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RESEARCH ARTICLE

Smart Agriculture: Precision Farming Through Sensor-Based Crop Monitoring and Control System

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ABSTRACT - The escalation of the global population and the depletion of natural resources have propelled the evolution of smart agriculture and precision farming, underpinned by sensor-based crop monitoring and control systems, which are anticipated to revolutionize the agricultural sector. Notably, prevalent smart agriculture systems predominantly emphasize either IoT components for data monitoring and control or machine learning components for data analysis. Consequently, this project endeavours to develop a system that seamlessly integrates both IoT and machine learning components, culminating in an advanced system capable of real-time crop monitoring and growth prediction. Collaborating with the Urban Farming Farm under the auspices of the Kulliyyah of Economics and Management Science, an IoT system comprising soil moisture, temperature, and humidity sensors, alongside an actuator, is devised to facilitate data acquisition and required intervention specifically for Okra Fruit during the pre-harvesting stage. Subsequently, four distinct algorithms are trained with the collected dataset to ascertain the most optimal algorithm for predicting crop growth and harvesting time, resulting in the selection of the Random Forest Regression model, which attains the highest model score of 86%. Upon its integration into the comprehensive system for monitoring new data and predicting fruit growth, the model achieves an impressive 98% accuracy score. Future endeavours for this project aim to enhance its applicability and predictive capabilities through the incorporation of diverse datasets from various plant species, the expansion of crop predictions to encompass the entire growth cycle, the integration of additional sensors, and the enhancement of the system's scalability to cover larger areas.

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1.0 INTRODUCTION

The projected global population surge to nearly 10 billion by 2050 heightens the urgency for improving agricultural output to ensure food security and alleviate hunger [1]. Tackling the multifaceted challenges associated with food production, agricultural land expansion, and greenhouse gas emissions is important to enable UN Sustainability Goals 2030 to be achieved. Keating et al. [2] identified three important remedies – reducing food demand, increasing food production, and optimising capacity of food supply chain. Notably, smart farming and precision agriculture emerge as one of the avenues within these strategies [3], [4], offering substantial promise in increasing food production while ensuring the sustained capacity of food systems. Leveraging a suite of technologies such as sensors [5], [6], drones [7], [8], and data analytics [9], smart farming are able to optimize resource utilization, refines farm management, and mitigates environmental impact [10], [11].

The integration of emerging technologies, including the Internet of Things (IoT) and machine learning, presents considerable potential for precision agriculture and smart farming [12], [13]. IoT sensors enable real-time monitoring and automation of farming operations, empowering farmers to make informed decisions which is grounded in agricultural data housed in the cloud [14]. Complementing this, machine learning algorithms improves decision-making processes by processing real-time data captured from IoT sensors, contributing to more efficient and sustainable farming practices [15]. The amalgamation of smart farming, precision agriculture, IoT, and machine learning [16]are therefore able to address the intricate challenges of food production and sustainability. This, ultimately foster a balanced future characterized by sustainable diets, minimized waste, biodiversity conservation, and resilient food systems.

2.0 METHODS AND MATERIAL

In this investigation conducted at the Urban Farming Farm under the purview of the Faculty of Economics and Management Science project, the methodology is centred on elucidating the pre-harvest dynamics of Okra fruit plant growth, specifically focusing on the fruit's length. Okra fruit also known as *Abelmoschus esculentus*, is a green, elongated

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fruit with a tapering shape. The fruit typically grows to be between 10–25 cm in length and belongs to the Malvaceae family. It is commonly used in cooking and has potential health benefits, including antidiabetic properties [17].

The approach integrates sensor-derived readings and manual measurements using callipers at hourly intervals to ensure a comprehensive and precise depiction of fruit development. The adoption of a high-frequency data collection regimen affords a nuanced insight into growth dynamics previously studied by Dantas et al. [17]. Further, the sensor technology enables facilitation of an uninterrupted surveillance of environmental parameters enabling better prediction of plant growth. The emphasis on fruit length as a key metric offers valuable inferences pertaining to plant vigour, maturity, and prospective yield. The dataset procured will undergo a machine learning process for exhaustive data scrutiny, with the objective of deploying predictive modelling techniques capable of unravelling crop growth patterns and predict optimal harvesting periods. This data-driven methodology resonates with the overarching ambition of augmenting agricultural efficacy and output, thereby enriching the sustainable progression of urban farming methodologies.

2.1 System Architecture

The system architecture of the smart agriculture system shown in Figure 1 encompasses a fusion of hardware and software components. The schematic represents the integration of technology aimed at fostering efficient and sustainable farming practices through the utilization of sensors and actuators, data transfer, communication network via the internet, cloud services, and machine learning to predict crops growth.

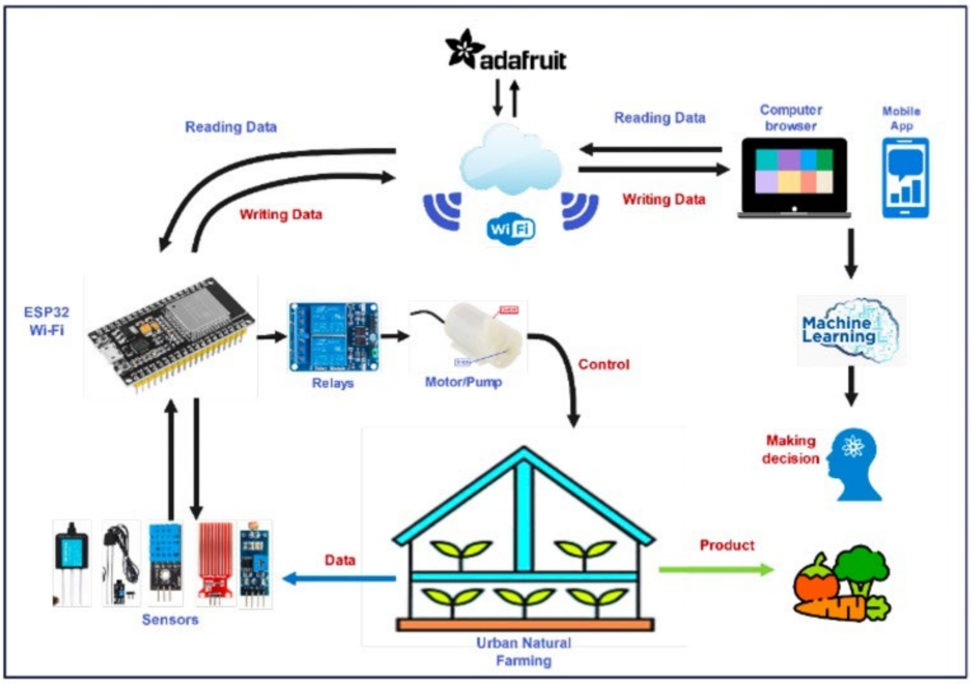

Figure 1. System Architecture

2.2 Instrument for Data Collection

The data collection methodology in smart agriculture harnesses sensor technology to monitor and regulate farm parameters. However, to address the constraints inherent in sensor-based data collection, a dual approach is adopted, encompassing sensor-based measurements for environmental parameters and manual measurements for fruit dimensions. The placement of the instruments (left) and the system setup (right) could be seen in Figure 2, with choice of system hardware implementation shown in Figure 3.

Figure 2. Placement of Instruments for Data Collection (Left) and System Setup for Data Collection (Right)

In the context of sensor-based measurements, sensors designed to gauge environmental variables such as temperature and humidity sensor using DHT 11 which have a temperature range of 0ºC – 50ºC and 20% - 90% respectively is used. In addition, soil moisture SG00325 is utilised to identify the dryness of the soil. Rain sensor module SN-RAIN-MOD and other sensors are strategically placed within the farming environment to enable real-time data acquisition. These sensors are interfaced with microcontrollers, notably the ESP32 [18], which undertake the collection and transmission of sensor readings as shown below in the hardware implementation. The amassed data is subsequently synchronized with both the Adafruit IO and Google Sheet platforms, enhancing accessibility and flexibility. This integration facilitates the exportation of data into diverse file formats, thereby laying the groundwork for comprehensive analysis through the application of data analytics and machine learning methodologies. The procedural workflow is summarised in the accompanying flowchart shown in Figure. 4. Conversely, manual measurements entail the periodic assessment of fruit length using vernier callipers at hourly intervals as shown in Figure. 5. The recorded data are stored in Google Sheet with sensor-derived data.

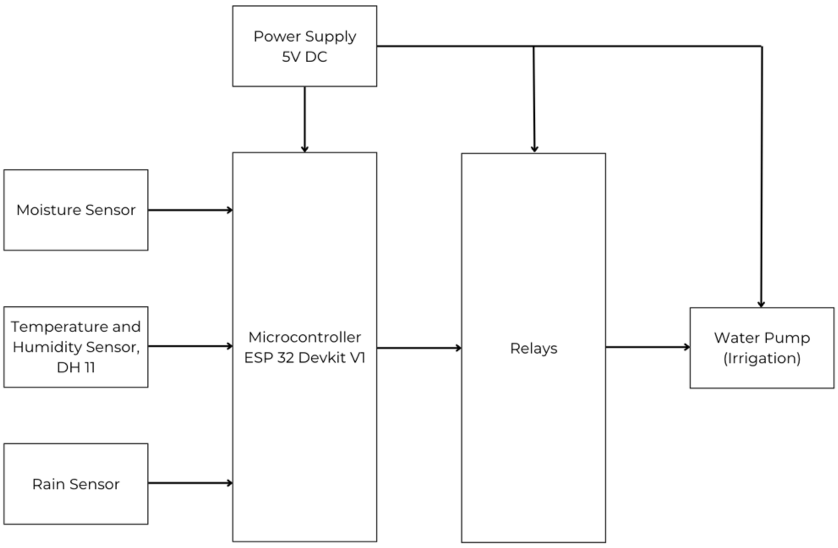

Figure 3. System Hardware Implementation

2.3 Data Collection

The prediction of fruit growth is facilitated through the deployment of a machine learning algorithm, leveraging historical data patterns for accurate model construction, as depicted in Figure 6. However, prior to commencing any data analysis, the collected dataset necessitates meticulous cleaning and pre-processing. For instance, circumstances may arise where the periodic measurement of fruit length at hourly intervals becomes impracticable, particularly during nocturnal hours due to human constraints. Under such circumstances, any absent data points are extrapolated linearly or through polynomial interpolation, as illustrated in Table 1.

In order to ensure the efficacy of the machine learning algorithm in generating precise forecasts, an ample historical training dataset is needed. Accordingly, a growth dataset as shown in Table 2 is incorporated to furnish additional input for the machine learning algorithm. The implementation of the machine learning algorithm is executed through the utilization of the widely recognized Scikit-Learn (SKL) library in Python [19].

Each variable within the dataset undergoes comprehensive analysis to ascertain its impact and significance for training within the model. The initial step entails the partitioning of the dataset into a training set (X-Train and Y-Train) and a testing set (X-Test and Y-Test), as delineated in Table 3, where X-Train and X-Test is represented by light blue and dark blue respectively and Y-Train and Y-Test is represented by light green and dark green respectively. This partitioning is accomplished through the employment of the train_test_split() function from the SKL library. It is noteworthy that distinct machine learning models exhibit varying performances contingent upon the specific scenario and data types [20]. To identify the most suitable model for the given scenario, the library from SKL model.score() is employed to compute the score for the different machine learning models. Subsequently, only the model with the highest score is selected for training and thus testing within the system.

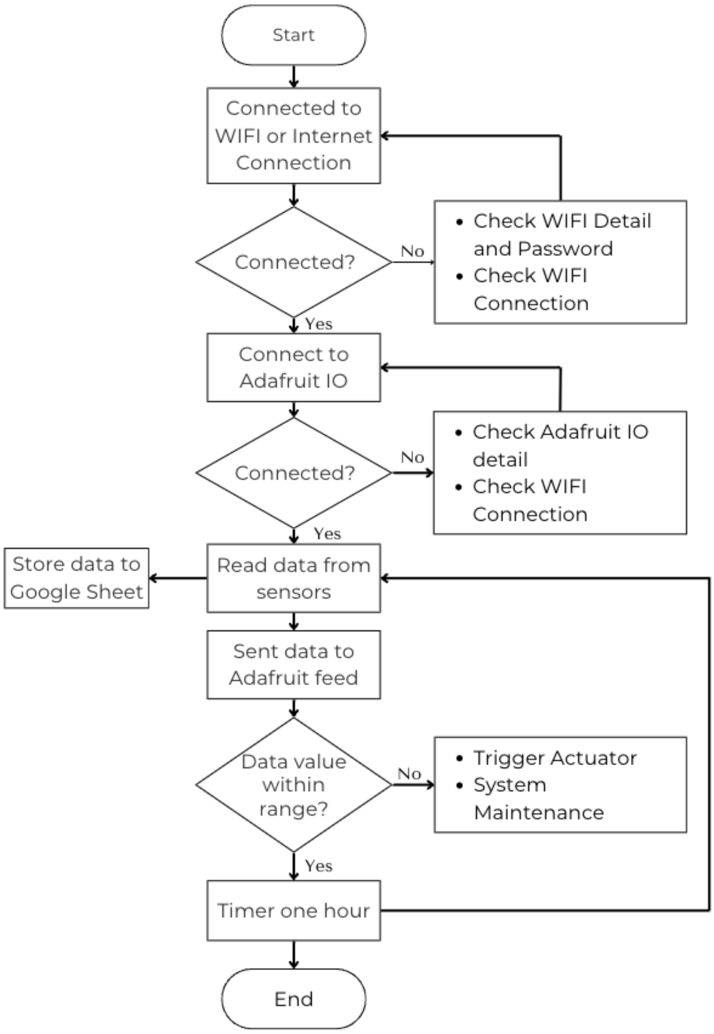

Figure 4. Sensor Based Data Collection

Figure 5. Measuring Okra Fruit Length Using a Calliper

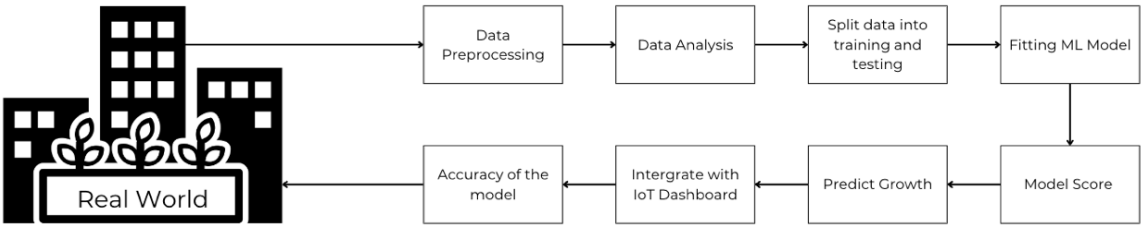

Figure 6. Machine Learning Process

Table 1. Length Datasets containing a) Missing Values b) Extrapolated/Interpolated Values

Index	Temp (°C)	Humidity (%)	Soil Moisture (%)	Length
0	28.0	86	37.14	12.75
1	29.3	85	39.07	NaN
2	30.3	87	38.22	NaN
3	60.1	30	40.00	NaN
4	45.8	67	39.98	NaN
...	...	...	...	...
147	48.3	49	31.40	NaN
148	60.1	27	34.63	NaN
149	55.0	45	36.00	119.10
150	49.8	49	34.51	NaN
151	38.0	68	34.53	NaN

(a)

Index	Temp (°C)	Humidity (%)	Soil Moisture (%)	Length
0	28.0	86	37.14	12.75
1	29.3	85	39.07	12.76
2	30.3	87	38.22	12.77
3	60.1	30	40.00	12.78
4	45.8	67	39.98	12.79
...	...	...	...	...
147	48.3	49	31.40	116.42
148	60.1	27	34.63	117.76
149	55.0	45	36.00	119.10
150	49.8	49	34.51	119.10
151	38.0	68	34.53	119.10

(b)

Table 2. Datasets with Growth Data

Index	Date	Temp (°C)	Humidity (%)	Soil Moisture (%)	Length	Growth
0	Wednesday, December 20, 2023 - 09:50:07	28.0	86	37.14	12.75	0.00
1	Wednesday, December 20, 2023 - 10:50:07	29.3	85	39.07	12.76	0.01
2	Wednesday, December 20, 2023 - 11:50:07	30.3	87	38.22	12.77	0.01
3	Wednesday, December 20, 2023 - 12:50:06	60.1	30	40.00	12.78	0.01
4	Wednesday, December 20, 2023 - 13:50:06	45.8	67	39.98	12.79	0.01
5	Wednesday, December 20, 2023 - 14:50:06	44.9	66	39.41	12.80	0.01
6	Wednesday, December 20, 2023 - 15:50:06	46.2	66	42.17	12.95	0.15
7	Wednesday, December 20, 2023 - 16:50:06	41.1	72	39.17	13.10	0.15
8	Wednesday, December 20, 2023 - 17:50:06	41.1	75	37.90	13.25	0.15
9	Wednesday, December 20, 2023 - 18:50:06	33.3	86	42.05	13.40	0.15

Upon the utilization of the training dataset for model training, a test dataset is employed to evaluate the forecast accuracy of the model. The model's predictions are generated using the model.predict() function from the SKL library.

The comprehensive integration process between machine learning and IoT Adafruit IO is encapsulated in the flowchart depicted in Figure 7. The integration commences with the acquisition of parameters from Adafruit feeds, encompassing soil moisture, humidity, temperature, and fruit length. Following the reception of the complete dataset, the trained machine learning model predicts the current fruit growth based on the received parameters. Simultaneously, an analysis of the received data is conducted to ascertain its adherence to specific ranges. In the event of data falling outside the established ranges, a text notification is dispatched to the IoT dashboard to inform the users. Pertaining to the forecasted growth anticipated by the model, the data is utilized to calculate the current fruit length and ascertain the optimal harvesting time. The calculated harvesting time is prominently displayed in the dashboard's text box. Furthermore, all the data is automatically stored in a .csv format for subsequent analysis and the refinement of system predictions. Notably, a 60-minute timer is employed to facilitate continuous and automated data retrieval from Adafruit IO, fruit growth prediction, and subsequent update within the Adafruit IO platform.

Table 3. Splitting Data into Train and Test

Index	Date	Temp (°C)	Humidity (%)	Soil Moisture (%)	Length	Growth
0	Wednesday, December 20, 2023 - 09:50:07	28.0	86	37.14	12.75	0.00
1	Wednesday, December 20, 2023 - 10:50:07	29.3	85	39.07	12.76	0.01

2	Wednesday, December 20, 2023 - 11:50:07	30.3	87	38.22	12.77	0.01
3	Wednesday, December 20, 2023 - 12:50:06	60.1	30	40.00	12.78	0.01
4	Wednesday, December 20, 2023 - 13:50:06	45.8	67	39.98	12.79	0.01
5	Wednesday, December 20, 2023 - 14:50:06	44.9	66	39.41	12.80	0.01
6	Wednesday, December 20, 2023 - 15:50:06	46.2	66	42.17	12.95	0.15
7	Wednesday, December 20, 2023 - 16:50:06	41.1	72	39.17	13.10	0.15
8	Wednesday, December 20, 2023 - 17:50:06	41.1	75	37.90	13.25	0.15
9	Wednesday, December 20, 2023 - 18:50:06	33.3	86	42.05	13.40	0.15

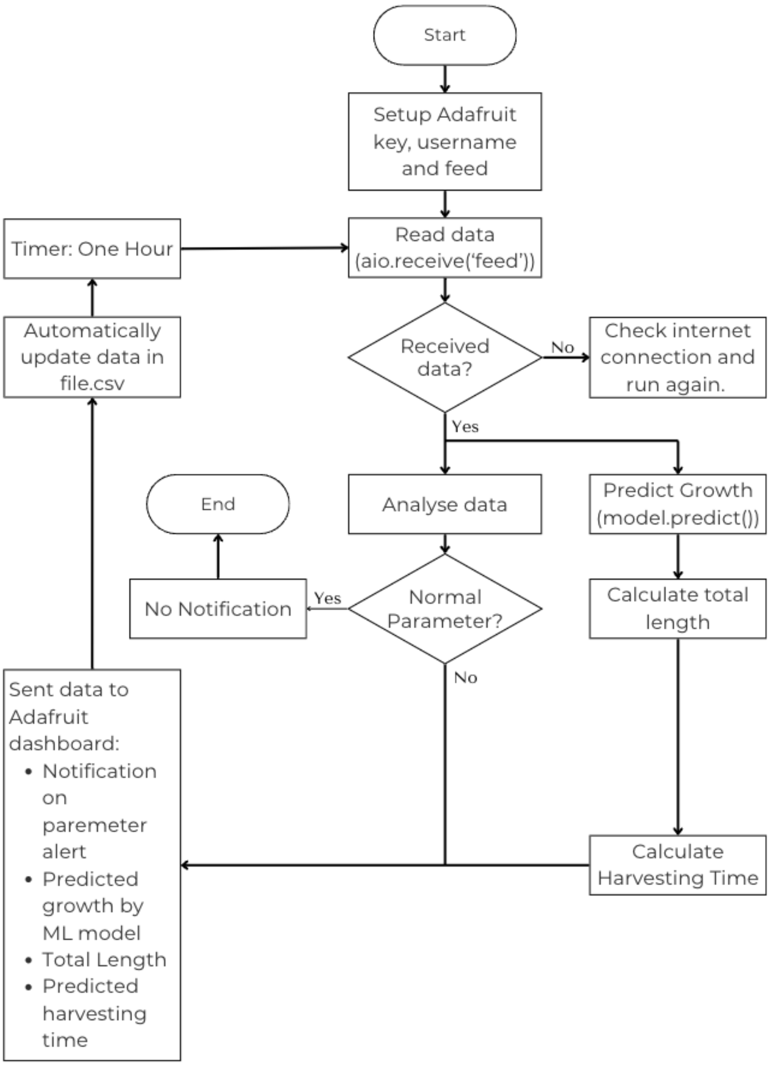

Figure 7. Flowchart integration of machine learning model and IoT platform

2.4 Accuracy of Model

The assessment of the machine learning system's proficiency in predicting fruit length entails the utilization of fundamental regression metrics, including the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), represented by Equation (1)-(3) correspondingly. Additionally, the Coefficient of Determination (R-squared) is employed to gauge the congruence between the predicted and actual data. Substantially lower MAE, MSE, and RMSE values are indicative of superior model performance, while a higher R-squared value signifies a heightened alignment of the model with the actual data.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_{actual,i} - y_{predicted,i}\right| \tag{1}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_{actual,i} - y_{predicted,i}\right)^2 \tag{2}$$

$$RMSE = \sqrt{MSE} \tag{3}$$

3.0 RESULTS AND DISCUSSION

This section delineates the outcomes of the project, encompassing the analysis of the collected sensor data, the findings derived from machine learning outputs, and the comprehensive evaluation of the system's performance. Furthermore, it engages in a discourse on the challenges and issues encountered during data monitoring and gathering, along with potential strategies to surmount these obstacles.

3.1 IoT System Output

The discussion of results in our IoT system involves analysis of the outcomes, particularly focusing on data accuracy and reliability, data insight, energy consumption and efficiency.

Ensuring accurate and reliable data from our deployed sensors is crucial for the success of the smart farming project. Three key sensors - the soil moisture sensor, DHT11 for temperature and humidity, and a rain sensor are utilised. To enable good prediction, soil moisture sensor needs to be regular recalibrated through diverse field tests to confirm its consistency in performance whilst considering external factors for optimum irrigation guidance. Similarly, the DHT11 sensor, used for temperature and humidity is tested and has demonstrated accuracy through evaluation against certified instruments. Rain sensor deployed to detect rain fall for every hour. However, during the data acquisition, the rain sensor value does not fully able to representant current weather condition. Thus, in the training dataset, the rain sensor data is removed to preserve the performance of the model. Implementation of shielding mechanisms and regular checks ensure reliable microclimate data. Adafruit dashboard shown in Figure 8 provides real-time data visualization and insight with line graph including growth data, temperature, humidity, and soil moisture allowing users to analyse the trend and take necessary steps such as to water plant to increase yield when data parameters are out of desired range. Two prominent features of the system are a real-time notification for out of parameters and predicted harvest time. These two allows farmers to plan and optimise their crop harvest and receive an alert for an effective maintenance.

The dashboard effectively enhances user decision-making and proactive management in the IoT system, by providing comprehensive data visualization, real-time monitoring, and predictive insights, facilitating a holistic understanding of crop conditions, thus enabling timely interventions for optimal agricultural practices.

3.2 Energy Consumption

A 20,000 mAh power bank operated the IoT system, including the ESP32 microprocessor, sensors, and actuator. Continuous monitoring revealed the power bank could sustain the system for approximately 50 hours which equate to approximate energy consumption of 2 watts per hour.

Figure 8 .Adafruit IO dashboard

3.3 Data Analytics and Relationship of Different Datasets

In Figure 9, a series of scatter plots is presented to illuminate the pairwise relationships across a dataset, specifically focusing on the analysis of variables. Notably, the dataset under scrutiny pertains to the Okra fruit, with "Fruit 1" and "Fruit 2" denoting the same fruit type from two distinct plants at varying time points. It is discerned from Figure 9 that the data distribution patterns of temperature, humidity, and soil moisture exhibit remarkable similarity across both fruits. However, a substantial disparity is observed in the data distribution patterns of length and fruit growth between the two fruits, signifying that environmental parameters alone do not wholly account for the variations in fruit length and growth. This observation suggests the existence of additional parameters influencing fruit growth, with the current fruit length or size posited as a potential influential factor.

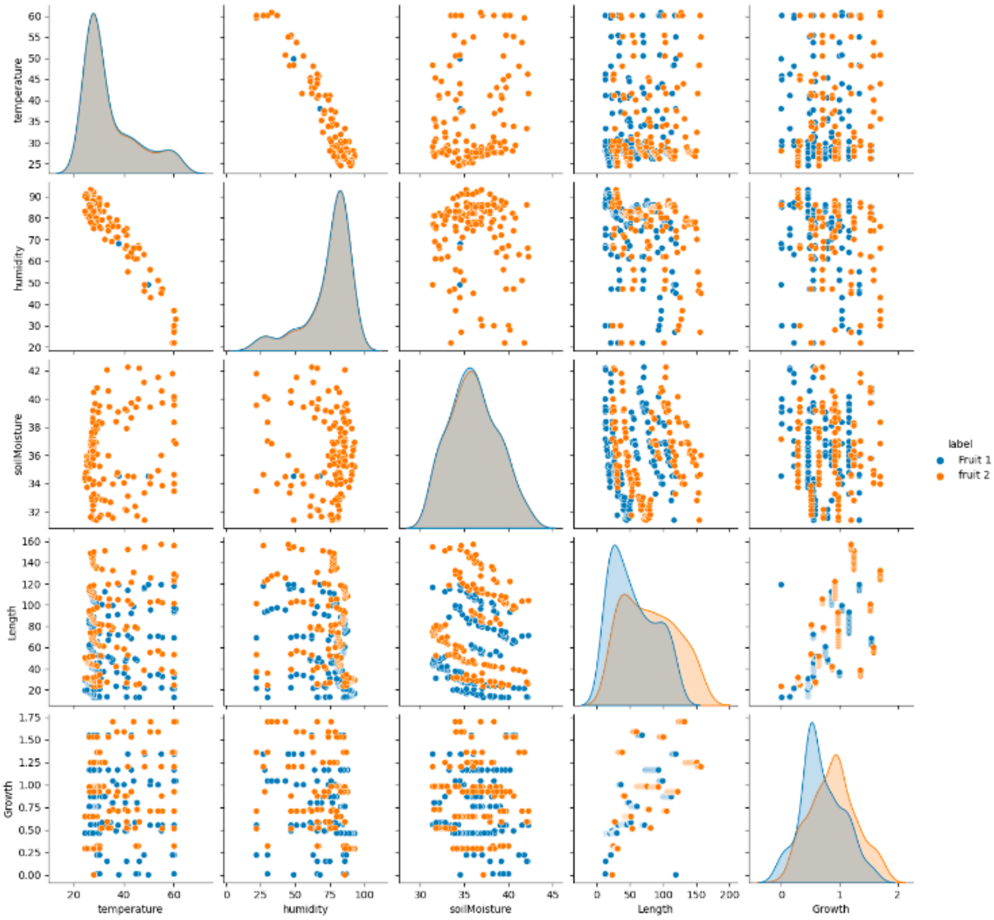

Figure 9. Pair plot the relationship between all variables.

To probe the relationship between fruit growth and length, a scatterplot graph of growth versus length is depicted in Figure 10. The analysis reveals that during the initial stages of fruit growth, characterized by a fruit length of approximately below 35 mm, the growth rate ranges from 0.01 mm to 0.6 mm per hour. In contrast, during the subsequent phase, encompassing the fruit's maturation until it reaches harvestable status, the growth rate escalates to between 0.6 mm and 1.75 mm per hour. This discernible pattern underscores the influence of fruit length on its growth rate.

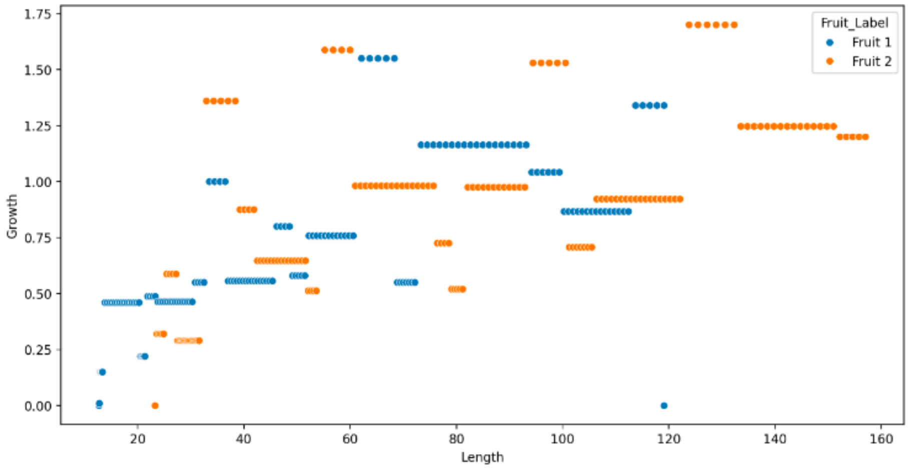

Figure 10. Scatterplot graph growth vs length

Consequently, the next phase of training data for the machine learning model involves the investigation of two distinct cases:

- Case A: Exclusion of the "length" dataset from model training.
- Case B: Inclusion of the "length" dataset in model training.

The objective is to validate the aforementioned data analysis observation, specifically to ascertain whether the inclusion of fruit length in the features dataset enhances the accuracy of the model's predictions, thus substantiating the influence of fruit length on growth.

3.4 Training Score for Different Regression Models

In order to ascertain the impact of incorporating the length dataset into the training features (X Train) on the model's performance, the dataset is subjected to training utilizing four distinct machine learning regression models: Random Forest Regressor (RF) [21], Decision Tree Regressor (DT) [22], K-Nearest Neighbours Regressor (KNN) [23], and Support Vector Machine (SVM) [24]. The outcomes of the different model scores are depicted in Figure 12.

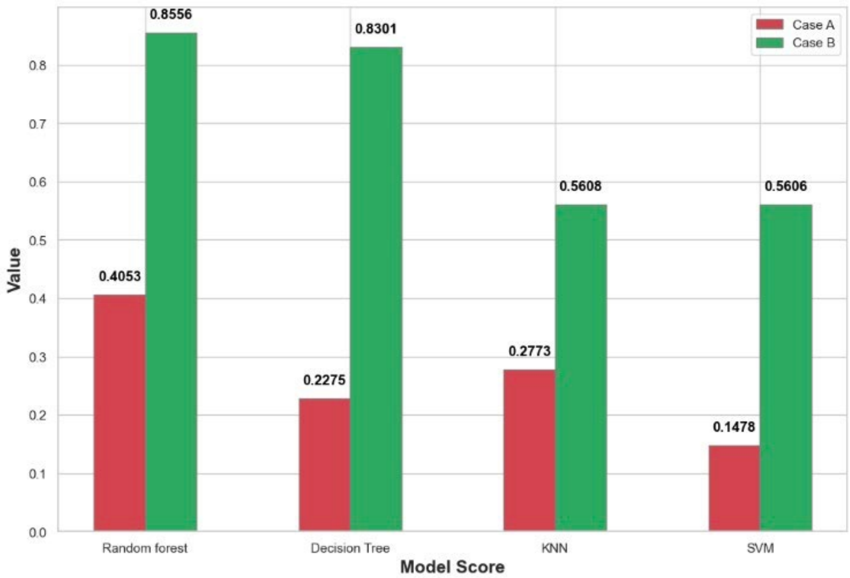

Figure 11. Comparison of machine learning models score toward both cases.

Notably, the scores of all models in case B consistently surpass those in case A. This observation leads to the inference that the inclusion of the "Length" dataset within the training dataset significantly enhances the system's performance. Furthermore, across all models in both cases, the Random Forest Regression model consistently exhibits the highest score.

Consequently, the Random Forest Regression model is deemed as the optimal choice for utilization within the smart agriculture system, facilitating the prediction of crop yield growth and the optimization of crop management practices.

3.4 System Performance

The one-to-one comparison between the system's predicted fruit length and the actual fruit length which includes extrapolated values is visually depicted in Figure 12. Figure 12 reveal a consistent growth trend in the predicted by machine leaning and actual length with extrapolated values, albeit with a minor tendency for the system to forecast slightly lower lengths. Although a small error is evident, the results remain remarkable and acceptable, empowering farmers to anticipate and plan harvesting times, thereby fostering enhanced farm management practices.

The predictive performance against actual growth measurements is further evaluated through key error metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), as illustrated in Figure 13. The MAE of 0.1537 signifies a modest average deviation of approximately 0.1537 mm in the model's predictions, aligning with the 0.01 mm to 2 mm per hour fruit growth range. Additionally, the MSE of 0.0528 and RMSE of 0.2298 highlight consistent and accurate predictions. Furthermore, the system's performance and accuracy with new data are gauged through the Coefficient of Determination (R-squared), as depicted in Figure 14. The substantial R-squared value of 0.98 underscores the system's precision in predicting new data, although the fortification of prediction robustness may necessitate additional data, considering the variability inherent in plant biological behaviours. In sum, the low error values and high score values substantiate the model's proficiency in predicting fruit growth.

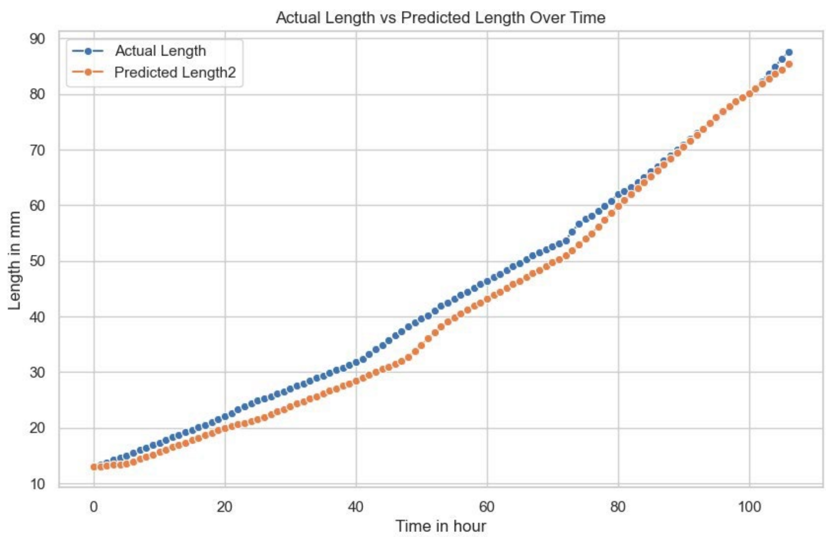

Figure 12. Comparison between actual length and predicted length.

```
# Assuming your CSV has columns named 'Actual_Growth' and 'Predicted_Growth'
actual_growths = data1['Actual_Growth'].values
predicted_growths2 = data1['Predicted_Growth2'].values

# Calculate Mean Absolute Error (MAE)
mae = np.mean(np.abs(actual_growths - predicted_growths2))
print("Mean Absolute Error (MAE):", mae)

# Calculate Mean Squared Error (MSE)
mse = np.mean((actual_growths - predicted_growths2) ** 2)
print("Mean Squared Error (MSE):", mse)

# Calculate Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)
print("Root Mean Squared Error (RMSE):", rmse)
```

```
Mean Absolute Error (MAE): 0.1537772585607477
Mean Squared Error (MSE): 0.05282195022421974
Root Mean Squared Error (RMSE): 0.22983026394324088
```

Figure 13. Screenshot of the error metric calculated by the system

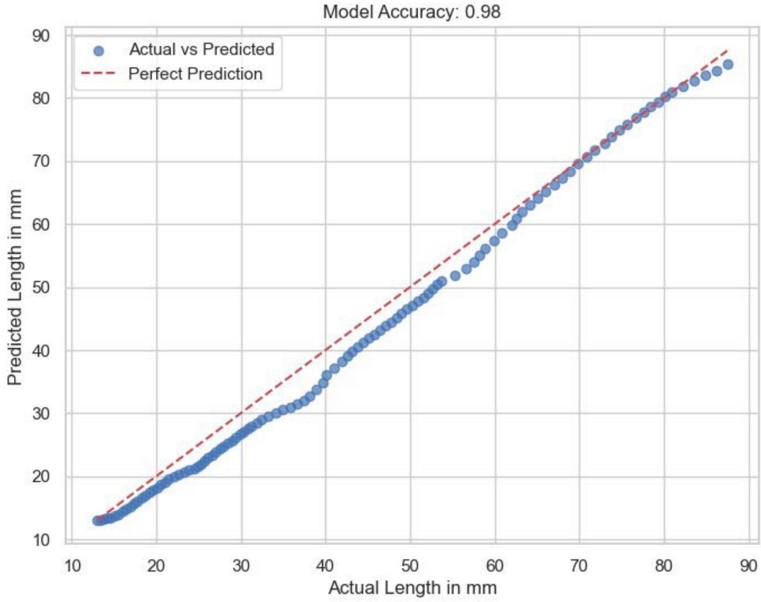

Figure 14 System accuracy towards new data collection

The integration of IoT technologies and machine learning in smart agriculture projects presents substantial potential for enhancing efficiency and improving yields. However, challenges manifest in the form of inaccurate and incomplete data, particularly in manual data acquisition utilizing less precise tools such as callipers. This underscores the imperative need for higher precision measurement tools, such as real-time calibrated augmented reality measurement, to elevate the accuracy of datasets. Reliability concerns arise from sensor malfunctions and maintenance issues, as exemplified by errors in soil moisture readings during data collection. Considerations related to cost are pivotal in designing an economically viable smart farming system, necessitating meticulous selection of microprocessors, sensors, and actuators. Furthermore, the deployment of hardware in open spaces mandates weather adaptability, addressed through the enclosure of components in a closed box. Power supply challenges necessitate the use of power banks, while internet connectivity demands continuous monitoring to avert interruptions in data acquisition. Lastly, the intricacies of crop growth influenced by biological factors underscore the significance of diverse and ample training data for precise machine learning predictions, prompting a focus on the pre-harvesting stage for data collection. A comprehensive understanding of these challenges is indispensable for the successful integration of advanced technologies into sustainable agricultural practices.

4.0 CONCLUSION

The smart agriculture system developed in this project has showcased remarkable accuracy and efficacy in predicting urban fruit growth, as evidenced by a Mean Absolute Error (MAE) of 0.1537 mm and low Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values. The consistent superiority of the Random Forest Regression model, culminating in a high R-Squared value of 0.98, underscores the system's predictive prowess. The seamless real-time integration of predictive insights into the Adafruit dashboard augments its practicality for farmers, despite encountering challenges such as inaccurate data and sensor maintenance. The successful mitigation of these obstacles substantiates the system's dependability. Notably, the project has met its objectives of furnishing an economical and data-centric solution for optimizing urban farming practices, marking a significant stride in agricultural technology.

Future endeavours for this smart agriculture project entail the assimilation of diverse datasets encompassing various plant species, alongside the expansion of crop predictions to encompass the entire growth cycle. Furthermore, the integration of additional sensors to monitor parameters such as soil pH, nitrogen, phosphorus, potassium, and rainfall, coupled with scalability enhancements for larger areas, reflects a commitment to bolstering the system's adaptability and predictive capabilities in precision farming.

5.0 CONFLICT OF INTEREST

The authors declare no conflicts of interest.

6.0 AUTHORS CONTRIBUTION

A.A. Mohamad Hakhrani (Methodology; Investigation; Data curation; Writing – original Draft; Validation)

S.B. Abdul Hamid (Conceptualisation; Writing - review & editing; Supervision; Formal Analysis)

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