°	18.7 c°	15.2 c°	19.9 c°
	16.7 c°	18.4 c°	17.9 c°	18.6	21.4 c°	23.3 c°	15.4 c°	24.6 c°
LSD	**0.490**	**0.490**	**0.490**	**0.490**	**5.541**	**5.541**	**5.541**	**5.541**

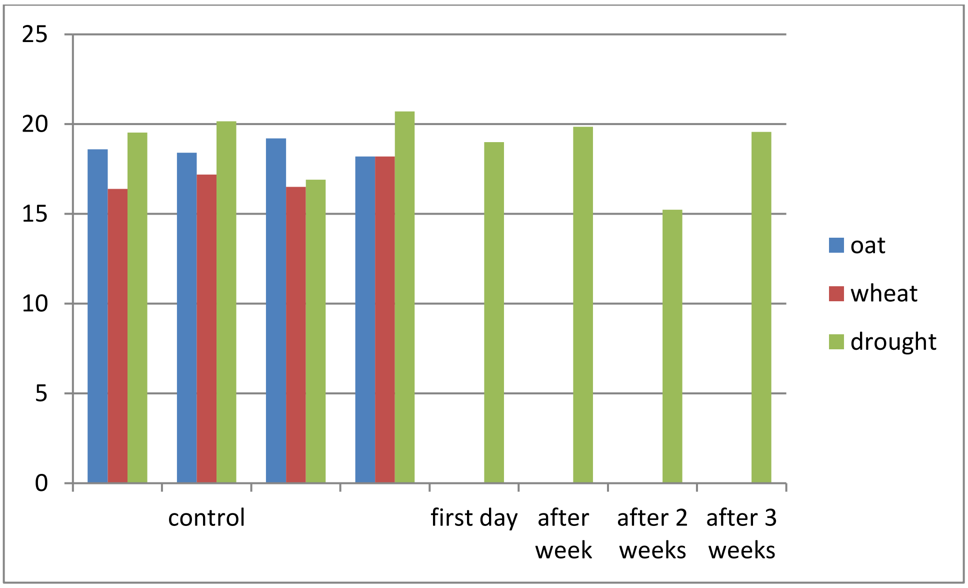


Figure (7) the effect of water stress on wheat and oat plants

Water stress in the study plants may be attributed to its impact on the physiological, biochemical, and molecular biological processes of the plant, affecting the severity and duration of drought and the ability of the leaves to adapt to it. Closing of the stomatal opening in leaves is accompanied by a reduction in leaf area across the entire plant, resulting in inhibition of new leaf growth or premature senescence of older leaves. In the case of prolonged stress, this reduction in leaf area leads to a decrease in incident radiation throughout the growing season and ultimately to a decrease in biomass production. Changing the leaf angle during drought to sharp angles reduces the total incident radiation but plays an important protective role in reducing excess solar energy.

Younger leaves tend to be more drought-tolerant than older leaves. This tolerance may be important in plants that experience a sharp reduction in leaf canopy size due to the shedding of older leaves, as it allows the plant to recover quickly after the drought. Recovery from severe stress occurs in two phases: the first occurs within the first hours or days after re-watering, which sees improved leaf water status and the reopening of stomata. The second phase takes several days and requires the synthesis of photosynthetic proteins. The severity or duration of stress is critical factors affecting both the speed and extent of photosynthesis recovery and the diagnosis of plant condition from the leaves and any stress-related symptoms.

Studies show that yellowing of leaves in both wheat and oat plants is caused by low chlorophyll content and water loss, a classic symptom of water stress (Jones, 2007). At later stages, other signs such as leaf spotting and leaf tip death may appear, as seen in some images (Wahid et al., 2007). Another study indicated that the use of color intensity is an early visual indicator for stress detection, a method used in agricultural studies and digital photography (Barbedo, 2016).

Studies also indicate that thermal image analysis over a ten-day period, consisting of ten images of wheat and oat plants subjected to drought stress, relied on red color intensity as an indicator of plant temperature increases in the affected areas. The results showed that the red intensity ranged between 0.61% and 0.96%, which are relatively weak thermal signals but indicate abnormal physiological activity, especially in the tips, often associated with poor water balance within the plant (Jones, 2007).

Thermal imaging is based on the principle that stressed areas exhibit different temperatures than healthy tissues, often preceding visible symptoms such as wilting and yellowing, making this technology suitable for early detection of water stress in plants (FLIR Systems, 2020). The results of a study indicate that combining optical colorimetric analysis with artificial intelligence diagnostics enhances the accuracy of early detection of water stress, and it is recommended to use at least two programs to compare and improve diagnostic results (Barbedo, 2016).

This agrees with studies indicating that drought causes plant weakness through wilting or dryness of the leaves (Duvnjak, 2023). Another study indicated that the roots and leaves of wheat plants are significantly affected by drought stress, depending on the plant's drought tolerance and environmental conditions (Duan, 2017). Another study confirmed that drought stress has an inhibitory effect on plant hormones and germination rates in most plants. The decrease in hormones may be associated with the balance of nutrients in leaves, toxic ions produced by free radicals due to oxidative stress resulting from drought stress, and decreased soluble osmotic potential (Yang, 2018). A study by Jeandet (2022) indicated that drought stress affects all stages of wheat plant growth and life cycle, including the activity of antioxidant plant hormones. Studies have confirmed that understanding the impact of high temperatures and simultaneous biotic stresses on crop productivity requires further research (Ramegowda, 2024).

High temperatures, which lead to increased rates of drought stress in plants, are directly linked to varying effects (positive or negative) on plant defenses against oxidative stress (Pandey, 2024). This increases the plant's susceptibility to or tolerance to biotic stresses. These effects depend on the order in which stress occurs in the leaves, the plant's growth stage, its genetic background, and the prevailing environmental factors in the growing area (Mahalingam, 2021). Another study indicated that prolonged exposure to high temperatures negatively affects plant health by increasing rates of drought stress in plant tissues (Manghwar, 2024). Another study confirmed that high temperatures negatively impact the physiological and molecular mechanisms involved in plant immune responses to drought stress. This could enhance crop productivity and help develop varieties that can withstand climate change resulting from drought (Duvnjak, 2023). This study agreed with Son (2022), who indicated in his research that there is an inverse relationship between high temperatures and drought stress. Arduini et al. (2019) indicated that temperatures rising above 20°C caused stress in the lower leaves of oat plants. A study (Ploschuk et al., 2023) showed that drought stress resulting from high temperatures caused a 40% reduction in leaf area in oat leaves.

A study confirmed that drought stress severely limits the growth, development, and productivity of oat plants (Raguindin, 2020). A study also indicated differences in the physiological responses of a group of different oat cultivars exposed to drought stress. The results of the study showed that antioxidant enzyme activities in the drought-resistant oat cultivar DA92-2F6 were significantly higher than those under natural conditions after 7 days of drought stress. Oat cultivars Asmap1 and Aspk11 showed a significant increase in antioxidant enzyme activity when exposed to drought stress. The change in the two cultivars' responses to stress, the metabolic pathways in leaf cells, or their activation of plant hormones may be the main factor behind the difference in antioxidant enzyme activity (Gao, 2018). A study also showed that soluble sugar and protein in a significant difference was recorded between two oat cultivars after 7 days of stress (Zhou, 2021). A study also indicated that the carbohydrate metabolism pathway in oat leaves is linked to the activation of water content in plant tissues under drought stress (Raguindin, 2020). A study showed significant differences between chlorophyll degradation and water content in the leaves of two oat plants, one of which was subjected to drought stress and the other grown under normal conditions (Wang, 2012).

Conclusions

The study concludes that water stress in the study plants attributed to its impact on the physiological, biochemical, and molecular biological processes of the plant, affecting the severity and duration of drought and the ability of the leaves to adapt to it. Leaves were accompanied by a reduction in leaf area across the entire plant, resulting in inhibition of new leaf growth or premature senescence of older leaves. In the case of prolonged stress, this reduction in leaf area leads to a decrease in incident radiation throughout the growing season and ultimately to a decrease in biomass production. Changing the leaf angle during drought to sharp angles reduces the total incident radiation but plays an important protective role in reducing excess solar energy.

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