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Evaluating the Performance of Data-Driven Models Combined with IoT to Predict the Onion Yield under Different Irrigation Regimes

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MAJOR international nutrition organizations are increasingly focusing on global agriculture production. In particular, food insecurity has emerged in Egypt due to climate change, population expansion, and rising food demand. Innovative techniques such as internet of things and machine learning are critical for farmers to make timely judgments that impact quality of agricultural harvests. A new open-source technology utilizing the Arduino Board was created to forecast the irrigation requirements of onion crops. The study implemented three different irrigation levels: 100%, 85%, and 70% of crop evapotranspiration (ET_c) ML models, namely, Artificial Neural Network (ANN), Random Forest (RF), and Decision Tree (DT) models were constructed to predict onion yield based on meteorological and agronomic variables. These variables include minimum, and maximum temperatures, relative humidity, sun shine hour, solar radiation, growing degree days, vapor pressure deficit, plant height, leaf number per plant, readily available water. The results highlight that the highest onion yield values were recorded in 100% ET_c (56.04 ton/ha), followed by 85% ET_c (51.52 ton/ha). The lowest values were recorded at 70% ET_c (43.36 ton/ha). The results also indicate that Arduino board optimize water usage by 13% and 28%, enhancing crop water productivity by 14.5 and 16 kg/m^3 at 85% and 70% ET_c, respectively. Additionally, the ANN model demonstrates a robust R^2 value of 0.94 in predicting onion yield, while the RF and DT models perform at 0.90 and 0.86, respectively. Our results highlight the effectiveness of technology in enhancing agricultural decision-making and crop management.

Key words: IoT, ML models, Automatic Watering System, onion, crop water productivity.

1. Introduction

Since onions are an export crop with a place in global trade, they rank among the most significant crops in Egyptian agriculture. In terms of vegetable and fruit crop exports, onions come in at number four with approximately 816 thousand tons exported in 2023, valued at approximately 145.8 million dollars. The Egyptian onion holds a prominent position in the majority of Egyptian households, where it is a staple ingredient in everyday meals for people. Its various culinary applications complement its many health advantages, which include lowering blood cholesterol and preventing thrombosis (Fangary and Adam 2020). Additionally, it helps prevent cancer cells from growing in the body and treats a few respiratory and digestive issues. It is also a significant industrial crop because the pickling and drying industries employ labor, create jobs, and make money (Abd-Elrahman and Shalaby 2017).

According to Tolba et al. (2023), Egypt's shifting climate and weather patterns have exacerbated the country's present land and water scarcity issues and continue to have a negative impact on the agricultural sector.

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Climatic variables are essential for forecasting agricultural output since they have a direct impact on the growth and development of plants. For example, temperature, precipitation, solar radiation, vapor pressure deficit (VPD), and growing degree days (GGDs) have been found to be increasingly significant drivers of reduced ecosystem productivity and plant mortality Omayio et al (2018). Additionally, Roberts et al. (2013) showed that there is a correlation between climate variance and roughly one-third of the variability in agricultural yields worldwide. According to Li et al. (2019), these factors are frequently utilized as the main climate variables for yield prediction and offer insightful information about growing conditions. Agronomic variables, in addition to meteorological variables, improve the models' forecasting accuracy. Onion crop water needs are better understood with the use of indicators like reference evapotranspiration (ET_o) and crop evapotranspiration (ET_c).

A significant amount of water is used worldwide in agriculture, especially irrigation. Consequently, the development of sophisticated technology-driven smart strategies and systems for efficient water use is imperative. Gebremedhin (2015) reports that the use of drip irrigation for onion crops saved approximately 29.4, 43.5, and 57.6% at 100, 80, and 60% respectively, when compared to traditional methods. This is enough to irrigate an additional 0.42 to 1.36 hectares, yielding higher economic returns than traditional methods. Since deficit irrigation methods (DI) optimize water use while maintaining respectable crop yields, they have attracted a lot of attention as a way to get around these challenges as mentioned by Enchalew et al. (2016), using DI with a drip irrigation system reduced the amount of water needed for irrigation by almost 20%. Mekala and Perumal (2017) found that employing smart agriculture technologies in place of conventional agricultural practices can give high production yields for the management of these issues. Also, Millogo et al. (2021) revealed that a well-designed smart drip irrigation control system coupled with deficit irrigation (DI) can save water and improve productivity of vegetables crop. Okasha (2017) developed an automatic pulse irrigation system prototype with an Arduino board. The researcher discovered that this prototype might save time, money, and effort by eliminating the need for manual on/off valves in the pulse irrigation system. Mahmoud (2020) designing an open-source technology (Arduino Board) based smart algorithm to predict the irrigation requirements of bottle gourd by using the soil moisture sensor, and found that, the Arduino device helps to rationalize a substantial amount of water by 66.5mm in comparison to the CROPWAT model. Additionally, Arduino achieves a strong yield production value for irrigation water use efficiency (IWUE) of (2.003 $kg.m^{-3}$), (5.09 $ton.fed^{-1}$) by lowering the overall amount of water applied.

Predicting agricultural production is a complicated process that involves using several datasets because it depends on a wide range of factors, such as soil, seed, air quality, and fertilizer kinds. Fortunately, the introduction of machine learning (ML) to agriculture has brought about a novel and sophisticated method to overcome the limitations of crop forecasting in a variety of environmental settings Sridhara et al. (2022). In order to improve irrigation systems and predict crop yields, researchers have been fusing IoT and machine learning techniques to develop new models in recent years. Singh et al. (2019) developed a device that gathers environmental data, such as air humidity and soil moisture, and uses standard machine learning techniques, like gradient boosted regression, random forest regression, elastic net regression, and multi-linear regression, to process the data and control the irrigation system's water pump. Cai et al. (2019) compared the three upgraded machine learning models; support vector machine (SVM), random forest (RF), and neural network (NN) with the conventional regression approach for predicting crop yield and their findings illustrated that, machine learning techniques outperformed the conventional regression approach. Additionally, Jeong et al. (2016) used RF and multiple linear regression (MLR) to forecast the yield of potatoes, maize, and wheat and came to the conclusion that RF was a more accurate crop production predictor than MLR.

Therefore, the objectives of this work are to address Egypt's agricultural challenges by utilizing internet of things (IOT) technology and ML: (a) designing an automated intelligent drip irrigation system (AIDIS) using Arduino Board to predict onion crop irrigation requirements under different water stress regimes 100%, 85% and 70% ET_c by sensing the current soil moisture using LM293 sensor and deciding the real time for making irrigation process; (b) enhancing onion yield prediction under deficit irrigation by integrating machine learning models, namely, Artificial Neural Network, Random Forest, and Decision Trees models with agronomic and meteorological variables; and (c) evaluating these models' propensity to predict onion yield under various water stress scenarios in order to determine which model is most appropriate.

2. Materials and Methods

2.1 Study Area Description

The current investigation was carried out in Talkha, Egypt's Dakahlia Governorate during the season of 2023–2024. This location is located at 31.04 N latitude, 31.38 E longitude, and 17 m above sea level. The average annual rainfall, maximum and minimum temperature of the experimental site were 57 mm, 26.58ºC and 16.06 ºC respectively.

2.2 Soil Analysis and Sampling

After irrigation, soil samples were taken for gravimetric soil moisture assessment from the experimental plots at two distinct depths (0–15 cm and 15–30 cm), as indicated in Table 1. The experimental site had sandy clay loam soil; it was neither saline nor calcareous. At field capacity and wilting point, the volumetric water content for the first 30 cm was 28.53% and 14.27%, respectively.

Table 1. Some physical and chemical properties of the homogeneous soil of the experiment were analyzed before cultivation.

Depth	Soil particle size distribution %			Texture	F.C %	P.W.P %	ECe (ds/m)	pH
	Sand	Clay	Silt					
(0-15) cm	49.17	27.53	23.30	Sandy Clay loam	28.53	14.27	0.79	8.28
(15-30) cm	46.77	9.78	43.46	Sandy Clay	31.07	15	0.61	8.34

Where, F.C: Field Capacity%, P.W.P: Permanent Wilting Point were determined as percentages in weight%, ECe: Electrical conductivity of the soil saturation extract for a given crop.

2.3 Cultivated Crop

The experiment employed onion seed from "Allium cepa var., Italian Red," the most widely produced variety in the research area. On December 15, 2023, the onion seedlings were transplanted at a distance of 0.2 m by 0.1 m and a depth of 1 cm, resulting in a crop density of 150 plants/plot, after 45 days of sowing, when the seedlings were reached at about 10-15 cm above the ground and at three true leaves. Onion growth was split into four stages: initial stage (0–20 days), development stage (21–30 days), mid-season stage (31–110 days), and late stage (111 days onwards). At the onion FAO 56 referenced growth stage, the usual crop coefficient (K_c) values are 0.5, (0.5–0.75), (0.75–1.05), and (1.05–0.85) Allen et al. (1998). During the crop cycle, 73 kg/ha N, 44 kg/ha P_2O_5, and 60 kg/ha K_2O were applied as fertilizer units. The onion crop was harvested when more than 50% of the field's plant tips became yellow, indicating crop maturity.

2.3 Experiment Design and Irrigation Treatments

As shown in Fig. 1, the experiment was set up in a split-plot design using an Automated Intelligent Drip Irrigation System (AIDIS), with an application efficiency of 90% under three deficiency levels (100%, 85%, and 70%) of crop evapotranspiration (ET_c). Every plot measured 3 m^2 (one meter wide by three meters long) and had five furrows, each with a lateral 16 mm P.E. emitter that could produce 4 lph of discharge at one bar of operating pressure. An end cap sealed off each lateral's end. Every treatment started with a solenoid valve that automatically adjusted the watering depth to the appropriate amount depending on the soil's current moisture content. The AIDIS scheduled the onion crop's irrigation based on the 100% ET_c control treatment. Based on the percentage of water level, the other treatment gets less water. After 15 days of transplanting, irrigation treatments were initiated to guarantee the seedlings' survival rate. The results of soil moisture sensors placed at each treatment were used to determine the rate of application. Before 15 days of harvesting, irrigation was discontinued in all three treatments.

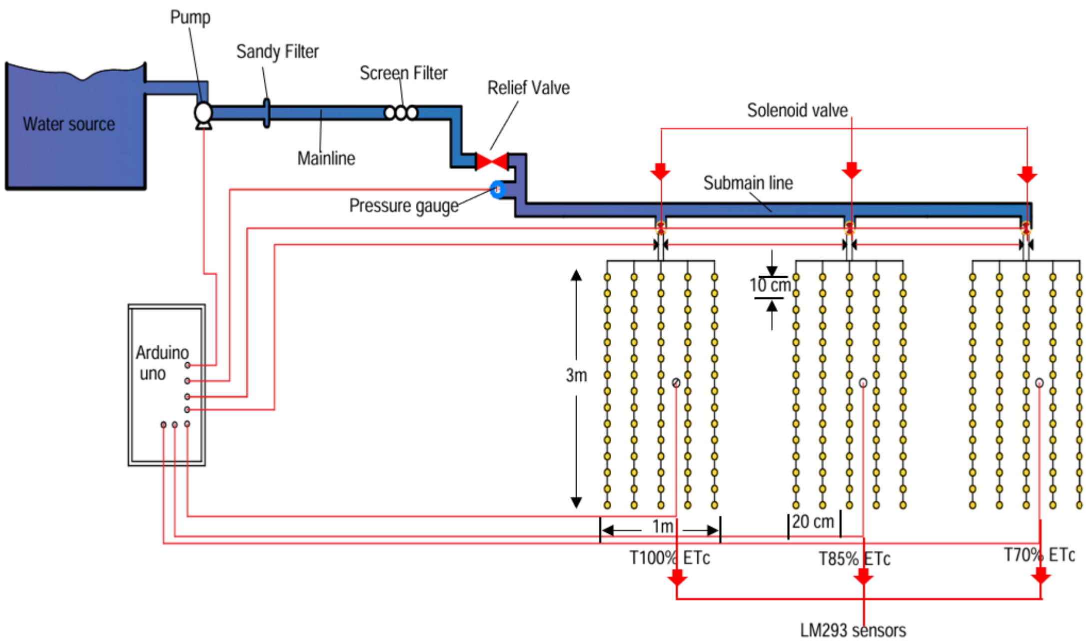

Fig. 1. Field layout of the experiment.

2.4 Description of An Automated Drip Irrigation System

In order to optimize water usage in agriculture, the current study focuses on the implementation of an automated intelligent drip irrigation system (AIDIS). This system uses an Arduino Uno, equipped with sensors for temperature, humidity (DHT22) and soil moisture (LM293). The AIDIS system underwent testing prior to its implementation in the experimental setting. Three LM293 sensors were placed at one-third the depth of onion crop root zone (10 cm), one for each treatment and one DHT22 sensor were utilized in this investigation to track real-time data on soil moisture and environmental conditions. According to the flow chart in Fig. 2, the Arduino Uno receives data from these sensors, processes it using algorithms unique to each sensor, and determines when to automatically start or stop the irrigation for each zone using an electrical valve. The decision is then displayed on an LCD. upper threshold (T_{upper})and lower threshold (T_{lower}) values were determined by taking into account the type of plant, age, and soil texture, all of which may be found in agricultural literature. T_{upper} and T_{lower} values for (100%, 85%, and 70%) ET_c were set at 149, 212, and 161 and 289, 460, and 590, respectively, for the onion crop. It's important to note that the sensor reading and moisture value are negatively correlated low moisture equals a high sensor reading, and vice versa. Thus, if the moisture level is higher than T_{upper} and lower than T_{lower}, the solenoid valve will automatically close and open. Furthermore, the valve's condition won't change if the moisture content is within the ideal range.

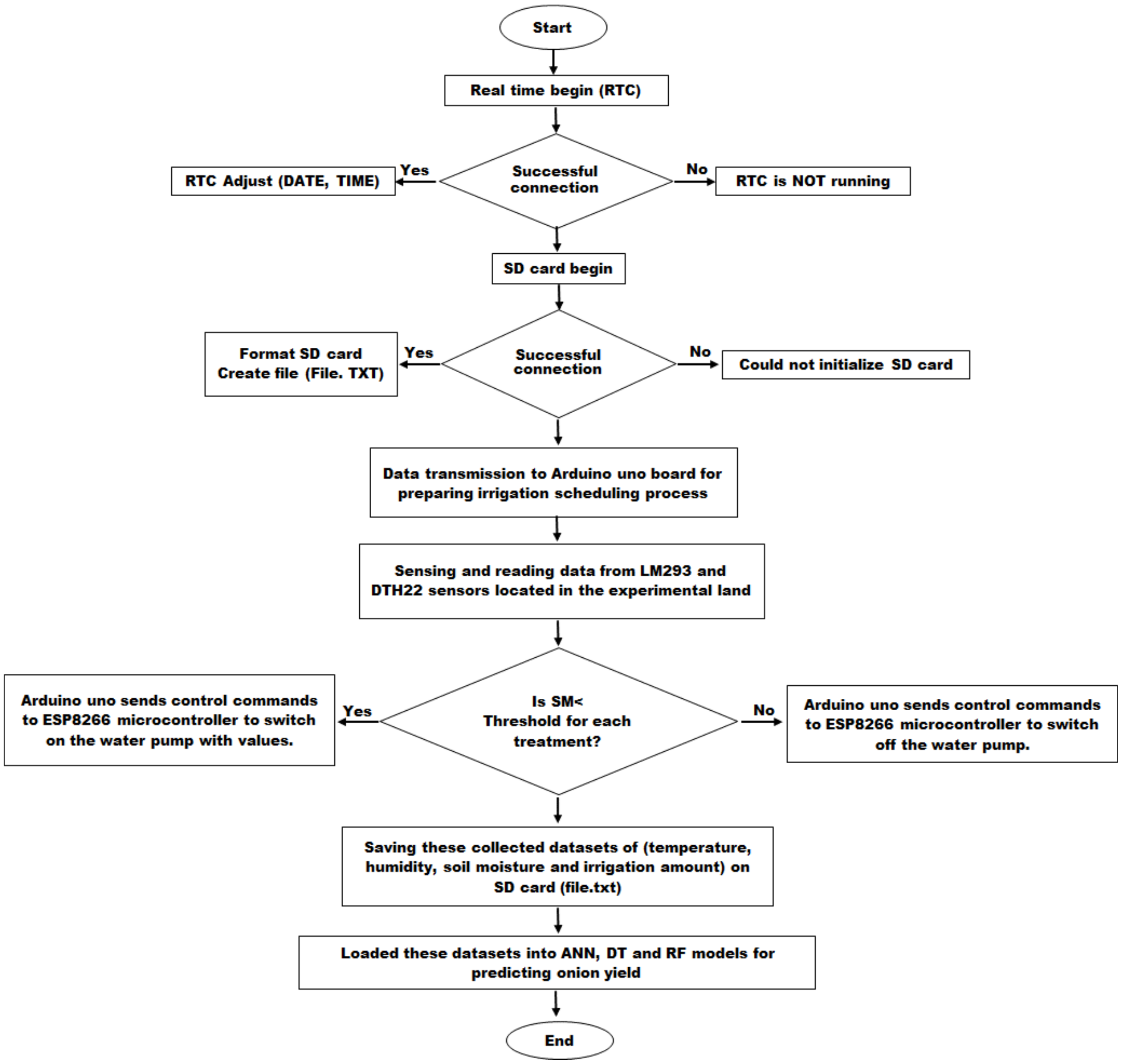

Fig. 2. Flow chart of AIDIS system.

2.5 Requirements for IoT devices' hardware and software

2.5.1 Hardware Components

Flowing Fig. 3 displays every component of the AIDIS system. Arduino: is a logic controller that can be programmed. It serves as the system's brain. It features a USB port, a power jack, a reset button, six analog input pins, and fourteen digital input/output pins. It gets data from DHT22 and LM293 sensors. It has all the information required to provide data support for the ESP8266 microcontroller. It also analyzes this data and uses preprogrammed logic to make decisions. Soil Moisture Sensor: the LM293 moisture sensor is equipped with three pins: one for ground, one for voltage, and one for the analogue input A0. It's used to gauge the soil's moisture content. Calibrating the soil moisture sensor was done by gathering samples from the soil of the experimental field then spreading the samples to allow it to air dry. Followed by eliminating any undesired objects, such as stones, boulders, or roots. The soil samples were separated among ten little plastic containers. Starting with the second plastic container, we added a tiny bit of moisture. The addition of moisture to the containers continued until the last one is filled with saturated soil. After that, the soil moisture sensors were used to detect the raw millivolt (mV). The saturated container will usually have the greatest mV value, while the air-dried sample would often have the lowest. And according to Kumar *et al.* (2013), there is an inverse relationship between the soil's water content and the sensor's output voltage. When the soil is moist, the output voltage decreases and vice versa. The sensor is attached to an Arduino Uno analog input pin to generate a digital number between 0 and 1024, where 0 denotes 100% wetness and 1024 represents 0% moisture. The onion crop in this study was subjected to three different levels of water stress, as previously mentioned: 100%, 85%, and 70% ET_c. A T_{lower} moisture at 100%, 85%, and 70% ET_c is equivalent to 289, 460, and 590, according to the data obtained from mapping the reading of the suggested soil moisture sensor in each treatment. In order to initiate the irrigation process at a specific irrigation time, the AIDIS system design includes a water pump that turns on when Arduino gets a moisture sensor reading above 289, 460, and 590.

Real Time Clock Module (RTC): is a module that uses an Arduino card to measure the time and calendar either independently or dependently. Even in the absence of electricity, the battery-operated RTC (CR2032-3V) maintains a record of the current time. Ground (GND) and Voltage at the Common Collector (VCC) are the pins in an RTC circuit. For analog data, these pins were linked to the Arduino Uno's A4 and A5 pins. SD Card Module: is employed for data transfer to and from common SD cards. is also employed for data logging and mass storage additions. The VCC, GND, 12, 11, and 13 pins of the Arduino Uno are directly compatible with the SD card pins for data storage. Liquid Crystal Display (LCD): is a kind of flat panel display technology that's found in many gadgets. Its 80.8 x 36.0 x 12.5 mm in size, with a 2 x 16 character-line format (2 rows and 16 columns). It serves as the base station for tracking the moisture content of the soil and the nodes' status (on or off). GND, VCC, Serial Data (SDA), and Serial Clock (SCL) are the pins on the LCD. The circuit is grounded by GND, the data and clock lines are represented by SDA and SDL, respectively, and the circuit voltage is regulated by VCC.

Solenoid Valve: is an electromechanical apparatus that regulates the water's flow. To open or close a water valve, electric current is received by the valve from the microcontroller. The parameters are 1.7W, 125mA, 24 V AC. DHT22 Humidity Sensor: is a combined sensor that measures the surrounding air's humidity and temperature. The DHT22 pin to Arduino Uno port pin displayed these output values as a digital signal. The temperature can be read between 40 and 80 ºC, while the humidity value (RH) spans from 0 to 100%.

Relay: is a programmable electrical switch that Arduino used to control an electrical valve. It is also regarded as a link between high-voltage devices and Arduino.

Breadboard: is a plastic board that is rectangular and has many tiny holes in it. These perforations made it simple to place electronic components into an electronic circuit prototype.

Water Pump: the water pump utilized in this experiment has an AC 220 V voltage, an elevation head of 33 meters, a suction head of 8 meters, and a maximum discharge of 40l/min. It may be electronically controlled by connecting it to an ESP8264 microcontroller, which will then turn it on and off in response to signals provided to it as needed. Pipes and Connectors: is employed to transport water from an irrigation source to irrigation lines. The experimental field's main, submain, and lateral lines have PVC diameters of 75, 63, and 16 mm, respectively.

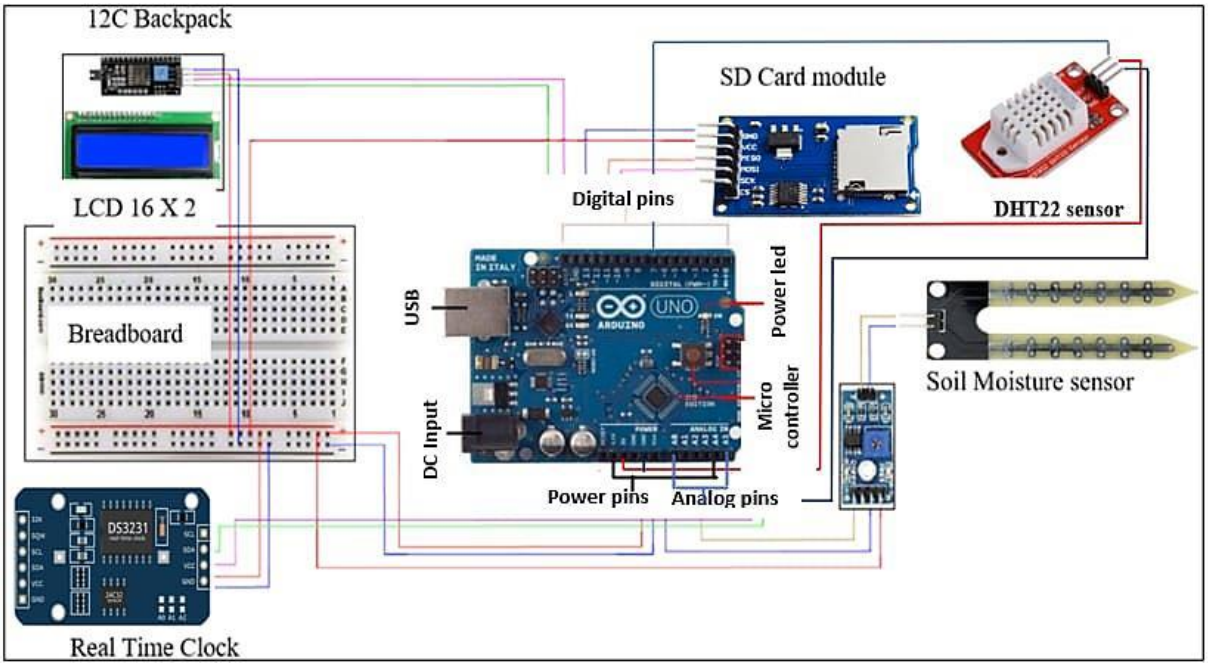

Fig. 3. Hardware components of AIDIS system.

2.5.2 Software Libraries

Python3.3: the Python programming language is used to implement the base station application.
Arduino IDE: is a free and open-source programming environment used to create and assemble Arduino module code. As illustrated in Fig. 4, its main components are a text editor for writing code, a text console, a message area, and a toolbar with buttons for frequently used functions.

Algorithms of AIDIS system.	Irrigation decisions
for each treatment (T) in the experimental field, do	
if M(T1) < Tlower (T1, 289)	; Irrigate T1
turn on Valve (T1)	
if M(T2) < Tlower (T2, 460)	; Irrigate T2
turn on Valve (T2)	
if M(T3) < Tlower (T3, 590)	; Irrigate T3
turn on Valve (T3)	
els if M(T1) > Tupper (T1, 149)	; Stop T1
turn off Valve (T1)	
if M(T2) > Tupper (T2, 212)	; Stop T2
turn off Valve (T2)	
if M(T3) > Tupper (T2, 161)	; Stop T3
turn off Valve (T3)	
end if	
end	

Fig. 4. Arduino software.

2.5.3 Data Collection

Since data collection provides the basis for ML model testing and training, it is a crucial stage in any machine learning work. Furthermore, the accuracy and quality of the final model are determined by it, thus it is important to make sure the data is reliable, pertinent, and impartial. Agronomic and meteorological variables that are essential to plant growth and development as well as yield prediction are included in the training and testing phases for ANN, DT and RF models. Our study used four groups of data to calculate input climate variables for different machine learning (ML) models. The groups encompassed the sum of data from the first day after transplanting (DAT) to 63, 92, 123, and 153 DAT. On the other hand, five onion plants were selected from each treatment at (63, 92, 123, 153 DAT) to calculate plant variables including, plant height, leaf number per plant, and bulb yield (target variable). The total samples that used after merge for training and testing ML models were 60 samples.

2.5.4 Climatic variables

The necessary meteorological data can be download from the NASA POWER | Data Access Viewer website: https://power.larc.nasa.gov/data-access-viewer/ and obtained using DHT22 sensor to investigate the relationships between onion yield and climate variables. These variables included mean, minimum, and maximum temperatures, relative humidity (RH), and sun shine hour (N). These variables were then used to calculate solar radiation (R_s), growing degree days (GDDS), vapor pressure deficit (VPD), reference and crop evapotranspiration (ET_o and ET_c), and gross irrigation depth (d_g) using the following formulas:

2.5.5 Solar Radiation (R_s)

According to Hargreaves et al. (1985), the following equations 1 and 2 can be used to compute daily R_s.

$$R_s = K_{Rs} * (T_{mean})^{0.5} * R_a \quad \text{(1)}$$

$$R_a = \frac{R_{so}}{(0.75 + 2 * 10^{-5} * z)} \quad \text{(2)}$$

Where; R_s: solar radiation (MJ m^{-2} d^{-1}), K_{Rs}: adjustment coefficient ($°C^{-0.5}$) $\cong 0.16$, T_{mean}: daily mean temperatures (°C), R_a: extraterrestrial radiation (MJ m^{-2} d^{-1}), R_{so}: Clear-sky solar or clear-sky shortwave radiation (MJ m^{-2} d^{-1}) which obtained from CROPWAT8.0 according to Allen et al. (1998) and z: elevation above sea level (m).

2.5.6 Growing Degree Days (GDDs)

Equation 3 illustrates how GDDs assess the cumulative exposure heat over the growth season.

$$GDDs = \sum_{i=1}^{n}(T_{mean} - T_b), \quad T_{mean} = \frac{T_{min}+T_{max}}{2} \quad \text{(3)}$$

Where; GDD is the growing degree-day (ºC), T_{mean} is the mean air temperature (°C), T_b is the base temperature for onion crop = 10 °C, according to Shanono et al. (2022), and T_{min} and T_{max} are the daily minimum and maximum temperatures (°C), respectively

2.5.7 Vapor Pressure Deficit (VPD)

The VPD is computed as the difference between the air's saturated capacity and its present capacity Huang (2018) equation 4. The impact of VPD on yield can be attributed to multiple mechanisms, including its association with yield-affecting weather patterns. Omayio et al (2018) states that the first way that VPD increases water demand is by driving water loss through plant transpiration. Second, diurnal temperature variation, precipitation, and cloud cover are related to VPD. Water requirements therefore increase with very high VPD. The sun's radiation, which is essential for photosynthesis, is linked to increased VPD in contrast to lower cloud cover. Accordingly, we may anticipate a growing association between VPD and yield under conditions of sufficient soil moisture and a decreasing relationship under conditions of insufficient soil moisture Roberts et al. (2013).

$$VPD = e^{\left(\frac{17.269T_{max}}{237.3+T_{max}}\right)} - e^{\left(\frac{17.269T_{min}}{237.3+T_{min}}\right)} \quad \text{(4)}$$

Where; VPD: Vapor pressure deficit (ºC), T_{min} and T_{max} are the daily minimum and maximum temperatures (°C), respectively.

2.5.8 Reference Evapotranspiration (ET_o)

The "FAO Penman–Monteith method" (refer to equation (5)) is regarded as an accurate representation of the physiological and physical elements controlling evapotranspiration.

$$ET_o = \frac{0.408\,\Delta(R_n - G) + \gamma\left(\frac{900}{T+273}\right)u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (5)$$

Where: ET_o is the reference evapotranspiration (mm.day^{-1}), R_n is the net radiation (MJ.m^{-2}.day^{-1}), G is the soil heat flux density (MJ.m^{-2}.day^{-1}), T is the mean daily air temperature at 2m height (°C), U_2 is the wind speed at 2m height, es is the saturation vapor pressure (kPa), ea is the actual vapor pressure (kPa), (es - ea) is the vapor pressure deficit of the air (kPa), Δ is the slope vapor pressure curve (kPa. °C^{-1}) and γ is the psychometric constant (kPa. °C^{-1}).

2.5.9 Crop Evapotranspiration (ETc)

A set of coefficients or parameters that rely on the type of crop and growth phases are typically used to correlate ET_c with ET_o using equation (6).

$$ET_c = ET_o * K_c \quad (6)$$

Where; ET_c is the crop evapotranspiration [mm day^{-1}] and K_c is the crop coefficient.

2.5.10 Gross Irrigation depth (d_g)

Arduino Uno uses the information from DHT22 and LM293 sensors to calculate the amount of water and time needed to execute the irrigation operation by calculating:

2.5.11 Total available water (TAW)

TAW is the maximum amount of water that a crop can draw from its root zone; this amount is determined by the kind of irrigated soil and the depth of the effective roots. Equation 7 was utilized by Al-Janabi (2018) to compute it:

$$TAW = 1000(\theta_{FC} - \theta_{WP}) * Z_r \quad (7)$$

Where; TAW is the total available water [mm], θ_{FC} is the moisture content at field capacity [m^3 m^{-3}], θ_{WP} is the moisture content at wilting point [m^3 m^{-3}], and Z_r is the rooting depth [m].

2.5.12 Readily Available Water (RAW)

RAW is a part of TAW that can be calculated based on equation 8 (Al-Janabi 2018). Moreover, formulas 9 and 10 by Allen et al. (1998) can be used to calculate the necessary net and gross irrigation amount.

$$RAW = \rho * TAW \quad (8)$$

$$TAW = (\theta_{FC} - \theta_{Cm}) * Z_r \quad (9)$$

$$d_g = \frac{d_n}{E_a} \quad (10)$$

Where; ρ is the typical percentage of TAW that can be extracted from the root zone prior to the decrease in ET. d_n is the current quantity of net irrigation (mm), $\boldsymbol{\theta}_{Cm}$ is current soil moisture content (m^3/m^3), d_g is the total irrigation amount (mm) and E_a efficiency of the system (%).

2.5.13 Time of Irrigation (T)

$$T = \frac{(d_g * 60)}{(q_e * N_e * 1000)} \quad (11)$$

Where; T it's time for irrigation (minute), d_g is gross irrigation amount (mm), q_e is emitter discharge rate (L/hr) and N_e is number of emitters.

2.5.14 Agronomic Variables

Agronomic data, including plant height (PH), leaf number per plant (LN), and bulb yield (BY) were randomly collected for each treatment from five plants in the middle rows. To prevent border effects, one plant was excluded from the beginning and end of each row. NL was counted by hand, and PH was measured from the soil's surface to the apex of the longest mature leaf. Bulbs were manually collected at the end of the season by pulling them up from each plot, weighing them, and then converting them into a hectare as shown in equation 12 by (Abdulaziz and Croock 2022).

$$\text{Bulb yield (ton/ha)} = \frac{\text{Bulb yield (kg/plot) x10}}{\text{Net harvested area of plot (m}^2\text{)}} \quad \ldots\ldots \quad (12)$$

2.5.15 Crop Water Productivity (CWP)

CWP calculates how well irrigation levels convert the total amount of water applied to yield. It was calculated using formula 13, which represents the ratio of onion yield to the total dg applied during the growing season (Mosa et al. 2020).

$$\text{CWP, (kg/m}^3\text{)} = \frac{\text{Yield (kg/ha)}}{\text{Total dg applied (m}^3\text{/ha)}} \quad \ldots\ldots \quad (13)$$

2.5.16 Percent of yield Reduction (YR) and Water Saving (WS)

According to Hassene and Seid (2017), equations 14 and 15 were used to compare the WS and YD with deficit irrigation to full irrigation, 100%.

$$\text{YR (\%)} = \left(\frac{\text{YFI} - \text{YDI}}{\text{YFI}}\right) * 100 \quad \ldots\ldots \quad (14)$$

$$\text{Ws (\%)} = \left(\frac{\text{TWUFI} - \text{TWUDI}}{\text{TWUFI}}\right) * 100 \quad \ldots\ldots \quad (15)$$

Where; YR: Yield loss percentage as a result of inadequate irrigation, YFI: Yield from complete irrigation (100%) in kg per hectare and YDI: Yield from deficit irrigation (85% ET_c and 70%ET_c), expressed in kg per hectare, WS: Water conservation because of insufficient irrigation, TWUFI: Total water using in full irrigation (mm) and TWUDI: Total water using in deficit irrigation (mm).

2.6 Proposed machine learning Models for Onion Yield Prediction

One of the most challenging in agriculture is predicting yield, given the numerous variables that influence it, including agronomic and atmospheric variables. Machine learning (ML) models are a useful tool for making decisions in this context. Three ML models, namely, artificial neural network (ANN), decision tree (DT), and random forest (RF) models, were chosen for forecasting onion yield under water stress regimes. The input variables for these models comprised agronomic and atmospheric data. These models were constructed using the Python Scikit-learn library and Spyder software. These models' input datasets were split into 70% for training and 30% for testing. Using a grid search approach, the hyperparameters were tuned for each model to obtain the optimal hyperparameter sets that provided the lowest prediction error and best score. As Mijwel (2021) pointed out, the structure of any ML model is usually determined by experience and testing.

2.6.1 Artificial Neural Network model

The purpose of the artificial neural network (ANN) model is to simulate the functionality of biological neurons in order to facilitate decision-making processes. The structure of an ANN model consists of three categories: input, hidden, and output layers. The hyperparameters for this model include (i) the number of neurons in each layer, which ranged from 2 to 10. (ii) the number of hidden layers, which ranged from 1 to 5. (iii) the number of iterations (500, 600, 700, 800, 900, and 1000). (iv) the learning rate (0.0001). (v) the activation functions that are shown in equation (16-19), according to Awad (2019).

$$\text{ReLu} = \text{Max}(0, x) \quad \ldots\ldots \quad (16)$$

$$\text{Tanh} = \frac{(e^x - e^{-x})}{(e^x + e^{-x})} \quad \ldots\ldots \quad (17)$$

$$\text{Sigmoid} = \frac{1}{1+e^{-x}} \quad \text{……………………………………………………………} \quad (18)$$

$$\text{Identify} = x \quad \text{……………………………………………………………} \quad (19)$$

Additionally, the ANN model's loss function is illustrated in equation (20):

$$\text{loss} = \frac{1}{2n}\sum_{i=1}^{n}(Y_a - \grave{Y}_p)^2 \quad \text{……………………………………………………………} \quad (20)$$

where; n is the number of observations data, Y_a and $\grave{Y}_p$ is the actual and predicted values by the ANN model.

Stochastic gradient descent (SGD) method was utilized as an optimization approach, as shown in equation (21), according to Oymak and Soltanolkotabi (2019). SGD was used to modify the weights and minimize the difference between the actual and predicted values.

$$\Theta_{j+1} \coloneqq \Theta_j - \alpha.\left(Y_a^{(i)} - Y_p^{(i)}\right).x_j^{(i)} \quad \text{……………………………………………………………} \quad (21)$$

Where: Θ_{j+1}: Weights of next iteration, Θ_j: Weights of current iteration, α: Learning rate, $x_j^{(i)}$: input feature, $Y_a^{(i)}$: Actual value and $Y_p^{(i)}$: Predict value in (ton/ha).

2.6.2 Decision Tree model

The decision tree (DT) model is one of the most effective models for predicting or classifying the target variable. In our study, two major hyperparameters were considered for the DT model, including (i) the maximum tree depth, which ranged from 1 to 10. (ii) the criteria options such as mean squared error (MSE) and mean absolute error (MAE) methods (refer to equations 22 and 23), according to Li et al. (2018).

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_a - Y_p)^2 \quad \text{……………………………………………………………} \quad (22)$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_a - Y_p\right| \quad \text{……………………………………………………………} \quad (23)$$

Where: Y_a and Y_p are the actual and predicted yield in (ton/ha), n is the number of observations.

2.6.3 Random Forest model

The random forest (RF) model merges many decision trees for classification or regression tasks. It is also extensively utilized in many researches, particularly in crop prediction Jeong et al. (2016). Three major hyperparameters were considered in our study, including (i) the maximum depth of each individual tree, which varied from 1 to 10. (ii) the number of trees in the forest, which varied from 1 to 20. (iii) the criterion function such as MSE and MAE methods (refer to equations 22 and 23). The random forest's output is assessed by averaging the results from multiple trees.

2.6.4 Evaluation the Performance of Selected ML Models

According to Müller and Guido (2016), the performance of ANN, DT and RF models was evaluated using three metrics, such as MSE, MAE, and R^2, as shown in equations 22, 23 and 24. The R^2 assess the predictive quality of the regression mode, while MSE and MAE measure the errors between the actual and predicted values.

$$R^2 = \frac{\sum(Y_a - Y_p)^2}{\sum(Y_a - \bar{Y})^2} \quad \text{……………………………………………………………} \quad (24)$$

Where:Y_a, Y_p, $\bar{Y}$: represents the actual, predicted, and mean observations in (ton/ha), respectively.

2.7 Statistical Analyses

The experiment was laid out in a randomized complete block design (RCBD) with three treatments. All collected data were subjected to analysis of variance (ANOVA) in order to examine the response of plant variables and onion bulb yield to different water stress regimes. SPSS version 28.0 software was used to analyze the data. Significantly different means were separated using least significant differences method (LSD) as Meier (2006), to distinguish the means at a significance threshold of $p < 0.05$

3. Results

Irrigation requirements for onion crop

An onion crop is used as a case study to evaluate the suggested irrigation scheme. It took 200 days in total to complete its 4 development stages. As shown in Tables 2 and 3, each stage has unique water requirements based on changes in crop coefficients and climate conditions. In Table 2, the highest average relative humidity (ARH), average sunshine hour (AN), average solar radiation (AR_s), total growing degree days (TGDDs), and average vapor pressure deficit (AVPD) values during the onion crop's growing season were 73%, 11.92 hours, 26.47 MJ/m^2.day, 1692.1°C, and 4.43°C at the late stage, respectively. These values still indicate a reasonably favorable and conducive environment for onion production, as shown by the ET_o and ET_c values at the different treatments in Table 3. The greatest ET_o value was 410.1 mm during mid-stage, while the lowest was 84.6 mm during initial stage. Furthermore, the highest ET_c values for 100%, 85%, and 70% ET_c were 370, 314.5, and 259 mm during the mid-stage, while the lowest values were 43.1, 36.6, and 30.2 mm at the initial stage, respectively. Regarding total gross irrigation depth (d_g), the maximum and minimum seasonal d_g were 617.6 and 443.7 mm/season at 100% and 70% ET_c, respectively.

Table 2. Climatic variables during the growing season of onion crop.

Growing stages	Stage length	**ARH**	AN	AR_S	TGDDs	AVPD
	days	%	hours	MJ / m^2.day	°C	°C
Initial	20	69.0	9.67	11.24	235.3	1.2
Development stage	30	70.49	10.73	15.03	460.25	1.49
Mid stage	110	70. 66	11.98	20.10	1163.5	2.52
Late stage	40	73	11.92	26.47	1692.1	4.43

Where; ARH: Average relative humidity (%), AN: Average sunshine hour (hours), AR_S: Average Solar radiation (MJ /m^2.day), TGDDs: Total growing degree days (°C) and AVPD: Average vapor pressure deficit (°C).

Table 3. Seasonal gross irrigation water depth of onion crop at each growth treatments through a smart drip irrigation system.

Growing stages	Stage length	ET_o	100% ET_c			85% ET_c			70% ET_c		
			ET_c	d_n	d_g	ET_c	d_n	d_g	ET_c	d_n	d_g
	days	mm/stage	mm/stage			mm/stage			mm/stage		
Initial	20	84.6	43.1	21.6	23.5	36.6	18.4	19.9	30.2	15.1	16.4
Development stage	30	93.8	73.2	59	64.1	62.2	50.2	54.5	51.3	41.3	44.9
Mid stage	110	410.1	370.0	335.8	365	314.5	280.3	304.6	259.0	223.1	242.5
Late stage	40	176.2	170.5	152	165	144.9	145.8	158.4	119.3	128.7	139.9
Total	200				617.6			537.4			443.7

Growth parameters

Table 4 presents a statistically significant ($P \leq 0.05$) correlation between various irrigation levels and the growth parameters of onions. These growth parameters include average plant height (APH), average leaf number (ALN), average bulb weight (ABW), and crop water productivity (CWP), which are periodically recorded. The results illustrate that the maximum APH was 53.04 cm at 100% ET_c, followed by 45.92 cm at 85% ET_c and 38.4 cm at 70% ET_c. Furthermore, the greatest and lowest ALN per plant were 10.23 and 8.67 leaves at 100% and 70% ET_c, in that order. In terms of ABW, the highest and lowest values were 85.3 and 66 gm at 100% and 70% ET_c, respectively.

Onion yield and water productivity

In Table 4, the results highlight that the highest onion yield values were recorded in 100% ET_c (56.04 ton/ha), followed by 85% ET_c (51.52 ton/ha). The lowest values were recorded at 70% ET_c (43.36 ton/ha). Regarding the crop water productivity (CWP), the highest CWP values were observed at 70% ET_c (16 kg/m^3), followed by 85% ET_c (14.5 kg/m^3). The lowest WP values were recorded with 100% ET_c (13.8 kg/m^3).

Table 4. Effect of water stress levels on onion growth parameters.

Treatments	APH	ALN	ABW	Onion Yield	CWP
	cm	leaf	gram	Ton/ha	kg/m^3
100% ET_c	53.04^a	10.23^a	85.3^a	56.04^a	13.8^a
85% ET_c	45.92^b	10.04^a	78.4^{ab}	51.52^{ab}	14.5^{ab}
70% ET_c	38.4^c	8.67^b	66^b	43.36^b	16^b
S.E m ±	4.23	0.49	5.64	0.87	0.64
CV	15.98	8.82	12.77	5.40	7.61

Where; APH: Average plant height (cm), ALN: Average leaf number (leaf), ABW: Average bulb weight (gram), and CWP: Crop water productivity (kg/m^3).

Yield reduction (YR) and Water saving (WS)

Fig. 5 illustrates the relationship between WS and YR of the onion crop under varying irrigation levels of 100%, 85%, and 70% ET_c. Compared to 100% ET_c, 85% ET_c approximately 13% of irrigation water was conserved, resulting in an 8% reduction in bulb yield. Additionally, 70% ET_c conserved nearly 28% of irrigation water and led to YR of 22.63% compared to 100% ET_c.

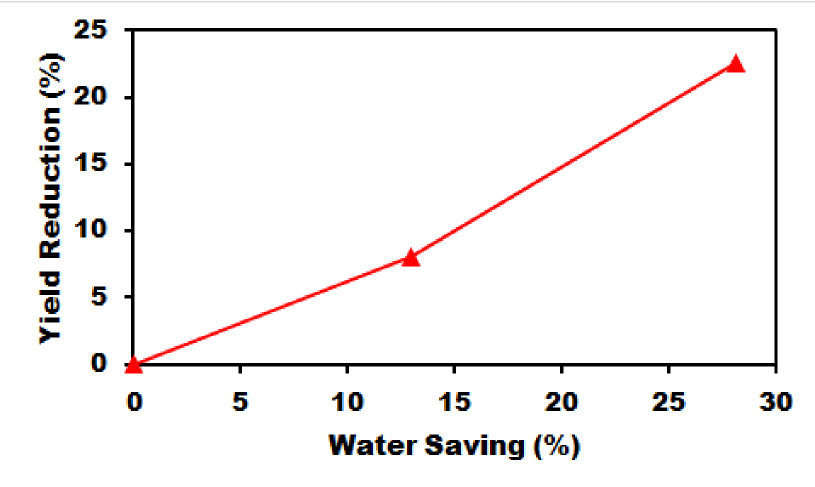

Fig. 5. Optimum production of onion crop using water saving and yield reduction.

Evaluating Onion Yield using ML Models

As shown in Table 5, the DT model produced the lowest MAE and MSE values during the training phase (1.98, 10.76 ton/ha), followed by RF model (2.48, 24.59 ton/ha), while the highest values were recorded with ANN model (2.72, 46.31 ton/ha). In terms of R^2, DT and ANN models recorded the highest and lowest R^2 values of 0.98, 0.92, respectively. During the testing phase, the ANN model produced the highest R^2 value of 0.94, with the lowest MAE and MSE values of 4.087, 46.39 ton/ha. RF model followed with MAE, MSE, and R^2 values of 4.71, 85.16 ton/ha and 0.90, respectively. Among the models, the DT model had the lowest R^2 value and the greatest MAE and MSE values, as shown in Table 5. Based on the outcomes of these phases, the optimal ANN model was implemented using one hidden layer, six neurons, 500 iterations, a learning rate of 0.001, and Tanh activation function, as illustrated in Fig. 8. Additionally, the best hyperparameters were applied to the DT model with 2 maximum depths and MSE as the criterion function. For RF model was employed with 10 trees, 4 maximum depths, and MSE as a criterion function. Figs. 6 and 7 display the outcomes of ANN, DT, and RF models for forecasting onion productivity during the training and testing phases.

Table 5. Performance evaluation of three ML models for predicting onion crop yield.

Models	R^2 (%)		MAE (ton/ha)		MSE (ton/ha)	
	Training	Testing	Training	Testing	Training	Testing
ANN	0.92***	0.94***	2.72	4.09	46.31	46.39
DT	0.98***	0.86***	1.98	5.38	10.76	106.96
RF	0.96***	0.90***	2.48	4.71	24.59	85.16

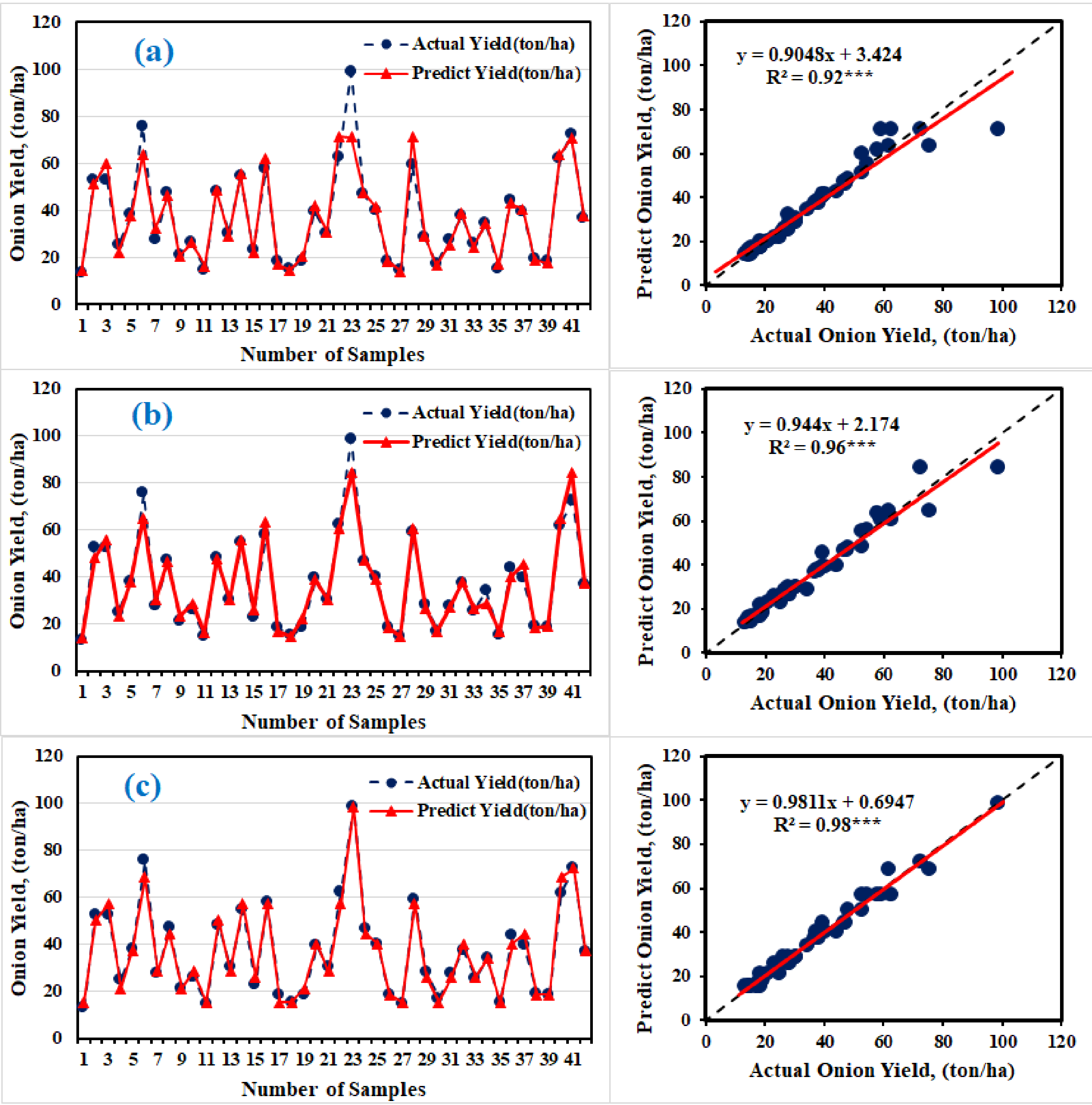

Fig. 6. Scatter diagrams of actual and predicted onion yield values (ton/ha) during the training phase for (a) ANN, (b) DT, and (c) RF models.

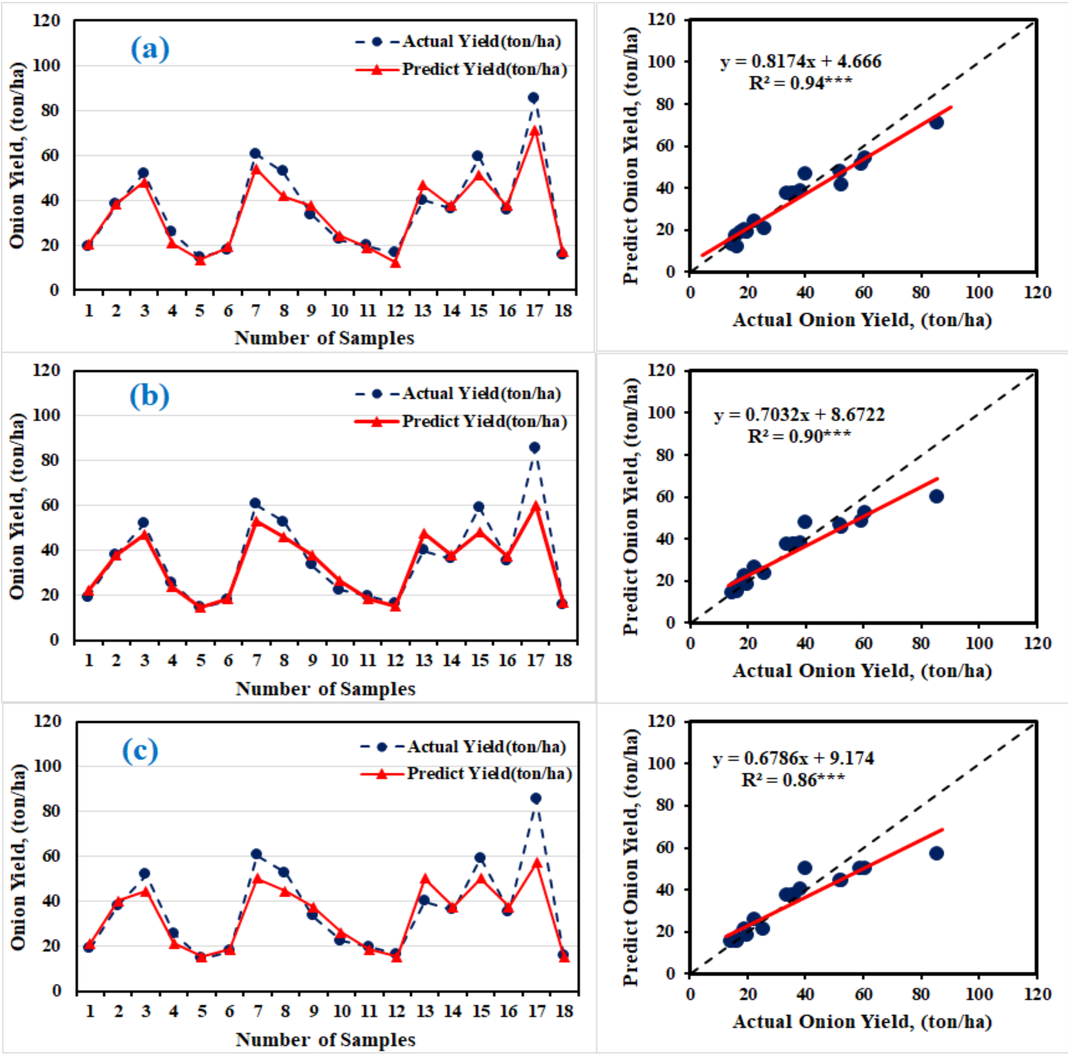

Fig. 7. Scatter diagrams of actual and predicted onion yield values (ton/ha) during the testing phase for (a) ANN, (b) DT, and (c) RF models.

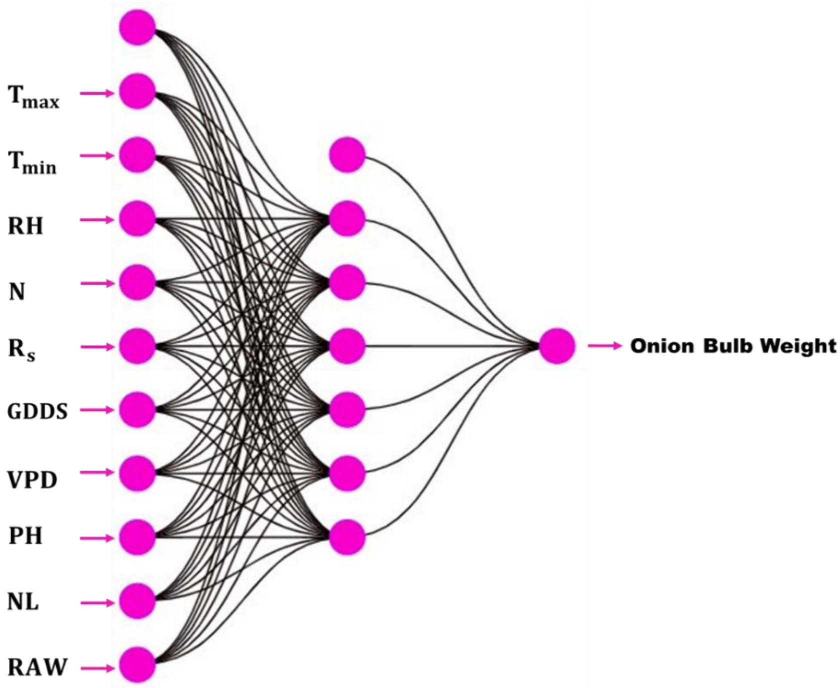

Fig. 8. ANN architecture for Onion yield prediction using the agronomic and atmospheric data.

4. Discussion

Irrigation requirements for onion crop

The findings illustrated in Tables 2 and 3 demonstrate a discernible impact of climatic variables and distinct water stress regimes on the values of ET_o and ET_c. ET_o values were seen to rise from the early to the mid-stage and then fall at the late stage. Additionally, ET_c followed the same trajectory as ET_o, and the drop in ET_c values at the end stage was caused by an increase in temperature at this time as well as a decline in the crop coefficient value. The earlier findings are consistent with those of study by ElGhamry et al. (2024), which demonstrated the critical importance of several climate characteristics, including temperature, solar radiation, and duration of sunshine, in influencing crop yield. Temperature affects flowering, growth rate, and metabolism in plants. While photosynthesis and the availability of energy for crop development are influenced by the length of sunshine and solar radiation. According to Li et al. (2019), growers may make well-informed judgments and appropriate methods for yield optimization by understanding the interplay between these parameters and crop-algorithms.

Regarding the overall dg quantities using the AIDIS system, the three treatments varied in terms of the stress coefficient and length of each growth stage. When the total amount of d_g for the onion crop was compared to the results of previously studies using traditional drip irrigation systems, it was discovered that the AIDIS system's use of Arduino technology optimized water management and maximizing crop yield. Through minimizing irrigation time and amount; avoiding over watering or under watering scenarios. By activating the water pump when soil moisture levels fell below the desired threshold and deactivated it when sufficient moisture levels were reached, as previously mentioned in the methodology. Our results agreed with Ali et al. (2019).

Growth parameters

The relationship between various soil moisture levels and growth factors is explained in detail by our results, which are displayed in Table 4. The onion's height climbed to 85, 88, and 95 DAT during 100%, 85%, and 70% ET_c, after which it declined for harvest. This resulted from the biomass's transfer into the bulb. Our results corroborated those of Enchalew *et al.* (2016), who found that the highest and lowest plant heights were at 90% and 50% ET_c, respectively. Furthermore, Abd-Elrahman and Shalaby (2017) highlighted that deficit watering causes plants to grow shorter because it closes their stomata to limit the evaporation of soil moisture, which lowers their absorption of nutrients and CO_2. With respect to ALN, ABW, P, and CWP, the findings showed that, with the exception of CWP, ALN, ABW, and P all followed the same PH pattern. 100% ET_c had the highest ALN, ABW, and P followed by 85% and 70% ET_c. On the other hand, 70% ET_c had the greatest CWP value. The reason behind this is the fluctuation in the quantity of irrigation applied for every treatment. 100% ET_c displayed the highest total dg, which promoted photosynthesis and nutrient availability for the onion plant's uninterrupted growth. These findings concur with those of Tsegaye et al. (2016), who demonstrated that improved onion output was largely due to an increase in photosynthetic area in response to moisture availability. Additionally, in 85% ET_c and 70% ET_c plants, stomata are closed to reduce water loss through transpiration, restricting gas exchange inside the leaf; as a result, growth and photosynthesis slow down. Furthermore, according to Rop et al. (2016), the 90% ET_c had the highest onion LN, while the 50% ET_c had the lowest. Furthermore, researchers Ramadass and Ramanathan (2017) discovered an inverse association between CWP and soil moisture availability and a linear correlation between LN and soil moisture availability.

Yield reduction (YR) and Water saving (WS)

85% ET_c was deemed the best treatment used during the study period based on the YR and WS data in Fig. 5; in contrast, 70% ET_c was classified as performing poorly in all yield components when compared to 100% ET_c. These findings concur with those of Temesgen (2018), who observed that 50% ET_c reduces onion bulb output by 30 to 45.4 when compared to conventional drip irrigation systems.

Evaluating Onion Yield using ML models

It is crucial to consider the practical implications of the observed performance metrics for three ML models. These changes may be small variation, but it can nonetheless have important practical ramifications. In agricultural settings, even a small increase in yield prediction accuracy can result in major financial gains for farmers by facilitating more efficient resource allocation and harvest scheduling. The ANN model exhibited the highest accuracy in predicting onion yield under deficit irrigation during testing phases. Constructed with one hidden layer comprising 6 neurons, utilizing the Tanh activation function, and undergoing 500 iterations, as depicted in Fig. 8. This configuration guarantees that meaningful correlations are recorded free from noise. To further increase forecast accuracy, future study could benefit from investigating more complex architectures or ensemble techniques, guaranteeing that farmers have access to the greatest resources for well-informed decision-making.

After a thorough analysis of the literature, the ML models are a crucial technique for crop productivity. Dahikar and Rode (2014) conducted a study on various crops, including cotton, sugarcane, jawar, bajara, soyabean, corn, wheat, rice, and groundnut, using an ANN model for yield prediction. This model was employed based on various soil and atmospheric parameters such as soil type, PH, nitrogen, phosphate, potassium, organic carbon, calcium, magnesium, sulphur, manganese, copper, iron, depth, temperature, rainfall, and humidity. Their study concluded that the ANN model is the most accurate technique for yield prediction. Another study by Kalichkin et al. (2021) used the DT model to predict spring wheat yield, factoring in agrometeorological resources such as cumulative air temperatures and precipitation as well as factors such as intensification levels, soil cultivation practices, and the placement of the crop after steam. They found that the DT model has high accuracy for yield prediction. Furthermore, Sharma et al. (2023) investigated the possibility of utilizing the RF model in conjunction with historical productivity and climate data for predicting the yield of six important crops. These crops included barley, wheat, mustard, gram, and groundnut. Their finding revealed that the RF model achieved an accuracy of 92.3%. These findings, along with our results, emphasize the importance of harnessing ML models in improving yield predictions and minimizing potential losses.

5. Conclusion

In this empirical study, Arduino Board was used to implement Automated Intelligent Drip Irrigation System (AIDIS). Machine learning models, namely, Artificial Neural Network (ANN), Random Forest (RF), and Decision Trees (DT) models were constructed to predict onion yield under different water stress regimes based on meteorological and agronomic variables. These variables include minimum, and maximum temperatures, relative humidity, sun shine hour, solar radiation, growing degree days, vapor pressure deficit, plant height, leaf number per plant, readily available water. Three irrigation levels, namely, 100%, 85%, and 70% of crop evapotranspiration (ET_c) were employed to onion crops. The results evidenced that AIDIS emerges as a compelling solution for advancing water management practices. By leveraging its capacity to gather real-time data, assess soil moisture levels through the LM293 sensor, and determine optimal irrigation timings. Total gross irrigation depth was applied using AIDIS were 617.6, 537.4, and 443.7 mm/season at 100%, 85% and 70% ET_c, respectively. The result also showed that the highest plant height and leaf number per plant values were recorded at 100% ET_c, followed by 85% ET_c and 70% ET_c . The results also observed that the highest onion yield values were recorded in 100% ET_c (56.04 ton/ha), followed by 85% ET_c (51.52 ton/ha). The lowest onion yield values were recorded at 70% ET_c (43.36 ton/ha). Furthermore, 85% and 70% ET_c optimize water usage by 13% and 28%, enhancing crop water productivity by 14.5 and 16 kg/m^3 compared to 100% ET_c, respectively. The ANN model exhibited the highest accuracy ($R^2 = 0.94$) in predicting onion yield, while the RF model and DT models perform at 0.90 and 0.86, respectively. The variation between models' performance was small. However, even modest improvements in yield prediction accuracy can have substantial real-world consequences in agricultural contexts, translating into significant economic benefits for farmers through better resource allocation and optimized harvest planning. The implications of this research extend beyond onion crop; similar modeling approaches could be applied to other crops, enhancing yield predictions and resource management across various agricultural systems. However, potential challenges and limitations may arise when scaling these models for widespread use. Variability in local climatic conditions, soil types, and crop management practices can influence model performance, necessitating adaptations for different contexts. Additionally, data availability and quality can vary significantly, impacting the accuracy and reliability of the models. Future research should explore more sophisticated architectures or ensemble methods to further enhance predictive accuracy and address these challenges, ensuring that farmers have access to the best tools for informed decision-making across diverse agricultural landscapes. Our results also highlight the effectiveness of technology in enhancing agricultural decision-making and crop management.

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