Pertanika J. Sci. & Technol. 32 (6): 2737 - 2751 (2024)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

The Application of Smart Drip Irrigation System for Precision Farming

Suhardi[1], Bambang Marhaenanto[1] and Bayu Taruna Widjaja Putra[1,2]*

[1]*Agricultural Engineering, Faculty of Agricultural Technology, University of Jember, Jember 68121, Indonesia*
[2]*Center of Excellence in Artificial Intelligence for Industrial Agriculture, University of Jember, Jember 681213, Indonesia*
[3]*Laboratory of Precision Agriculture and Geoinformatics, University of Jember, Jember 68121, Indonesia*

ABSTRACT

Managing water resources in urban areas is relatively expensive due to the costs of electricity and water distribution from wells and water companies. Therefore, water resource management for urban agricultural purposes needs to be made efficient, such as through smart irrigation technologies, one of which is the drip irrigation system that engages soil moisture sensors and the Internet of Things (IoT) to control the amount of distributed water. This study aims to apply and evaluate the performance of a drip irrigation system based on soil moisture sensors and IoT in urban agriculture. The results showed that the distribution uniformity in the system was identified at fair levels, with a Coefficient of Uniformity (CU) of 90.15% and 86.58%, respectively. Furthermore, our study also found that the IoT-assisted drip irrigation system that engaged a Deep Neural Networks (DNN) model to meet the water requirement led to better peanut yield than the irrigation system based on soil moisture as a control.

Keywords: Coefficient of uniformity, drip irrigation, IoT, soil moisture

ARTICLE INFO

Article history:
Received: 27 December 2023
Accepted: 09 May 2024
Published: 25 October 2024

DOI: https://doi.org/10.47836/pjst.32.6.17

E-mail addresses:
hardi.ftp@unej.ac.id (Suhardi)
bmarhaen@unej.ac.id (Bambang Marhaenanto)
bayu@unej.ac.id (Bayu Taruna Widjaja Putra)
* Corresponding author

INTRODUCTION

Overpopulation in urban areas has increased the need for housing, employment opportunities, water, and food resources. Water and food resources are strongly related to basic needs in that food from the agricultural sector largely relies on the availability of water resources. This becomes even more critical for urban

ISSN: 0128-7680
e-ISSN: 2231-8526

agriculture since it depends on wells and water companies. Inefficient management of water resources will increase the costs of living due to the higher usage of electricity to extract and distribute water.

Smart irrigation is one solution for regulating and monitoring agricultural irrigation to maintain the efficient use of water resources and subsequently improve farmer's economy (Jaafar & Kharroubi, 2021). Therefore, smart irrigation technology has become a decent complement to urban agriculture, as indicated by improved efficiency in water management (Gimpel et al., 2021; Kullu et al., 2020; Mason et al., 2019; Quimbita et al., 2022). Previous work has confirmed that the technology has been widely applied to drip irrigation in distributing water and has, in turn, saved water by 48% compared to traditional irrigation systems (Jaafar & Kharroubi, 2021). Other research results also show that the drip irrigation system increased the efficiency of water usage by 36% compared to the border irrigation system (Y. Wang et al., 2021). Simply put, drip irrigation can be a decent choice for the most efficient irrigation despite limited water resources (Zahid et al., 2020).

In general, using smart irrigation can increase the efficiency of water distribution to plants. However, its use in urban agriculture needs to be studied further to determine the efficiency level in using water resources, especially in drip irrigation systems. The selection of the appropriate microcontroller and sensors is decisive in the efficiency of irrigation water distribution. Smart irrigation systems based on soil moisture controllers and those based on the Internet of Things (IoT) adapted to plant evapotranspiration (ETc) are alternative smart irrigation systems in urban agriculture. These two smart irrigation systems need to be studied to determine the efficiency level of water distribution and its effect on plant growth. This IoT-based smart irrigation system utilizes temperature (T) and air humidity (RH) data on agricultural land to predict evapotranspiration so that the distribution of irrigation water is adjusted to the amount of evotranspired water.

Smart irrigation utilizes microcontrollers and sensors as control systems, including NodeMCU ESP8266, ESP32, and Arduino. Soil moisture sensors are often used to monitor soil water and increase water management efficiency (Ferrarezi et al., 2020). Meanwhile, NodeMCU helps to monitor and control irrigation with the aid of IoT by engaging Blynk, telegram, and other applications from a distance. NodeMCU has been widely used for IoT-assisted irrigation research (Rani et al., 2022). Likewise, Arduino is often used in automatic irrigation control based on soil water content detected by soil moisture sensors. When the water content reaches a predetermined minimum or maximum limit, the microcontroller triggers the relay to activate the drip irrigation system even without data on plant water requirements. On the other hand, an IoT-assisted irrigation system needs data on crop water requirements as a reference for deciding the volume and duration of water distribution. The data are produced by calculating water requirements using trained and tested DNN models to reach exemplary reliability and accuracy. The present study was projected to evaluate and apply a drip irrigation system based on soil moisture sensors and IoT in an urban agricultural setting.

MATERIALS AND METHODS

Study Site

The research examined peanut growth as sample plants at the University of Jember, East Java, Indonesia, from October 2022 to January 2023. The university is located at -8.16346^{o} and 113.71305^{o} and is characterized by a tropical climate with two seasons: dry and rainy. The dry season occurs from June to October, while the rainy season occurs from November to May.

Dataset

This study examines the use of intelligent irrigation systems in conditions of limited water resources, especially in the dry season. High temperatures and low air humidity during the dry season greatly influence the level of plant evapotranspiration, thus affecting the water requirements of plants. Therefore, IoT-based temperature (T) and air humidity (RH) data collection was carried out to monitor the temperature and RH conditions at the research site in real time. Next, TMean and RHMean data for 4 hours for 7 days were used as input data for the DNN-based evapotranspiration prediction model. Previous research shows that DNN-based evapotranspiration predictions are accurate with TMean and RHMean input data of 4 hours duration (Suhardi et al., 2023). Thus, the IoT-based smart irrigation system was carried out every 7 days based on the DNN model output. On the other hand, a smart irrigation system based on soil moisture sensors was also used to control the distribution of irrigation water to plants. The volume of water distributed to plants, plant height and plant canopy diameter were recorded periodically.

This study was carried out on two demonstration plots measuring 1m x 1m in a greenhouse. The distance between peanuts in each plot was 25 cm x 25 cm with the following drip irrigation systems. The first system was a drip irrigation system controlled by an Arduino Uno microcontroller based on a soil moisture sensor with a pump control that started when water content reached 17%, and the pump stopped at >30% water content. The other was a drip irrigation system using NodeMCU ESP8266 with Blynk to control the pump to meet water requirements. The irrigation was performed every 7 days with the amount of water emitted following the DNN-based ETo and Kc prediction model. Pipes were installed on the plot to channel water through each emitter around the peanut roots (Figure 1).

The reservoir's water level was monitored to determine the volume of water distributed through the system. Furthermore, the height and diameter of the peanut canopy were also observed at the initial crop development and mid-season stages. The cost of this IoT-assisted irrigation was fairly affordable at US$289.00 (Table 1).

As seen in Figure 1, the soil moisture sensor is placed 10 cm from the plant stem and is responsible for delivering data to the microcontroller. At ≥ 30% soil moisture content, the relay turns off the system, and it will be active when the water content is ≤ 17%. The IoT-assisted system uses the Blynk by pressing the switch button. When Blynk is activated via Smartphone, the NodeMCU ESP8266 microcontroller will control the relay to connect and disconnect the power line from a 220V AC source to the pump. Blynk determines this

Table 1
The list of development costs for the IoT-assisted system

Instruments	Functions	Cost (USD)
Bamboo, insect net, transparent wave fiber, plastic	Supporting plant cultivation to protect plants from pests	$ 195.00
IoT-assisted tools to measure temperature, RH, and soil water content	Monitoring temperature, RH, and soil water content in demonstration plots	$ 16.00
Drip irrigation system	Maintaining the drip system for the plants	$ 78.00
	Total	$ 289.00

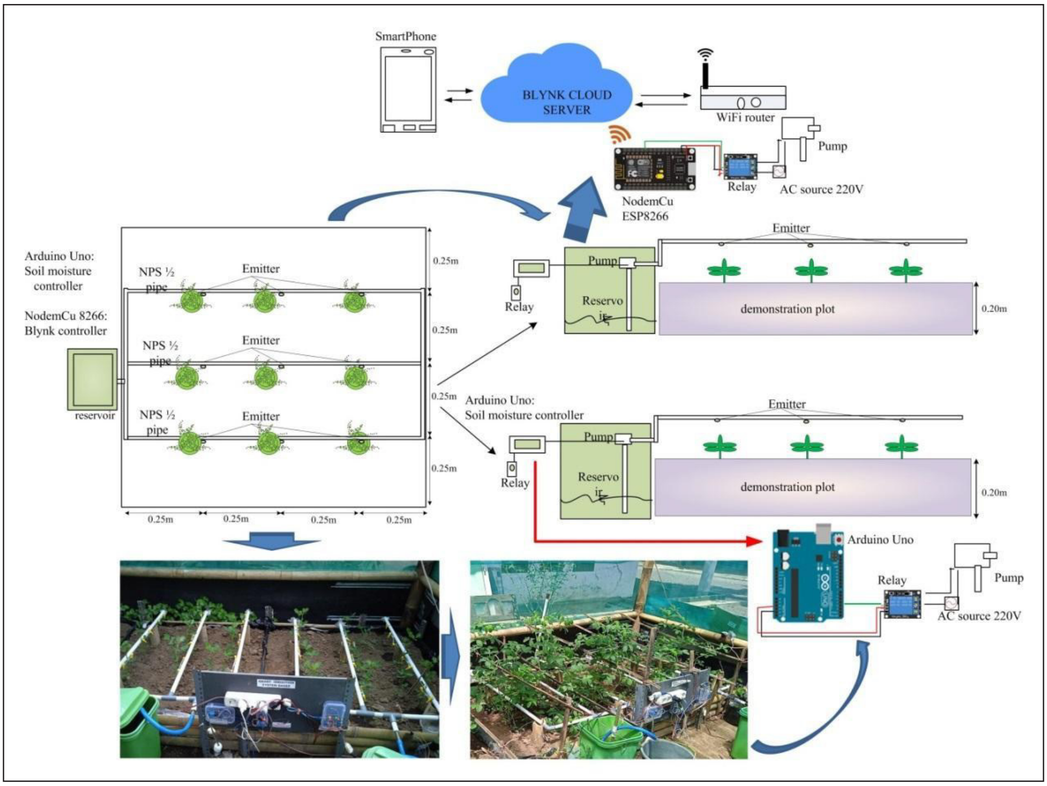


Figure 1. The plan and design of the drip irrigation system

mechanism when calculating crop water requirements. The instrument specification of the IoT-assisted system can be seen in Table 2.

Figure 2 shows two drip irrigation systems: a drip irrigation system based on a soil moisture sensor assisted by an Arduino Uno microcontroller and an IoT-assisted drip irrigation system with a NodeMCU microcontroller. The employment of these different microcontrollers was aimed at the ease of compiling the codes. Automatic drip irrigation systems based on soil moisture sensors with Arduino Uno have been widely used to ease programming code. However, this system is less effective because it requires a wireless transceiver module as a microcontroller and signal receiver. Likewise, adding a soil moisture sensor will make programming code more complex and affect the success rate and completion of the irrigation system. Coupled with Blynk, the NodeMCU Esp8266 microcontroller is equipped with an onboard antenna, making accessing and programming the code more practical.

Table 2
Specification of soil moisture sensor, water pump, Arduino Uno, and nodeMCU ESP8266

Instruments	**Specification**
Soil moisture sensor	Working Voltage: 3.3–5.5VDC; Output Voltage: 0–3.0VDC; Port: PH2.54–3P; Material: Plastic; Item size: 9.8 * 2.3 * 0.7cm (L * W * H); Item weight: Approx. 9g/0.32oz; price: US$1.62.
Aquarium pump Powerhead SP 1200	AC Power: 220–240 V; Frequency: 50/60 Hz; Max Rate: 1.000 L/H; Head Max: 1.0 m; Power: 7 Watt; Price: US $1.62.
Arduino Uno R3	Microcontroller: ATmega328; Operating Voltage: 5V; Input Voltage (recommended): 7–12V; Input Voltage (limits): 6–20V; Digital I/O Pins: 14 (of which 6 provide PWM output); Analog Input Pins: 6; DC Current per I/O Pin: 40 mA; DC Current for 3.3V Pin: 50 mA Flash; Memory: 32 KB; SRAM: 2 KB; EEPROM: 1 KB; Clock Speed: 16 MHz; Length: 68.6 mm Width: 53.4 mm; Price: US $ 6.48.
NodeMCU ESP8266	Chip: ESP8266 (ESP-12E); Pin I/O digital: 11; Pin I/O analog: 1; Operating Voltage: 3.3 V; Clock speed: 80Mhz/160Mhz; Flash: 4M USB; price: US $ 4.53

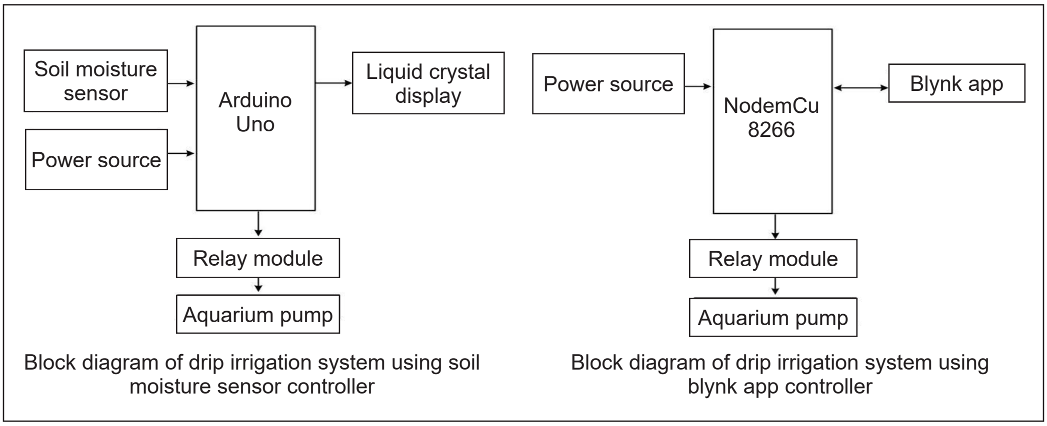


Figure 2. Block diagram of drip irrigation system

Coefficient of Uniformity (CU) Analysis

Drip irrigation is a well-known technology that reduces water consumption in the event of limited water resources while enabling proper plant growth (Kumar et al., 2022). Water distribution using drip irrigation technology utilizes hoses or pipes attached to a water tank with specific management to allow a constant water flow. It is necessary to perform a distribution uniformity test to maintain an even output, as this helps to determine the feasibility of system installation (Chaer et al., 2016; Mohamed et al., 2019). The distribution uniformity is considered very good when CU is over 90% (Henrique & França, 2022). CU ranging from 80%–90% corresponds to a good rate, while any lower rates between 70%–80% are classified under fair CU, and poor CU ranges between 60%–70% (Darimani et al., 2021). Researchers have widely used CU as a parameter to estimate the uniformity of drip irrigation (Al-Mefleh et al., 2021; Henrique & França, 2022; C. Liu et al., 2022). CU can be calculated using Equation 1.

$$CU = 100\left(1 - \frac{\sum_{i=1}^{N} |xi - \underline{x}|}{\sum_{i=1}^{N} xi}\right) \quad [1]$$

Where: Cu: coefficient of uniformity in drip irrigation (%); xi : average volume of water of the i^{th} container (ml); and $\underline{x}$: average volume of water (ml)

Crop Evapotranspiration (ETc) Analysis

The crop evapotranspiration (ETc) is obtained by multiplying evapotranspiration (ETo) and plant coefficient (Kc) using Equation 2. However, the Kc value is calculated using Equation 3 in conditions of limited water resources. Meanwhile, the Ke value is calculated using Equation 4, which is converted from the fraction of vegetation cover (Fc) value (Zhang et al., 2019; T. Wang et al., 2021). Fc value based on FAO is between 0–0.1 at the initial stage, 0.1–0.8 at the crop development stage, 0.8–1 at the mid-season stage, and 0.8–0.2 at the late season stage. The present study measured the Kcb rate for the peanut samples by using the DNN model, as shown in Figure 3.

$$ETc = Kc + ETo \quad [2]$$

$$Kc = Kcb + Ke \quad [3]$$

$$Ke = 0.9 * (1 - Fc) \quad [4]$$

The site's ETo rate was examined using the DNN model based on Tmean and RHmean resulting from 4 hours of observation (Figure 4). Meanwhile, the daily Tmean and RHmean are the conversion result of the 4-hour Tmean and RHmean observations (Figure 5). The ETo value was calculated every 7 days as a reference for managing the irrigation on day 8. Next, the aggregate ETo rate for 7 days was multiplied by Kc. The

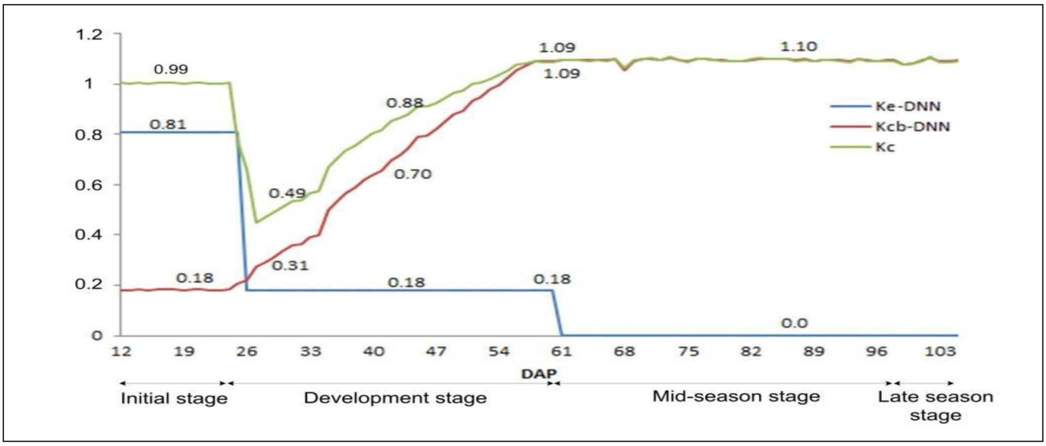


Figure 3. Value of Ke, Kcb, and Kc of peanuts

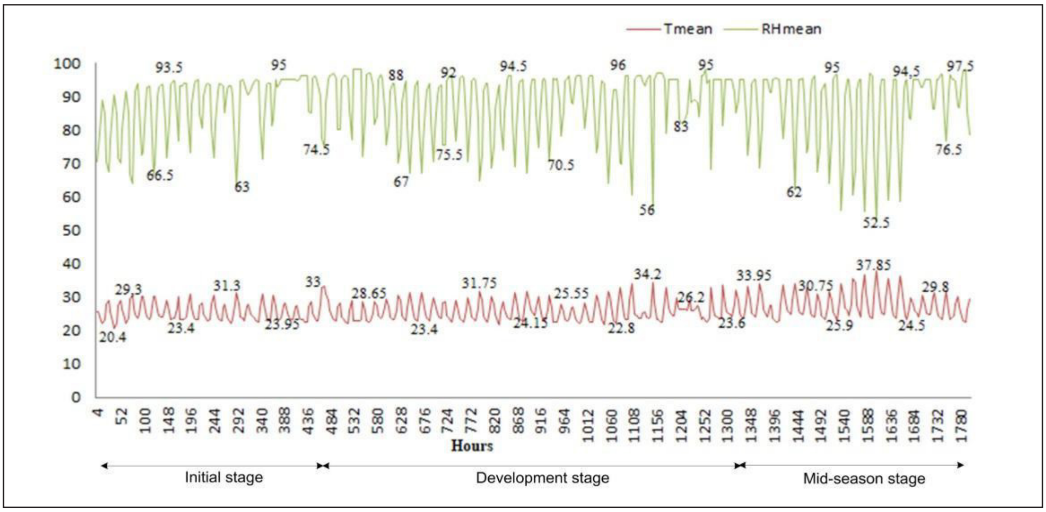


Figure 4. TMean and RHMean across stages

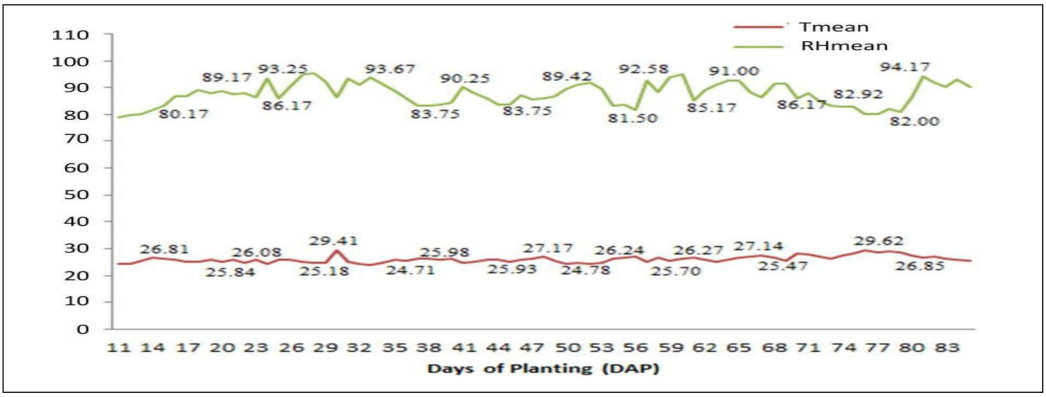


Figure 5. Daily RHmean and Tmean across DAPs

findings show that the area of the demonstration plot positively relates to the amount of water given to the plants.

DNN and Artificial Neural Networks (ANN) employ similar learning principles: supervised, semi-supervised, and unsupervised. However, DNN has more than 3 hidden layers, where multiplying and adding weights, inputs, and biases occurs in each neuron in the hidden layer using Equation 5. This difference gives DNN better performance than ANN (Ali et al., 2022; Han et al., 2018; Irfan et al., 2021). Meanwhile, the results of the multiplication and addition in the previous hidden layers are used as the input for the next hidden layer (Figure 6). The DNN architecture in this research is shown in Figure 7.

$$Y = \emptyset(\sum_{i=1}^{n} \quad Wi * Xi + b) \qquad [5]$$

Where: Y = Output; Ø = activation function; W = weights; Xi = input; and b=bias

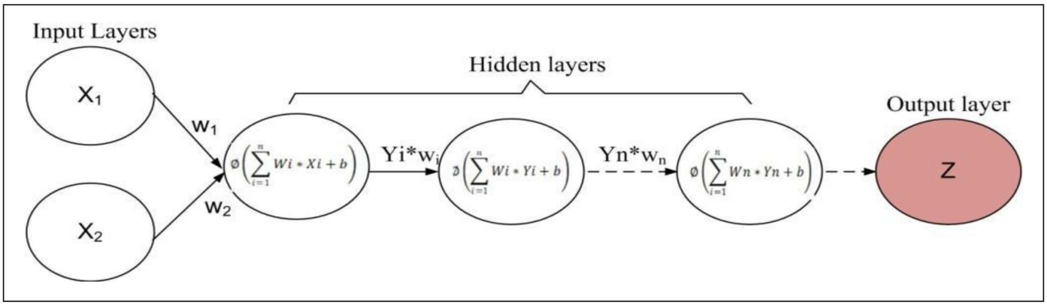


Figure 6. Calculation in DNN

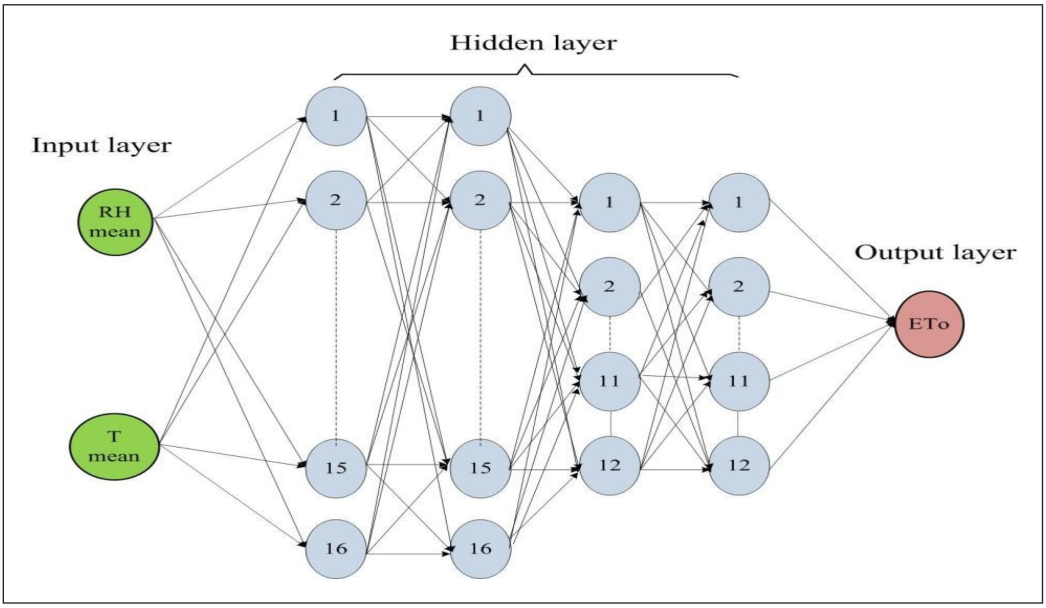


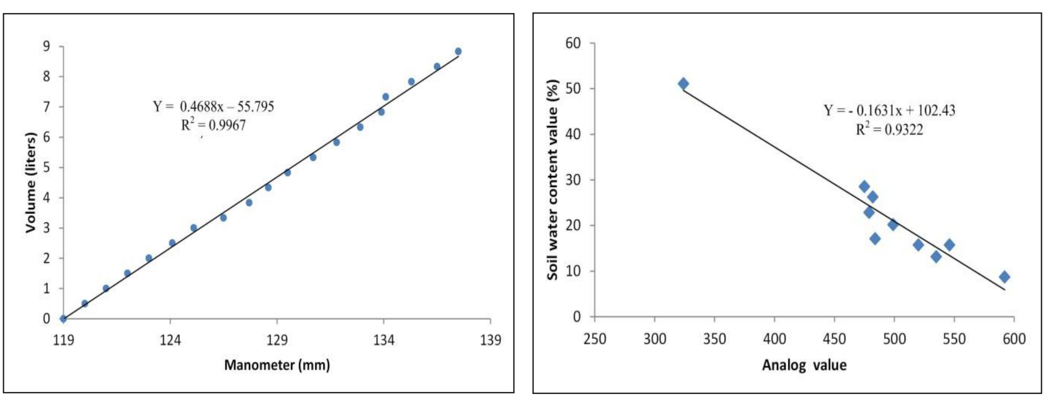
Figure 7. DNN architecture

RESULTS AND DISCUSSION

The Calibration of Reservoir and Soil Moisture

The drip irrigation system's water tank as a reservoir was calibrated to monitor the water volume. The calibration was performed using a measuring cup to find a linear relationship between the water level and volume in the tank and to predict the water distribution in the system using a linear equation. The soil moisture sensor was used to detect soil moisture or soil water content indicated by an analog value after the soil moisture sensor had been connected to an Arduino microcontroller or ESP8266 NodeMCU. Therefore, the soil moisture sensor had to be calibrated to the soil water content using the gravimetric method to predict the linear equation, as shown in Figure 8.

Figure 8 shows two essential calibration results. The first result corresponds to a strong positive correlation in the water tank with the equation $Y= 0.688x – 55.795$ and $R^2 = 0.997$. Afterward, this equation was used to calculate the volume of water distributed through the irrigation system. Another result confirmed a robust negative linear correlation between the soil moisture sensor's analog output and the gravimetric method's water content with the equation $Y= - 0.1631x + 102.43$ and $R^2 = 0.932$. This linear equation was formulated in programming the code and uploaded to the Arduino Uno microcontroller to generate the data on soil water content. A drip irrigation system based on a soil moisture controller is expected to detect soil water content accurately. It is crucial to manipulate the duration of water distribution to meet predetermined water requirements.



(a) (b)

Figure 8. Calibration of: (a) water tank (a); and (b) soil moisture sensor

Coefficient of Uniformity (CU)

CU was measured on 2 different drip irrigation systems, namely drip irrigation systems with soil moisture controller and Blynk controller. The measurements were carried out at 9 emitter points with 2 repetitions (Table 3). Previous work demonstrated a decent CU of water discharge (Q) flowing through each emitter, as indicated by CU over 90% and between 80%–90% (Martinez et al., 2022). The present study also reported similar results where the drip irrigation system with soil moisture and Blynk controller generated CUs of 90.15% and 86.58%, respectively. This difference was presumed to occur due to the challenge of maintaining uniform water flow at each emitter.

Table 3
The CU of drip irrigation system

Emitter	**Controller System**			
	Soil moisture		**Blynk**	
No.	Q1 (ml/min)	Q2 (ml/min)	Q1 (ml/min)	Q2 (ml/min)
1	77.14	62.96	50.00	51.85a
2	77.14	77.78	36.36	51.85
3	60.00	74.07	50.00	44.44
4	68.57	81.48	31.82	44.44
5	60.00	70.37	59.09	44.44
6	77.14	81.48	59.09	62.96
7	68.57	59.26	50.00	62.96
8	68.57	66.67	50.00	44.44
9	51.43	66.67	63.64	59.26
CU (%)	90.15		86.58	
Drip Irrigation Discharge (ml/min)	624.66		458.33	

Crop Evapotranspiration (ETc)

Evapotranspiration (ETo) was examined using a DNN model with 4 hidden layers and 2 input parameters, temperature (T) and air humidity (RH), logged for 7 days with a 4-hour observation each day. Next, the ETo rate predicted by DNN (ETo-DNN) was multiplied by the Kc for peanuts to determine ETc and water requirements for each demonstration plot.

Figure 9 shows that the ETo rates in the initial and development phases are higher than the ETc rates. However, at the end of the development phase, the Kc rate reaches 1.09, which implies a higher ETc rate than ETo. Meanwhile, the ETo rate varies across phases, apparently because it was generated by the DNN model on different rates of temperature (T) and air humidity (RH) across days after planting (DAPs). It is congruent with previous studies stating that increasing temperature leads to higher ETo rates, while a negative correlation applies to RH (Dong et al., 2020; Zhu et al., 2022).

Crop Growth

Providing irrigation to plants will escalate plant growth and yields. It can only be achieved when water resources are used efficiently to maximize growth. In this regard, excessive or

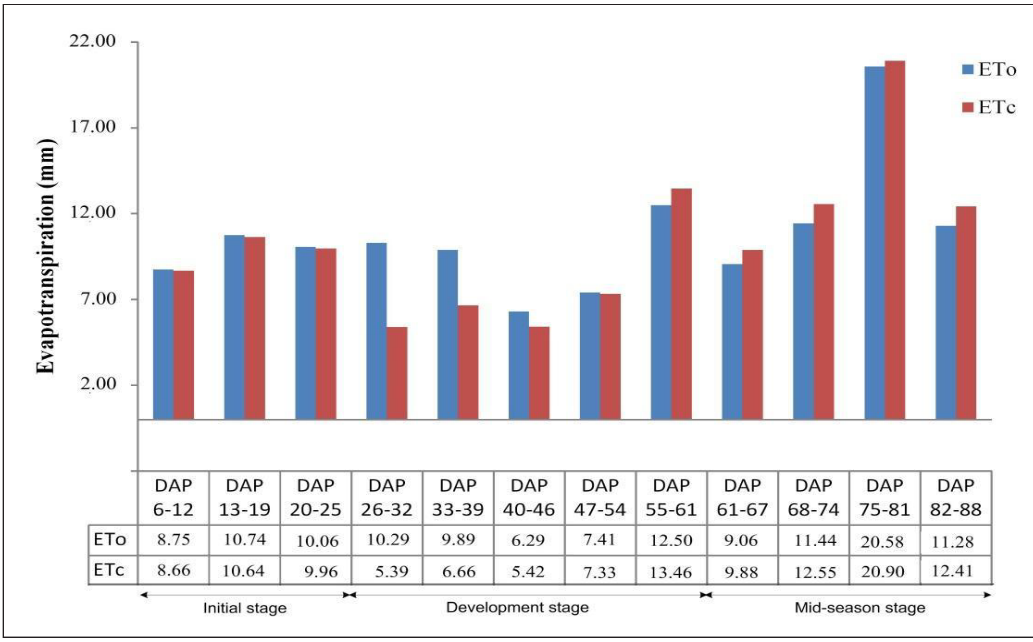


Figure 9. ETo and ETc rates for the peanut samples

insufficient water supply will adversely affect plant growth, so irrigation must be adjusted to the water required (Sezen et al., 2022).

The growth of peanuts was significantly influenced by the water availability in the soil, as shown by the growth of plant height and canopy area. The irrigation system also influenced plant growth due to differences in the volume of water emitted on plant surfaces. It can be seen in Figure 10, which shows that the irrigation system driven by a soil moisture sensor controller (SC) leads to a better height in the initial phase than the irrigation system with the Blynk controller (BC). However, in the development and mid-season phases, a higher water supply with BC results in better height than SC.

The canopy diameter increases in line with the increment of DAP, which affects the increasing evapotranspiration (Figure 10). It is also evidenced by the increasing water supply in each irrigation system from the initial phase to the mid-season phase. The figure also documents that the BC-based irrigation system generates an exemplary effect on plant height and canopy diameter due to the optimal water supply.

Yield

The use of AI-based analysis to generate ETc-DNN models helps to accurately determine the volume of water flow relative to crop water requirement, thus ensuring optimal photosynthesis, metabolism, and transportation of food materials from the roots to all parts of the plant. The results of the previous study also confirm a positive linear

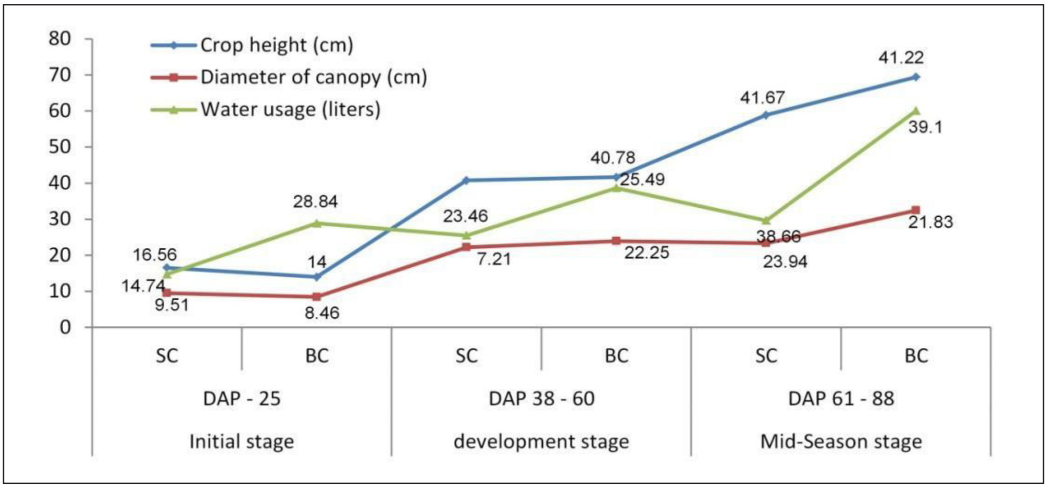


Figure 10. The height and diameter of the peanut canopy

relationship between crop yields and crop water requirement, where appropriate water supply stimulates better harvest (Bennett & Harms, 2011; J. Liu et al., 2022). Figure 11 shows higher peanut yield in a drip irrigation system that engages the AI-based analysis (ETc-DNN) to determine water requirement compared to another system assisted by a soil moisture sensor controller (SC), which determines soil water content around plant roots (ETc-SC).

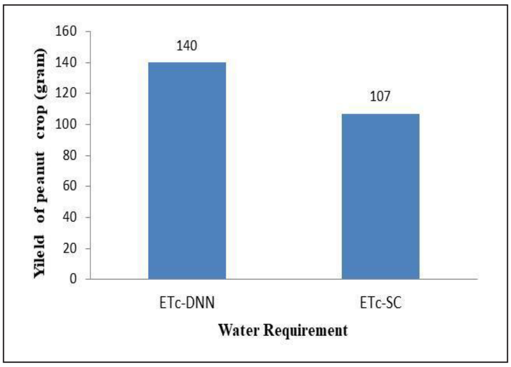


Figure 11. Peanut yield in irrigation systems based on soil moisture, blynk, and timer controllers

CONCLUSION

This study has corroborated that the IoT-assisted drip irrigation system with AI-based analysis (ETc-DNN) has helped meet crop water requirements better than ETc-SC. The system has also been influential in attaining higher peanut yields than a drip irrigation system with a soil moisture sensor controller (SC). Another advantage of using an IoT-assisted irrigation system with AI-based analysis is better efficiency in water distribution based on the plant's water needs. Thus, the plants' height and canopy area were improved, and their growth and yields improved.

ACKNOWLEDGEMENT

The authors extend their utmost gratitude to their mentors and all who have contributed to this research.

REFERENCES

Ali, A., Rehman, A. U., Almogren, A., Eldin, E. T., & Kaleem, M. (2022). Application of deep learning gated recurrent unit in hybrid shunt active power filter for power quality enhancement. *Energies*, *15*(20), Article 7553. https://doi.org/10.3390/en15207553

Al-Mefleh, N. K., Talozi, S., & Naser, K. A. (2021). Assessment of treated wastewater reuse in drip irrigation under different pressure conditions. *Water*, *13*(8), 1–15. https://doi.org/10.3390/w13081033

Bennett, D. R., & Harms, T. E. (2011). Crop yield and water requirement relationships for major irrigated crops in Southern Alberta. *Canadian Water Resources Journal*, *36*(2), 159–170. https://doi.org/10.4296/cwrj3602853

Chaer, M. S. I., Abdullah, S. H., & Priyati, A. (2016). Application of arduino microcontroller on drip irrigation system for mustard plant (*Brassica juncea*). *Jurnal Ilmiah Rekayasa Pertanian Dan Biosistem*, *4*(2), 228–238.

Darimani, H. S., Kpoda, N., Suleman, S. M., & Luut, A. (2021). Field performance evaluation of a small-scale drip irrigation system installed in the Upper West Region of Ghana. *Computational Water, Energy, and Environmental Engineering*, *10*, 82–94. https://doi.org/10.4236/cweee.2021.102006

Dong, W., Li, C., Hu, Q., Pan, F., Bhandari, J., & Sun, Z. (2020). Potential evapotranspiration reduction and its influence on crop yield in the North China Plain in 1961-2014. *Advances in Meteorology, 2020*(1), Article 3691421. https://doi.org/10.1155/2020/3691421

Ferrarezi, R. S., Nogueira, T. A. R., & Zepeda, S. G. C. (2020). Performance of soil moisture sensors in Florida sandy soils. *Water, 12*(2), Article 358. https://doi.org/doi:10.3390/w12020358

Gimpel, H., Graf-Drasch, V., Hawlitschek, F., & Neumeier, K. (2021). Designing smart and sustainable irrigation: A case study. *Journal of Cleaner Production*, *315*, Article 128048. https://doi.org/10.1016/j.jclepro.2021.128048

Han, R., Yang, Y., Li, X., & Ouyang, D. (2018). Predicting oral disintegrating tablet formulations by neural network techniques. *Asian Journal of Pharmaceutical Sciences*, *13*(4), 336–342. https://doi.org/10.1016/j.ajps.2018.01.003

Henrique, G., & França, F. (2022). Advance time to determine injection and flushing times in drip fertigation. *Horticulturae Article*, *8*(1103), 1–11.

Irfan, M., Ramlie, F., Widianto, Lestandy, M., & Faruq, A. (2021). Prediction of residential building energy efficiency performance using deep neural network. *IAENG International Journal of Computer Science*, *48*(3), 1–7.

Jaafar, H., & Kharroubi, S. A. (2021). Views, practices and knowledge of farmers regarding smart irrigation apps: A national cross-sectional study in Lebanon. *Agricultural Water Management*, *248*, Article 106759. https://doi.org/10.1016/j.agwat.2021.106759

Kullu, P., Majeedullah, S., Pranay, P. V. S., & Yakub, B. (2020). Smart urban farming (entrepreneurship through Epics). *Procedia Computer Science*, *172*(2019), 452–459. https://doi.org/10.1016/j.procs.2020.05.098

Kumar, C. N., Selvam, S. P., Ramanathan, S. P., Kalarani, S., Nagarajan, G., & Duraisamy, S. (2022). Effect of drip irrigation and inter cropping systems on growth characters of maize. *International Journal of Plant & Soil Science*, *34*(2), 36–42. https://doi.org/10.9734/ijpss/2022/v34i230834

Liu, C., Wang, R., Wang, W., Hu, X., Wu, W., & Liu, F. (2022). Different irrigation pressure and filter on emitter clogging in drip phosphate fertigation systems. *Water*, *14*(6), 1–18. https://doi.org/10.3390/w14060853

Liu, J., Sun, B., Shen, H., Ding, P., Ning, D., Zhang, J., & Qiu, X. (2022). Crop water requirement and utilization efficiency-based planting structure optimization in the Southern Huang-Huai-Hai Plain. *Agronomy*, *12*(9), 1–21. https://doi.org/10.3390/agronomy12092219

Martinez, C. G., Wu, C. L. R., Fajardo, A. L., & Ella, V. B. (2022, June). Hydraulic performance evaluation of Low-cost gravity-fed drip irrigation systems under constant head conditions. In *IOP Conference Series: Earth and Environmental Science* (Vol. 1038, No. 1, p. 012005). IOP Publishing. https://doi.org/10.1088/1755-1315/1038/1/012005

Mason, B., Rufí-Salís, M., Parada, F., Gabarrell, X., & Gruden, C. (2019). Intelligent urban irrigation systems: Saving water and maintaining crop yields. *Agricultural Water Management*, *226*, Article 105812. https://doi.org/10.1016/j.agwat.2019.105812

Mohamed, A. Z., Peters, R. T., Zhu, X., & Sarwar, A. (2019). Adjusting irrigation uniformity coefficients for unimportant variability on a small scale. *Agricultural Water Management*, *213*, 1078–1083. https://doi.org/10.1016/j.agwat.2018.07.017

Quimbita, W., Toapaxi, E., & Llanos, J. (2022). Smart irrigation system considering optimal energy management based on model predictive control (MPC). *Applied Sciences*, *12*(9), 1–18. https://doi.org/10.3390/app12094235

Rani, S. B., Venu, N., Ananthula, M. K., & Engli, A. (2022). IoT based smart irrigation system using node MCU. *International Journal for Innovative Engineering and Management Research, 11*(06), 100–106.

Sezen, S. M., Ahmad, I., Habib-ur-Rahman, M., Amiri, E., Tekin, S., Oz, K. C., & Maambo, C. M. (2022). Growth and productivity assessments of peanut under different irrigation water management practices using CSM-CROPGRO-Peanut model in Eastern Mediterranean of Turkey. *Environmental Science and Pollution Research*, *29*(18), 26936–26949. https://doi.org/10.1007/s11356-021-17722-w

Suhardi, Marhaenanto, B., Taruna, B., Putra, W., & Winarso, S. (2023). IoT-based evapotranspiration estimation of peanut plant using deep neural network. *INMATEH - Agricultural Engineering*, *70*(2), 487–496. https://doi.org/https://doi.org/10.35633/inmateh-70-47

Wang, T., Melton, F. S., Pôças, I., Johnson, L. F., Thao, T., Post, K., & Cassel-Sharma, F. (2021). Evaluation of crop coefficient and evapotranspiration data for sugar beets from landsat surface reflectances using micrometeorological measurements and weighing lysimetry. *Agricultural Water Management*, *244*, Article 13. https://doi.org/10.1016/j.agwat.2020.106533

Wang, Y., Li, S., Cui, Y., Qin, S., Guo, H., Yang, D., & Wang, C. (2021). Effect of drip irrigation on soil water balance and water use efficiency of maize in northwest China. *Water*, *13*(2), Article 217. https://doi.org/10.3390/w13020217

Zahid, B., Ansari, R., Cheema, M. J. M., & Anjum, L. (2020). Evaluation of deficit irrigation regime, row spacing and dual plantation of drip irrigated tomato under high tunnel. *Journal of Central European Agriculture*, *21*(4), 851–860. https://doi.org/10.5513/JCEA01/21.4.2990

Zhang, Y., Han, W., Niu, X., & Li, G. (2019). Maize crop coefficient estimated from UAV-measured multispectral vegetation indices. *Sensors*, *19*(23), 1–17. https://doi.org/10.3390/s19235250

Zhu, B., Zhang, Q., Yang, J. H., & Li, C. H. (2022). Response of potential evapotranspiration to warming and wetting in Northwest China. *Atmosphere*, *13*(2), Article 21. https://doi.org/10.3390/atmos13020353