“Entry to the Stockholm Junior Water Prize 2022”

Conservation of Irrigation Water Through a Novel AI Drought Assessment (AIDA) Model in Field Grown Tomato *(Solanum lycopersicum)* Using a Custom-Built “Spectra-Rover”

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I. Abstract

Development of an early detection tool to assess drought stress in plants is crucial in reducing irrigation water used to grow agricultural crops. The AIDA model was developed using field data and variables that are physiologic and direct indicators of drought stress. A custom-built Spectra-Rover was constructed with infrared (IR) and RGB cameras to capture radiometric IR and RGB plant canopy images. Radiometric IR temperature, red, green, and blue light reflectance values, and soil moisture readings were used to train the AIDA model. Eighty percent (80%) of the data was used in the training dataset and the remaining 20% was used in the validation dataset. The AIDA model validation output was very close to the actual CWSI values with a low mean absolute error. A prediction output program was coded and appended to the AIDA model to output an AIDA score. This accurately approximated the manually calculated CWSI values. If this novel AIDA model with an AIDA score is used on all tomato farms in California, approximately 26 billion gallons of irrigation water can be saved each season.

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III. Key Words

Early detection of drought stress in plants; machine learning; artificial intelligence model; light reflectance values; radiometric infrared canopy temperature

IV. Abbreviations and Acronyms

AI – Artificial Intelligence; AIDA model – AI Drought Assessment model; IR – infrared; RGB – Red, Green and Blue; POP – Prediction Output Program; CWSI – Crop Water Stress Index

V. Acknowledgements

We would like to thank our mentor, Dr. Dave Goorahoo, at Fresno State University. He gave us very valuable advice while we were working on our project. He answered a lot of our questions regarding plant physiology, soil science, and agriculture in general. He had a wealth of knowledge and experience that he was willing to share with us. Mrs. Kaye Barrie our school (Clovis North High School) science fair coordinator, also provided a lot of guidance on how we can further improve our project. She painstakingly read our research paper and gave us valuable suggestions and ideas on how we can present it effectively.

VI. Biography

John Estrada is a junior at Clovis North High School in Fresno, California. His elementary and middle school research topics range from analyzing the effects of the visible light spectrum on crops to using a remote sensing unmanned aerial vehicle to collect multispectral data for the calculation of vegetation indices. His high school research involves the use of AI in the development of drought assessment tool to accurately predict the earliest sign of drought stress in plants. John's project was recognized as one of the top awardees at the Regeneron ISEF 2021 competition, garnering first place in the Plant Science category, as well as the prestigious Gordon E. Moore Award for Positive Outcomes for Future Generations. The AIDA model also won first place in the Plant Science category at the 2021 California Science and Engineering Fair. This year, John and Pauline are presenting the poster of this project at the American Society for Horticultural Science Annual Conference. Aside from his interest in science research, John loves to do ballet. He has performed lead roles in the Lively Arts production of "The Nutcracker". He also competes at the Youth America Grand Prix and was awarded as one of the top 6 senior male dancers in a recent competition in February 2022.

Pauline Estrada is a freshman at Clovis North High School in Fresno, California. Her research in both elementary and middle school were focused on using custom camera systems interfaced to a remotely operated vehicle or rover that she constructed to detect drought stress in plants. Pauline's sixth and seventh grade projects were selected as one of the top 30 finalists at the 2019 and 2020 Broadcom MASTERS competitions. She ultimately won the second place Technology award at the Broadcom MASTERS 2020 competition. Pauline and John are currently preparing for Regeneron ISEF, which is scheduled for May this year. Pauline is also an accomplished ballet dancer. She has won multiple awards in the Youth America Grand Prix ballet competition ranging from third to first place in both the classical and contemporary categories. Aside from doing science fair, she has also performed various lead roles in the Lively Arts production of "The Nutcracker".

Since 2019, John and Pauline have been mentoring young students who are interested in science fair. They are very proud of the remarkable achievements the students they mentored have achieved. These students have won multiple recognitions at various fairs. Some awards include BROADCOM Masters top 300, 4^{th} place at state, 1st place in their categories, and the sweepstakes award at regional competitions. John and Pauline want to raise student involvement in science fair to foster interest in STEM fields.

1.0 Introduction

California is the leading state in the production of fruits, nuts, and vegetables. Fifty percent of our nation's almonds, grapes and fruits come from Fresno County California [1]. Drought impacts 40% of the world's population and is the most serious threat to crops in nearly every part of the world [2], especially in California. Water in California is becoming scarcer especially with an almost permanent state of drought induced by the ongoing climate crisis. Drought has been, and will continue to be, a big problem in California. Because of this problem, the amount of irrigation water used to grow crops in California is gaining more attention. Irrigated agriculture accounts for 40% to 80% of total water supplies in California [3]. More emphasis should therefore be placed on efficient irrigation management through the accurate detection of the earliest signs of drought stress in plants. This will help farmers avoid unnecessary or over irrigation, as well as conserve water without sacrificing their yield.

Water plays a vital role in plant growth. Drought stress can be considered as one of the most important factors affecting plant health and decreasing plant yield. Drought induces stress in plants which negatively impacts crop yield and adversely affects global food sufficiency. Early detection of drought stress in plants even before it manifests physically can be of great importance in ensuring successful crop production. Drought stress can lead to early leaf aging that is characterized by color deterioration and nutrient loss [4]. Late detection of drought stress in plants can then lead to irreversible damage and yield loss.

There are commercially available methods of monitoring plant water status which include the pressure bomb and the leaf diffusion porometer [5]. However, these methods of measuring plant water content are invasive and detect plant drought stress late in the process. Plant drought stress can also be measured or predicted using qualitative assessments such as visual detection. The main problem with visual assessment is that it is subjective and dependent on the skill of the technician doing the evaluation or scoring. Also, when signs of water stress are already visible, the stress is already considered excessive and irreversible which leads to unavoidable yield reduction. Development of an early detection tool to assess drought stress in plants is crucial in reducing irrigation water used to grow agricultural crops.

The advancements in visible light spectrum and thermal imaging cameras have led to the development of remotely accessible, and non-destructive methods of determining the water status in plants. Thermal imaging cameras can capture thermal energy radiated off the surfaces of almost all heat emitting sources in our planet including living things, rocks, buildings, etc. Thermal energy is radiated as infrared (IR) waves, composed of different wavelengths: short, middle, and long IR waves. Hotter surfaces will emit more of the shorter IR waves and cooler surfaces will emit more of the longer waves. Different materials will also have different rates of absorption and emission of thermal radiation. Thermal imaging cameras can be used for "infrared thermography". IR thermography is a technique used to capture an infrared image and translate it into radiometric temperature measurements/values [6]. This technique can be used to measure the canopy temperature of almost all species of plants including solanaceous crops.

The plant's canopy temperature has been used as an indicator of water availability since 1962 [7]. Development of different devices and instruments that use infrared technology in measuring canopy temperature has led to the development of a quantitative method of water stress evaluation. The concept of crop water stress index (CWSI) to assess drought stress in plants was introduced by Ehrler in 1973 [8]. A plant that is suffering from drought stress will have higher canopy temperature compared to a normal and healthy plant. The values of CWSI range from 0-1, with values approaching one indicating that the plant is suffering from severe drought stress [5]. CWSI calculation uses variables that are mostly indirect indicators of drought stress in the plant, namely vapor pressure deficit, canopy, and air temperature.

The emergence of "artificial intelligence", particularly machine learning algorithms in agriculture have led to progress in predicting drought stress in plants. The most common deep learning method used is the "transfer learning" method that requires only a small dataset and less advanced hardware [9] but requires a predetermined and tested model. However, the use of a deep learning model approach, such as "train from scratch", can offer a better way of estimating and predicting drought stress in plants since it can change all the weights and parameters of the model during the training phase of the process.

Artificial intelligence (AI) has been used in various studies involving the prediction of vegetation health which used data from satellite images to calculate vegetation indices [10], estimation of canopy temperatures in the field using IR thermometers [11] and drought stress identification and classification in corn using image analysis [9]. However, the use of close proximity visible light spectrum RGB (red, green, and blue) light reflectance values combined with radiometric infrared plant canopy temperature readings and soil moisture to develop a robust and accurate machine learning model to detect early drought stress has not been previously explored.

In 2020, the use of machine learning was explored to develop an AI-based drought tool to predict drought stress in bell pepper plants utilizing the variables used in the CWSI calculation [12]. The tool worked marginally well, with a mean absolute error of 0.02.

In 2021, further improvements on the AI-based drought tool were done resulting in the development of the AI Drought Assessment (AIDA) model which utilized variables that were all physiologic and direct plant stress indicators, rather than the atmospheric variables that were used in CWSI calculation [13]. The variables used to develop the AIDA model were red, green, and blue or RGB light reflectance values, canopy temperatures, and soil moisture readings. These variables are considered direct indicators of drought stress in plants. RGB light reflectance values are intimately involved in photosynthesis and stimulation of stomatal opening. IR leaf canopy temperature on the other hand correlates with a plant's transpiration rate and soil moisture determines the amount of water available to the plant.

The AIDA model developed using data from a controlled bench laboratory environment was robust in predicting drought stress in bell pepper plants. Its output was a remarkably close prediction of the actual CWSI values with an extremely low mean absolute error (MAE) rate of 0.00048 achieved in only 28 "epochs" (repetitions of the machine learning algorithm).

In 2022, the AIDA model that was previously developed using data from an indoor bench laboratory experiment was trained, validated, and optimized using data from an actual field experiment. Although, the AIDA model developed in 2021 was very robust, it was deemed important to test and validate it under actual field conditions. A custom-built remotely operated vehicle (ROV) equipped with a visible light spectrum RGB and infrared camera, and telemetry-capable microcomputer system, referred to herein as the "Spectra-Rover" was used to measure and transmit plant canopy temperatures and visible light reflectance values.

Research Question: Can a trained Artificial Intelligent Drought Assessment (AIDA) model developed using actual field data quickly and more accurately detect early drought stress in tomato plants compared to CWSI?

Hypothesis: The trained Artificial Intelligent Drought Assessment (AIDA) model developed using field data can quickly and more accurately detect early drought stress in tomato plants compared to CWSI.

Research Objectives: This study was conducted to develop the novel AIDA model using field data with variables that are physiologic and direct indicators of drought stress. It also aims to generate a prediction output program (POP) that outputs a new AI Drought Assessment (AIDA) Score which can be used to determine whether the tomato plants are experiencing the earliest signs of drought stress. This score will help farmers decide when to irrigate as well as help them manage their irrigation water judiciously.

2.0 Materials and Methods:

Phase 1. Constructing and programming a custom-built remotely operated vehicle (ROV) equipped with RGB + IR Camera also referred to as the "Spectra-Rover" to measure plant canopy temperatures and light reflectance values.

A custom-built rover was utilized in this project. The rover was constructed from a 6-wheel drive chassis mounted with a GPS-equipped Arduino-based Pixhawk controller. A 6-inch microcomputer was mounted on the autonomous ground-based remotely operated vehicle (ROV), or rover. The microcomputer was then connected to a Samsung Tab A 8 tablet via Google Remote Desktop to allow capturing and transmission of images in "real time".

An infrared camera utilizing a Lepton 3.5 sensor with a 57-degree field of view and a resolution of 160 x 120 radiometric pixels was constructed and interfaced to the microcomputer. The custom-built IR camera and an 8-megapixel red, green, and blue (RGB) camera were then mounted together on the rover. Both cameras were then used to obtain RGB and radiometric thermal images concurrently.

Using ImageJ2 packaged in Fiji, the individual canopy pixel temperatures and visible light reflectance values in each pixel were extracted from the saved RGB and radiometric thermal images.

The custom-built remotely operated vehicle (ROV) fitted with a custom-made RGB + IR Camera was referred to as the **"Spectra-Rover"**. This new ROV set up proved to be versatile since close proximity RGB and thermal images from the custom-made RGB + IR camera can be captured, viewed, saved, and transmitted to the "cloud" from the on-board computer in real-time.

The "Spectra Rover" capturing RGB and IR images. (Photo credit: Pauline Estrada)

Phase 2. Growing and assessing tomato plants in the field that will be used to develop the AIDA model.

a. Planting the test crop. A field experiment on Tomato plants *(Solanum lycopersicum),* applied with different irrigation levels was used in this study. The field was located at California State University (CSU), Fresno. The texture of the soil was a sandy loam. There were 6 treatments or irrigation levels. Five individual water valves were installed to regulate and control the amount of irrigation water that were applied in each treatment. Plants were irrigated every day at the same time.

Transplanting tomato at CSU, Fresno, Agricultural Field. (Photo credit: John Estrada)

Individual valve for individual irrigation level/treatment. (Photo credit: John Estrada)

The irrigation time and Evapotranspiration (ET) level for each treatment is summarized below.

Treatment	Evapotranspiration Rate - ET (%)	Irrigation time (minutes)
A - Control	100	90
B	90	81
C	80	72
D	70	63
E	60	54
F	50	45

The same fertilization rate and pest management were applied in all the treatments.

b. Data collection. A HydroSense II Handheld Soil Moisture Sensor with 6" probe was used to measure soil moisture. The ambient temperature and relative humidity were measured using the UbiBot soil moisture meter (photo below). The lepton 3.5 sensor and the RGB camera system installed on the Spectra-Rover were used to measure the leaf canopy temperature and the RGB light reflectance values. Individual pixel temperatures in centiKelvin were extracted from the saved radiometric thermal images using ImageJ2. The RGB raster values were also extracted from the plain RGB images obtained through the RGB camera using ImageJ2 as well.

HydroSense II handheld soil moisture meter. (Photo Credit: Campbell Scientific)

UbiBot soil moisture, temperature & RH meter. (Photo credit: UbiBot product manual)

The data that were obtained using the Spectra-Rover (RGB light reflectance values and canopy temperatures) and the HydroSense II handheld soil moisture meter (Soil moisture readings) were then used to train and validate the AIDA model to accurately predict drought stress.

Phase 3. Training, validating and optimizing the AIDA model that predicts the CWSI using the actual field data.

The AIDA model was programmed on a Raspberry Pi 400A (photo below) using Python 3.7, running TensorFlow 1.14 (Google, Inc.), with the Keras API. A "Sequential" model with 3 neural net layers was constructed using Adam as the optimizer and mean squared error as the loss function. Metrics that were used in the model were mean squared error and mean absolute error. An early stopping function was incorporated to prevent overfitting.

Raspberry Pi 400A, Quad-Core 64-Bit 1.8GHz Processor
(Photo credit: Amazon)

Infrared images for each plant were then analyzed using the ImageJ2 Fiji software program. The plant canopy IR foliage image was used to obtain the most accurate average temperature which was then used to calculate the crop water stress index (CWSI).

The RGB images with 19,200 (160x120) pixels/plant were also analyzed using the ImageJ2 Fiji software program. Each image had 19,200 (160x120) pixels. A total of 230,400 raster values for each Red, Green & Blue light wavelength were collected. The soil moisture level for each treatment was measured the same time the images were obtained. The canopy temperatures, raster values for each Red, Green & Blue light wavelength and soil moisture data were used to re-train and adapt the AIDA model.

Phase 4. Coding the New Prediction Output Program (POP) which output an AIDA score.

The AIDA model was programmed on a Raspberry Pi 400A using Python 3.7, running TensorFlow 1.14 (Google, Inc.), with the Keras API. The prediction output program or "POP" running the re-trained AIDA model was used on a tomato plant not included in the training and validation datasets.

3.0 Results

Extraction of Canopy Temperatures and RGB Light reflectance Values Using the ImageJ2 Fiji software program.

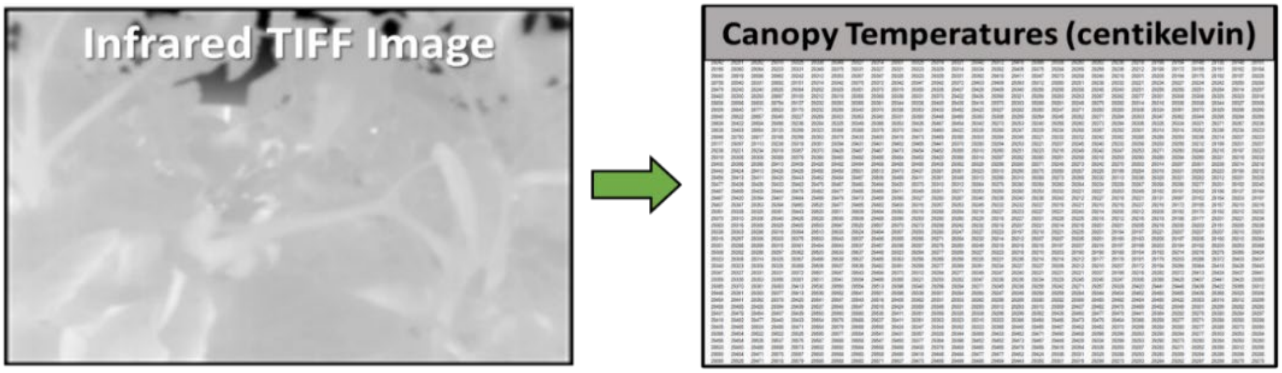

Image 1. Individual pixel temperatures in centiKelvin extracted from the saved radiometric thermal images using ImageJ. (Image credit: Pauline Estrada)

Radiometric plant canopy images were captured. Each image had 19,200 (160x120) pixels with corresponding temperature values that ranged from 20,308.00 to 40,288.00 centiKelvin. A total of 230,400 canopy temperature values were collected from the sample plants and used to develop the AIDA model (Image 1).

Image 2. Individual pixel values extracted from the saved RGB images using ImageJ. (Image Credit: Pauline Estrada)

The red, green, and blue (RGB) images were captured. Each image had 19,200 (160x120) pixels. A total of 230,400 raster values for each Red, Green & Blue light wavelength were collected from the sample plants and used to develop the AIDA model (Image 2).

Training and Optimizing AIDA Model for Tomato.

The program for the novel AIDA model was coded on a Raspberry Pi 400 A using Python 3.7 for machine learning analysis of the data. TensorFlow (version 1.14.0, Google) with a Keras application programming interface (API) was utilized.

```python
from __future__ import absolute_import, division, print_function, unicode_literals
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import pathlib

import tensorflow as tf

from tensorflow import keras
from tensorflow.keras import layers

print(tf.__version__)

import tensorflow_docs as tfdocs
import tensorflow_docs.plots
import tensorflow_docs.modeling
```

The CSV file containing the data array with the leaf canopy temperature values (IR), red (Red), green (Green) and blue (Blue) raster values, and soil moisture (Moisture) was loaded into the program. The crop water stress index values (CWSI) calculated from each plant canopy image was imported as well from the CSV file.

```python
column_names = ['IR','Blue','Green','Red','Moisture','CWSI']
data = pd.read_csv("IRBGRMC.csv", names=column_names)
print(data.head())
print(data.tail())
```

The neural network was designed as a sequential algorithm, as it was started from scratch. Eighty percent (80%) of the total collected data (230,400 unique rows with 6 columns each) was used as a training and validation sample. All data, including the isolated test data, were normalized.

```python
train_dataset = data.sample(frac=0.8,random_state=0)
test_dataset = data.drop(train_dataset.index)
sns.pairplot(train_dataset[["IR", "Green", "Red", "Blue", "Moisture", "CWSI"]], diag_kind="kde")
plt.show()

train_stats = train_dataset.describe()
train_stats.pop("CWSI")
train_stats = train_stats.transpose()
print(train_stats)

train_labels = train_dataset.pop('CWSI')
test_labels = test_dataset.pop('CWSI')

def norm(x):
  return (x - train_stats['mean']) / train_stats['std']
normed_train_data = norm(train_dataset)
normed_test_data = norm(test_dataset)
```

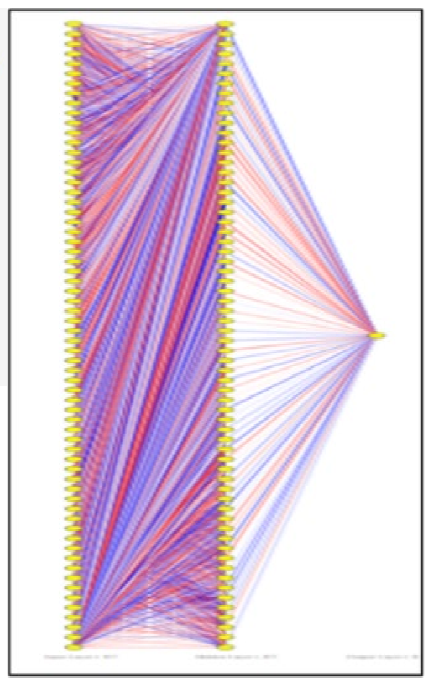
Diagram 1. Sequential neural network with 3 dense layers to predict CWSI. (Image credit: John Estrada

Three dense neural net layers (Diagram 1) were used to derive the appropriate weights and biases from the five variables collected utilizing the "Adam" optimizer with mean squared error being used as the loss function and mean squared error and mean absolute error as metrics, to formulate an AI model that tracked closely with the true value of CWSI.

```
def build_model():
  model = keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=[len(train_dataset.keys())]),
    layers.Dense(64, activation='relu'),
    layers.Dense(1)
  ])

  optimizer = keras.optimizers.Adam(learning_rate=0.001, beta_1=0.9, beta_2=0.999, amsgrad=False)

  model.compile(loss='mse',
                optimizer=optimizer,
                metrics=['mae', 'mse'])
  return model

model = build_model()
model.summary()
```

An early stopping function was incorporated into the model to prevent overfitting.

```
EPOCHS = 100

early_stop = keras.callbacks.EarlyStopping(monitor='val_loss', patience=10)

early_history = model.fit(normed_train_data, train_labels,
                    epochs=EPOCHS, validation_split = 0.2, verbose=0,
                    callbacks=[early_stop, tfdocs.modeling.EpochDots()])

hist = pd.DataFrame(early_history.history)
hist['epoch'] = early_history.epoch
print(hist.tail())

plotter = tfdocs.plots.HistoryPlotter(smoothing_std=2)
```

Once the AI model was rendered, it was tested on the remaining 20% of the dataset to measure the degree of correlation between the actual and predicted CWSI values.

```
loss, mae, mse = model.evaluate(normed_test_data, test_labels, verbose=2)

print("Testing set Mean Abs Error: {:5.2f} CWSI".format(mae))

test_predictions = model.predict(normed_test_data).flatten()

a = plt.axes(aspect='equal')
plt.scatter(test_labels, test_predictions)
plt.xlabel('True Values [CWSI]')
plt.ylabel('Predictions [CWSI]')
lims = [0, 1]
plt.xlim(lims)
plt.ylim(lims)
_ = plt.plot(lims, lims)
```

The following table shows the successful importation of the CSV file containing the data array with the leaf canopy temperature values (IR), red (Red), green (Green) and blue (Blue) raster values, and soil moisture (Moisture). The crop water stress index values calculated from each image (CWSI) was imported as well from the CSV file.

	IR	Blue	Green	Red	Moisture	CWSI
0	29282	71	60	62	17.14	0.0
1	29297	69	58	60	17.14	0.0
2	29242	72	63	66	17.14	0.0
3	29166	74	65	68	17.14	0.0
4	29040	72	63	66	17.14	0.0

	IR	Blue	Green	Red	Moisture	CWSI
230395	29871	99	67	54	5.16	0.780988
230396	29975	101	69	56	5.16	0.780988
230397	30119	103	71	58	5.16	0.780988
230398	30214	100	68	57	5.16	0.780988
230399	30198	101	69	58	5.16	0.780988

The following descriptive statistical parameters were obtained:

	count	mean	std	min	25%	50%
IR	184320.0	29545.379291	747.098973	20308.00	29138.00	29377.00
Blue	184320.0	115.858908	27.246262	0.00	94.00	121.00
Green	184320.0	102.114035	33.474429	40.00	76.00	103.00
Red	184320.0	90.359776	33.748969	19.00	68.00	92.00
Moisture	184320.0	8.465762	4.009460	5.16	5.98	6.64

	75%	max
IR	29864.00	40288.00
Blue	134.00	189.00
Green	117.00	201.00
Red	105.00	198.00
Moisture	8.42	17.14

The AI model was successfully built with the following output describing its characteristics:

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                384
_________________________________________________________________
dense_1 (Dense)              (None, 64)                4160
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 65
=================================================================
Total params: 4,609
Trainable params: 4,609
Non-trainable params: 0
_________________________________________________________________
```

The AI model was deployed, and 27 epochs were needed out of the planned 100 epochs before the early stopping function was activated to prevent overfitting:

```
Epoch: 0, loss:0.0008,  mean_absolute_error:0.0154,  mean_squared_error:0.0008,  val_loss:0.0003,  val_mean_
absolute_error:0.0118,  val_mean_squared_error:0.0003,
...........................            loss  mean_absolute_error  mean_squared_error  val_loss  \
23  0.000145            0.004672            0.000145  0.000198
24  0.000147            0.004765            0.000147  0.000155
25  0.000146            0.004754            0.000146  0.000169
26  0.000145            0.004769            0.000145  0.000159
27  0.000144            0.004672            0.000144  0.000176

    val_mean_absolute_error  val_mean_squared_error  epoch
23               0.007324                0.000198     23
24               0.003934                0.000155     24
25               0.005600                0.000169     25
26               0.005511                0.000159     26
27               0.005814                0.000176     27
46080/46080 - 3s - loss: 1.7235e-04 - mean_absolute_error: 0.0058 - mean_squared_error: 1.7235e-04
Testing set Mean Abs Error:  0.01 CWSI
```

Validation Phase Results

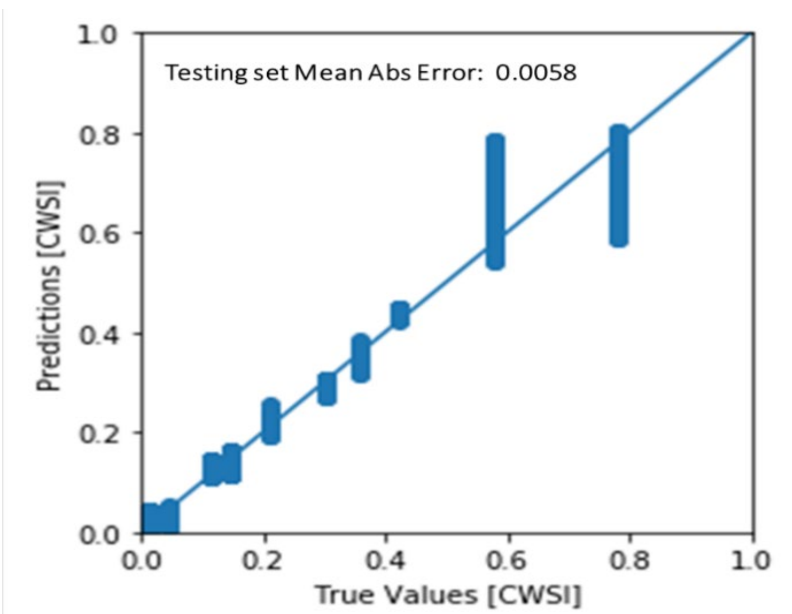

Figure 1. AI Model Created showing significant correlation with the true values of CWSI from the test dataset. (Graph credit: John Estrada)

The validation phase of the experiment applied the re-trained AIDA model on the test data samples which very closely predicted the true values of CWSI. Figure 1 showed this close approximation by the AIDA model output to the true values of CWSI from the test dataset with a very low mean absolute error rate of 0.0058 achieved in only 27 "Epochs" – repetitions of the machine learning algorithm.

Pair Plots Analysis

The pair plots showed a positive trend between the CWSI and the red raster values, the CWSI and the green raster values, as well as the CWSI and the blue raster values up to CWSI value of 0.3 (Figure 2). The red, blue and green raster values were increasing as CWSI value increased from 0 to 0.3. However, as soon as the plants experience late stages of drought stress, at CWSI values greater than 0.3, the red, green and blue raster values started to decline.

A positive relationship between green and red raster values, green and blue raster values, as well as red and blue raster values were observed. There was, however, a trend towards an inverse relationship between the CWSI and soil moisture values. With higher soil moisture values, lower CWSI values were observed (lower plant drought stress).

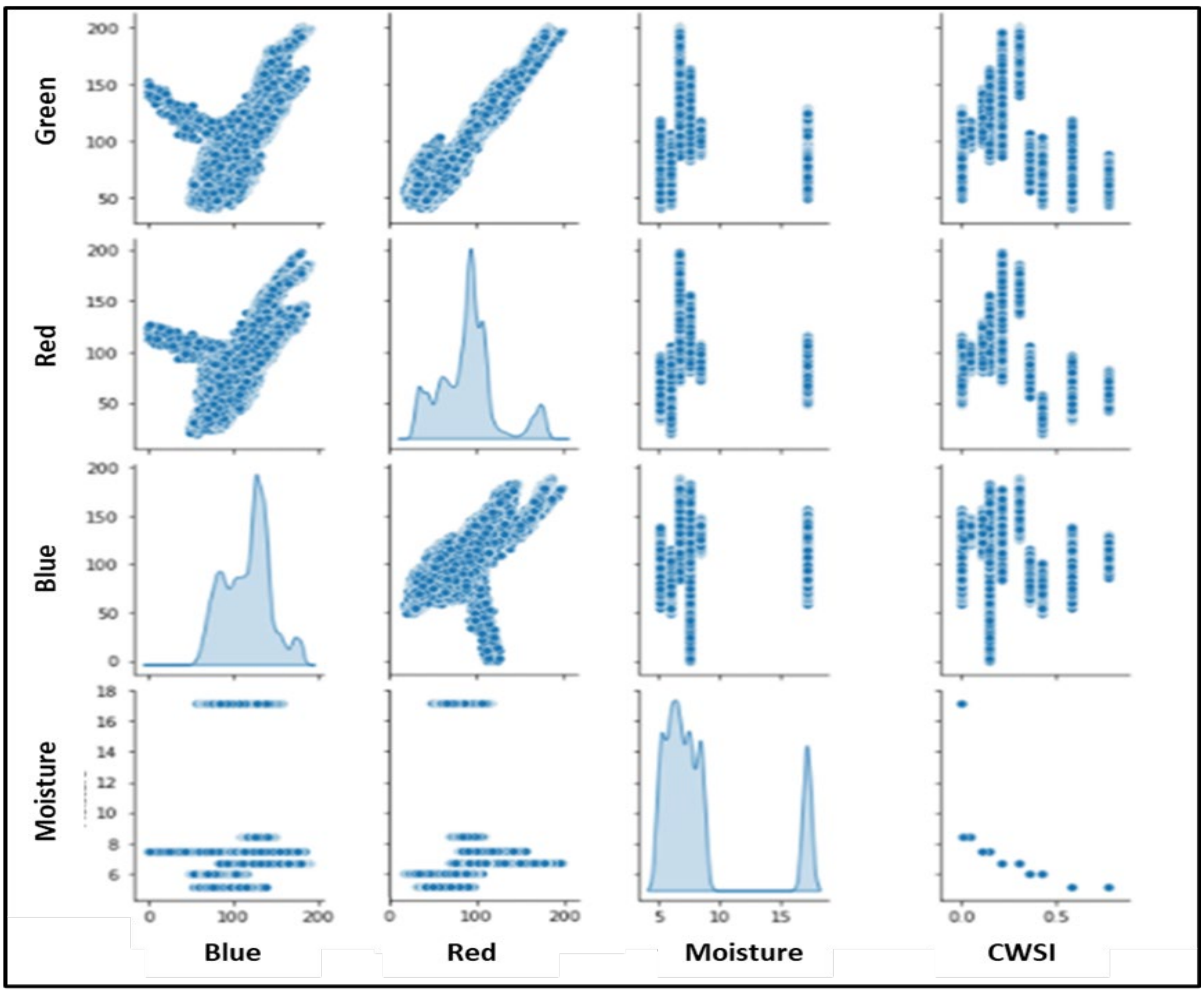

Figure 2. Pair plots for the dataset imported and analyzed in the program. (Graph credit: John Estrada & Pauline Estrada)

Field testing of the AIDA model and the New AI Drought Assessment (AIDA) Score on field grown tomato plants.

A Prediction Output Program (POP) was coded which output an AIDA Score from a plant not included in the training and validation datasets. The POP appended to the AIDA model was able to independently output an AIDA Score based on infrared radiometric data, red, green, and blue light reflectance, and soil moisture values. This closely approximated the manually calculated CWSI value of 0 for the independent test plant (Image 3).

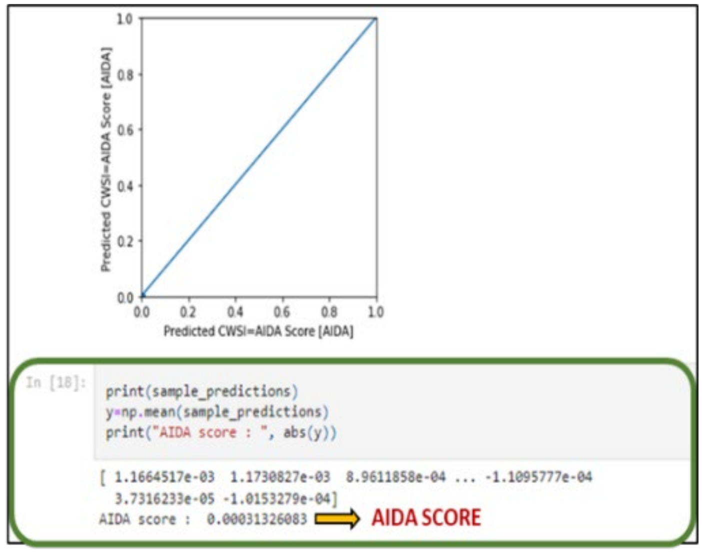

Image 3. Prediction output program which outputs an AIDA Score. (Image credit: John Estrada & Pauline Estrada)

4.0 Discussion

The AIDA model output was able to make very close predictions to the true values of CWSI, with a very low mean absolute error rate.

The results in the pair plots showed an increasing trend on the reflected green lights as the stress level in tomato plants reached a CWSI value of 0.3. However, a decreasing trend on the reflected RGB light was observed beyond 0.3. The likely explanation for this is the presence of the “stay-green” phenomenon in tomato plants.

The stay green phenomenon allows the leaf to still retain its green color even when its photosynthetic activity declines due to the failure in the chlorophyll degradation pathway [14, 15, 16]. This effect in tomato plants can only last up to a 0.3 CWSI value. Beyond this value, the stay green effect starts to decline leading to chlorophyll degradation and decreasing reflected green light.

The increasing trend in reflected red and blue light detected by the RGB camera as the tomato plants reached a CWSI value of 0.3 indicates decreasing amounts of red and blue light absorbed by the tomato plant as it becomes increasingly drought stressed. The decreased amount of red light absorbed is due to the declining photosynthetic activity induced by drought stress which leads to stomatal closing to prevent excessive water loss. Blue light triggered stomatal opening by guard cells is also reduced as drought stress worsens given its synergistic mechanism with red light induced photosynthetic activity which is also declining [17].

The positive relationship observed between red, green, and blue light reflectance can be explained by the physiologic adaptation of tomato plants to drought stress through photosynthesis and the regulation of stomatal opening and transpiration. Blue and red light are both involved in facilitating different signaling pathways which stimulate stomatal opening [18, 19]. Red light stimulates the opening of the stomata through its role in photosynthesis [20] while blue light triggers blue-light receptors - phototropins, that absorb blue light and facilitates stomatal opening [17, 21].

5.0 Conclusions

The outcome of this study supports our hypothesis that the newly trained AIDA model and resulting new AIDA Score, formulated and validated using field data, proved to be a quick and accurate way of determining early drought stress in tomato plants.

The AIDA model can detect early signs of drought stress in plants by exploiting the "stay green" phenomenon, a plant's early response and adaptation to drought stress, and by measuring radiated IR heat which is a measure of a plant's transpiration rate.

The "stay green" phenomenon manifested during early drought stress was captured by the RGB camera and was revealed in the extracted raster values. This early sign of drought stress is difficult to see if farmers were to rely on just visual evaluation or the calculated CWSI values.

The "stay green" phenomenon in tomato plants is observed during the early onset of drought stress until a CWSI value of 0.3. Beyond this value, the chlorophyll starts to degrade.

The green light reflectance increased abruptly from an AIDA Score value of 0.15-0.21 which indicated that at 0.15, the tomato plants were already experiencing early signs of drought stress. Irrigation for tomato plants should therefore be applied when the AIDA score reaches a critical value of 0.15 or higher.

Quick determination of the AIDA score can be accomplished using the Spectra-Rover equipped with its custom-built IR + RGB camera system which allows for consistent close proximity plant canopy measurements and real-time data transmission. This system allows for rapid detection of drought stress either on site, or even remotely if necessary. Other benefits, include being able to monitor their crop water status at multiple locations without the need for traveling to each site.

The AIDA model and AIDA Score will have a big impact with the way irrigation water is being managed in the field. By knowing the water status of the plants in real time, the farmers will have an idea when it is necessary to irrigate their field. They will avoid unnecessary and over irrigation.

Approximately 26 billion gallons of irrigation water every season can be conserved if all tomato farms in California use the AIDA model. This novel technique of determining drought stress in tomato plants can help farmers conserve water without sacrificing their yield.

The future direction of this study is to streamline point of service autonomous AI based drought stress evaluation and interface directly with existing irrigation systems for more precise real-time water application adjustments.

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