Automated Hydroponic Growth Simulation for Lettuce Using ARIMA and Prophet Models During Rainy Season in Indonesia

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***Abstract*—Hydroponic farming particularly lettuce cultivation, is gaining popularity in Indonesia due to its economical use of water and space, as well as its short growing season. This study focuses on developing of an Automated Hydroponic Growth Simulation for Lettuce Using ARIMA and Prophet Models during the Rainy Season in Indonesia. We developed a simulation model for lettuce development in the Nutrient Film Technique (NFT) hydroponic system using data collected over four harvest periods during the rainy season in early 2024. Two machine learning models, ARIMA and Prophet, are tested to see which is more effective at forecasting lettuce growth. The Prophet model has the greatest results, with a Mean Absolute Error (MAE) of 1.475 and a Root Mean Square Error (RMSE) of 1.808. Based on this, the Prophet model is utilized to create a web application using Streamlit for real-time growth predictions. Future studies should include more data, particularly from the dry season, to increase model flexibility, as well as investigate the use of other crops and machine learning methods, including hybrid models, to improve forecasts.**

Keywords—ARIMA; automated; growth; hydroponic; prophet; simulation

I. Introduction

Hydroponics is a method of cultivating plants without soil, instead using water and nutrient solutions as the growing medium. This technology has become increasingly popular in Indonesia due to its efficiency in water and space usage, as well as its ability to produce higher-quality crops compared to conventional methods [1]. The trend of using hydroponics in Indonesia has surged in response to growing urban populations and the need for sustainable farming in controlled environments [2]. In Indonesia, hydroponic farming, especially for crops like lettuce, has become a widely adopted technique due to its ability to optimize space and produce yields faster than traditional farming methods. However, hydroponic plant growth is highly dependent on multiple variables. Internal variables such as nutrient concentrations, water temperature, and pH levels directly influence the plant's ability to absorb nutrients. External variables, such as ambient temperature, humidity, and light intensity, further determine the overall growth environment. Managing the interaction between these internal and external factors is complex, as even slight changes in one variable can drastically affect plant health and growth rate [2], [3]. Farmers currently face the challenge of not being able to simulate or predict plant growth. They must wait through the entire growth cycle to observe results, without any predictive system in place. This reliance on post-harvest data leaves room for inefficiencies, and farmers are unable to make informed interventions during the growth phase [4]. As a result, the need for a simulation model that allows real-time prediction and optimization of hydroponic plant growth is critical. Such a system would help farmers simulate future growth patterns, enabling them to make proactive adjustments to environmental variables and optimize the hydroponic system accordingly.

Hydroponics relies heavily on various environmental factors such as temperature, humidity, pH levels, and nutrient concentrations in the water, all of which play crucial roles in determining the growth rate and yield of the crops [5]. To maximize productivity, this study uses the Nutrient Film Technique (NFT) system, where plant roots are continuously submerged in a circulating nutrient solution, ensuring direct access to both nutrients and oxygen [6].

In this study, lettuce (Lactuca sativa) was chosen as the primary subject because it is widely cultivated hydroponically and has a relatively short growth cycle [1]. Data on plant growth was collected daily over four crop cycles, measuring key variables such as temperature, humidity, pH, and nutrient concentrations in the hydroponic solution [7]. Given the complexity of managing these variables, farmers often cannot accurately simulate growth patterns, leading to reliance on reactive measures rather than predictive optimization. This research aims to address that challenge by proposing an automated simulation model, particularly critical during dynamic weather conditions like Indonesia's rainy season. Data collection was carried out using calibrated instruments that were regularly checked for accuracy to ensure precise measurements [8]. This approach provides detailed data on the dynamic interactions of hydroponic variables that influence lettuce growth, offering key insights into how these factors can be optimized to enhance overall yields [9], [10].

Currently, there is no existing model that automatically simulates plant growth in the context of hydroponics, especially during the rainy season. Previous studies, such as those by Sambo et al. (2019) and Ullah et al. (2019), explored the use of IoT to monitor hydroponic variables in real time. However, these studies still rely on manual control without integrating automated plant growth simulations based on actual data. Similarly, Schwartz et al. (2019) addressed automation in hydroponics, but the model they proposed only accounted for static environmental conditions, not considering seasonal variables like rainfall.

Other studies have utilized predictive models such as ARIMA and Prophet, as seen in the work of Rajendiran & Rethnaraj (2024) and López Mora et al. (2024), which predominantly focus on industrial sectors or weather forecasting, rather than hydroponic farming. The application of these models to predict plant growth in hydroponic environments, especially during the rainy season, remains largely unexplored. Additionally, while there are studies that use ARIMA and Prophet to predict temperature or weather patterns, no research to date has directly compared the performance of these models in the context of lettuce hydroponics in Indonesia.

The research gap is further highlighted by the absence of models capable of integrating automated simulations into a practical web-based application that allows real-time interaction for hydroponic farmers. Such an application would allow farmers to take preemptive measures by simulating growth conditions and understanding the influence of dynamic weather patterns, especially during unpredictable rainy seasons in Indonesia [1], [5]. There is a significant opportunity to develop a web-based solution that facilitates automated plant growth simulations under dynamic seasonal conditions, such as Indonesia's rainy season [1], [2], [5]

This study aims to develop an automated hydroponic simulation model using regression-based ARIMA and Prophet models, focusing on lettuce growth during Indonesia’s rainy season. The data used is based on daily observations from January to May 2024. The model is designed to predict environmental variables such as temperature, humidity, and pH to optimize plant growth automatically. Additionally, this study compares the performance of the two predictive models by evaluating their results using the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics. The findings indicate that the Prophet model outperforms ARIMA in predicting seasonal conditions, particularly during the unstable weather of the rainy season. Finally, the superior Prophet model was implemented into an interactive web application, enabling hydroponic farmers to simulate plant growth automation in real-time. This application aims to improve efficiency and optimize hydroponic production in tropical environments with dynamic weather conditions.

This research introduces a novel approach by developing an automated hydroponic growth simulation model using ARIMA and Prophet, leveraging actual data from Indonesia’s rainy season—an area that has rarely been explored in the context of hydroponic farming. This approach allows for more accurate predictions of lettuce growth under dynamic tropical weather conditions. The main contribution of this study is the implementation of the superior Prophet model into an interactive web application, which enables hydroponic farmers to perform real-time automated plant growth simulations, thereby enhancing production efficiency during the rainy season. The research addresses the gap in the literature concerning the lack of automated hydroponic simulation models during the rainy season while offering a practical technology-based solution for hydroponic farmers.

II. Materials and Methods

A. Hydroponics

Hydroponics is a method of cultivating plants without soil, where nutrient-enriched water serves as the primary medium to meet the plants' nutritional needs. Hydroponics involves the use of water as a medium for the cultivation of crops [11]. This method is becoming increasingly popular in Indonesia due to its efficiency in using water and land, as well as its ability to produce higher-quality crops compared to conventional farming methods [1]. One of the most commonly used techniques in hydroponics is the Nutrient Film Technique (NFT), where a thin film of nutrient solution flows around the plant roots, providing direct access to oxygen and nutrients [2].

Key variables in a hydroponic system include temperature, humidity, pH, and nutrient concentration in the solution. The ideal temperature range for plant growth is between 18°C and 25°C, while the optimal pH level is between 5.5 and 6.5. Nutrient concentration is measured by Electrical Conductivity (EC), with the ideal range for lettuce being between 1.2 and 1.8 mS/cm. Additionally, the ideal humidity for hydroponic plants is between 50% and 70% [6]. If these variables are not properly controlled, plants can experience stress, negatively affecting crop yields [5]. Table I summarizes the ideal values for key variables in growing lettuce in a hydroponic system.

TABLE I. Ideal Variables for Growth Phase Lettuce in Hydroponic Systems [8]

Variable	Ideal Range
Temperature	18°C - 25°C
pH	6.0 - 7.0
Humidity	50% - 75%
EC (mS/cm)	1.2 - 1.8
Nutrients (ppm)	800 - 1000 ppm

Modern hydroponic systems often use automated sensors to monitor these variables in real-time, allowing for immediate adjustments if there are drastic changes in environmental conditions, such as during the rainy season. These sensors can detect temperature, pH, humidity, and nutrient levels, sending real-time data to a server for analysis and automatic adjustments [8]. Automated simulations based on seasonal environmental data are essential for maintaining the stability and efficiency of plant growth, especially during unpredictable weather conditions [2].

B. Machine Learning in Hydroponic Agriculture

Machine learning, a branch of artificial intelligence, enables computers to learn from data, recognize patterns, and make decisions or predictions without being explicitly programmed. In various fields, including agriculture, machine learning has become a powerful tool for optimizing processes and improving outcomes by utilizing predictive algorithms. In the agricultural sector, machine learning is widely applied to predict crop yields, manage resources, and monitor environmental conditions affecting plant growth. The use of machine learning in hydroponic systems helps farmers make faster and more accurate decisions based on real-time data collected from sensors in the field [12].

One common approach in machine learning is supervised learning, where models are trained using labeled data to predict specific outcomes or decisions. In hydroponics, supervised learning is often used to predict variables that influence plant growth, such as temperature, humidity, pH levels, and nutrient concentrations. Algorithms frequently employed in this context include Random Forest, Decision Trees, Support Vector Machines (SVM), and Neural Networks. These algorithms can help farmers manage resources efficiently and increase crop productivity [13]. For example, Random Forest is particularly useful for predicting the non-linear relationships between environmental variables that affect crop yields in hydroponic systems [14].

Machine learning applications in agriculture, particularly hydroponics, also involve models like Long Short-Term Memory (LSTM) and ARIMA, which are designed to handle time-series data. LSTM, a type of neural network, is used to process sequential data and is well-suited for predicting time-related variables such as temperature or humidity in hydroponic systems [15]. On the other hand, ARIMA is used to analyze seasonal data and make long-term predictions based on historical trends. Both models are instrumental in optimizing hydroponic systems by maintaining ideal conditions for plant growth [16].

In IoT (Internet of Things)-based hydroponic systems, sensors collect real-time data that is then processed by machine learning algorithms. This technology allows for automated simulations that adjust key plant growth parameters, such as nutrient supply and temperature control. These models provide predictive recommendations to farmers, enabling them to manage hydroponic systems efficiently without the need for continuous manual intervention [17]. Overall, the integration of machine learning has revolutionized hydroponic management, from monitoring environmental variables to automating production processes [12].

Moreover, machine learning enhances the accuracy of yield predictions by analyzing environmental variables that influence plant growth. For example, regression models can predict plant growth behavior in hydroponic systems based on historical data, allowing farmers to make more informed decisions regarding crop management. With the increasing adoption of machine learning technology in agriculture, these predictive models hold significant potential for improving efficiency and productivity in modern farming environments [12], [18].

C. ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model is a widely used statistical method for analyzing and predicting time-series data. It is particularly popular for its ability to process data with seasonal patterns, trends, and stochastic components, which often occur in datasets related to price forecasting, weather, and, in this context, agriculture and hydroponics. ARIMA is highly effective at handling non-stationary data, where the data distribution changes over time—a pattern frequently seen in environmental variables such as temperature, humidity, and nutrient levels in hydroponic systems [19].

The ARIMA model consists of three main components: Autoregressive (AR), Integrated (I), and Moving Average (MA). The AR component predicts future values based on the past values of the variable. The I (Integrated) component is used to transform non-stationary data into stationary data by calculating the differences between consecutive data points. The MA (Moving Average) component predicts future values based on the errors (residuals) of previous predictions (Pindipo et al., 2023). The ARIMA model is commonly written as ARIMA(p, d, q), where p refers to the order of the autoregressive component, d is the degree of differencing to make the data stationary, and q is the order of the moving average component [20].

The general formula for ARIMA can be expressed as follows:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \qquad (1)$$

In this equation, Y_t represents the actual value at time t, c is a constant, ϕ_i are the AR coefficients, θ_j are the MA coefficients, and ϵ_t is the residual error at time t. The ARIMA model focuses on two key aspects of time-series data: trends and residual errors. In this context, the observed trends in past data are used to predict future values, while the influence of random fluctuations is minimized [21].

The ARIMA process begins by examining whether the data is stationary. If it is not, the model applies differencing to stabilize the data by calculating the differences between consecutive values until the data becomes stationary. Once the data is stationary, the autoregressive (AR) component predicts future values based on past data, while the moving average (MA) component accounts for prediction errors from the AR model [22]. This approach allows ARIMA to handle time-series data with seasonal patterns and complex trends, making it well-suited for predicting environmental variables such as temperature, humidity, and nutrient levels in hydroponic systems [20].

One of the key strengths of the ARIMA model is its ability to handle non-stationary data, which is often a challenge in time-series analysis. However, ARIMA also has limitations, such as its reduced flexibility in managing highly complex or non-linear data, where more advanced models like Long Short-Term Memory (LSTM) networks or Neural Networks tend to perform better. Therefore, in some studies, ARIMA is combined with other models to enhance prediction accuracy [19], [23].

In agriculture and hydroponic systems, ARIMA has been widely applied to predict environmental variables that influence plant growth. For example, Menculini et al. (2021) compared the performance of ARIMA with deep learning models in forecasting food prices, finding that while ARIMA is reliable for short-term predictions, deep learning models are better suited to handling more complex time-series data. In hydroponic systems, ARIMA has been used to predict humidity and temperature levels, which are crucial for maintaining a stable growing environment. The combination of ARIMA with real-time sensor data allows hydroponic farmers to make faster and more accurate decisions in managing environmental conditions [24].

Additionally, ARIMA is frequently used to forecast temperature and weather patterns, which are key factors in agriculture and hydroponics. For instance, Elseidi et al. (2024) applied ARIMA to predict high-frequency temperature data and combined it with the Prophet model to improve accuracy. Their findings showed that the hybrid ARIMA-Prophet model provided more accurate forecasts than ARIMA alone, particularly in cases where the data exhibited strong seasonal patterns or trends [20].

In another study, Pindiga et al. (2023) compared ARIMA with the Facebook Prophet model in predicting stock indices, which also exhibit seasonal patterns and trends similar to agricultural data. The results indicated that Prophet tends to outperform ARIMA when handling complex seasonal data, but ARIMA remains a strong choice for short-term predictions or simpler datasets [25].

ARIMA's applications in agriculture are not limited to environmental variable predictions. The model has also been used to forecast crop yields based on historical growth data and weather conditions. Kasthuri et al. (2021) used ARIMA in combination with Neural Networks to predict food production yields, offering more accurate crop yield forecasts in scenarios where environmental variables fluctuate significantly. This hybrid approach is becoming increasingly popular in time-series prediction, especially in the agricultural sector, which depends heavily on seasonal data and changing weather conditions [26].

Overall, ARIMA is a powerful and versatile model for time-series data analysis and forecasting. With its ability to process non-stationary data and handle trends and seasonal patterns, ARIMA is well-suited for use in hydroponic farming. However, for more complex or non-linear datasets, hybrid models or deep learning techniques may provide better results. Nonetheless, ARIMA remains one of the most widely used models for time-series forecasting due to its simplicity and reliability in processing relatively straightforward data [19], [21].

D. Prophet Model

The Prophet model is a time-series forecasting tool developed by Facebook (now Meta) designed to handle data with seasonal patterns, trends, and outliers. Prophet is often used for predicting data that exhibits instability in trends, such as sudden changes or irregular seasonal patterns. One of its key strengths is its ability to handle gaps (missing data) and outliers effectively, while still providing accurate predictions even in rapidly changing conditions [22].

Unlike traditional time-series models like ARIMA, Prophet uses an additive approach, where the trend, seasonal, and outlier components are treated separately and then combined to produce the final forecast. The model assumes that time-series data can be broken down into three main components: trend $g(t)$, seasonality $s(t)$, and holiday or event effects $h(t)$, with an additional residual or noise component ϵt. Mathematically, the Prophet model can be described by the following equation [27]:

$$y(t) = g(t) + s(t) + h(t) + \epsilon t \tag{2}$$

Where:

- $y(t)$ is the predicted value at time ttt,
- $g(t)$ is the trend component,
- $s(t)$ is the seasonal component,
- $h(t)$ represents holidays or special events,
- and ϵt is the noise component [28].

Prophet uses piecewise linear regression or logistic growth to capture trends in the data. One of its advantages is the ability to automatically adjust the number of change points in the trend, allowing the model to account for sudden shifts in direction. The seasonal component is defined by a set period, such as yearly, weekly, or monthly, enabling Prophet to capture recurring seasonal patterns more flexibly. The holiday or event component allows for the inclusion of external factors like holidays or recurring seasonal events, which can influence the data [29].

Prophet is highly intuitive to use because it automatically detects and handles missing data within the time-series. The model can also adjust the prediction intervals by giving more confidence to the trend and seasonal components, compared to more traditional time-series models [30]. Additionally, Prophet allows users to customize the prediction intervals, providing flexibility in terms of accuracy and margin of error based on the user's needs [31].

One common application of Prophet is in stock price forecasting and economic data predictions, which require accurate forecasts that can handle fluctuating seasonal trends and trends that are often unstable. For example, Jin et al. (2022) used Prophet to predict Google stock prices, while Angelo & Fadhilrahman (2023) compared the performance of Prophet and ARIMA in forecasting Bitcoin prices. Their findings indicated that Prophet excels in capturing complex seasonal trends and handling data with significant fluctuations [22], [32].

Prophet is also widely used in the energy and weather sectors. For instance, Elseddi et al. (2024) combined Prophet with ARIMA to forecast temperature data, achieving better accuracy than using ARIMA alone. This hybrid approach allows for more comprehensive forecasting by capturing different characteristics of the time-series data [20].

Overall, Prophet is a powerful and flexible model for forecasting complex time-series data, particularly when the data has irregular seasonal patterns. With its additive approach and its flexibility in handling outliers, Prophet offers significant advantages across various sectors, including economics, agriculture, energy, and weather forecasting. Its wide applications range from predicting food prices and crop yields to forecasting energy demand and weather patterns [24].

E. Evaluation Matrix

In evaluating the performance of predictive models, two of the most commonly used metrics are the Mean Absolute Error

(MAE) and the Root Mean Square Error (RMSE). These metrics are essential in assessing how well a model predicts data and provide insight into the level of error between predicted values and actual values.

1) Mean Absolute Error (MAE): The Mean Absolute Error (MAE) measures the average of the absolute differences between predicted values and actual values. MAE gives an overall sense of how much error the model makes on average, without considering whether the error is positive or negative, as all errors are treated equally. The general formula for calculating MAE is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

Where:

- y_i is the actual value,
- $\hat{y}_i$ is the predicted value,
- n is the number of data points.

MAE provides an intuitive and easy-to-understand result since it shows the magnitude of errors in the same units as the original data. For example, in a study by Kenyi and Yamamoto (2024), MAE was used to evaluate the performance of the SARIMA-Prophet model in predicting water flow, and the results showed that MAE helped identify the average level of prediction error at each time point [33]. Another study by Angelo and Fadhilrahman (2023) used MAE to compare the performance of ARIMA and Prophet models in predicting Bitcoin prices, demonstrating how MAE can measure the accuracy of time-series predictions in complex datasets [32].

2) Root mean square error (RMSE): Root Mean Square Error (RMSE) is another common metric for evaluating predictive model accuracy. RMSE calculates the square root of the average squared differences between predicted and actual values. Unlike MAE, which focuses on absolute differences, RMSE gives more weight to larger errors because the errors are squared before being averaged. The general formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

Where:

- y_i is the actual value,
- $\hat{y}_i$ is the predicted value,
- n is the number of data points.

RMSE is particularly useful when larger errors are more undesirable than smaller ones, as it penalizes large errors more heavily. In a study by Hamiane et al. (2024), RMSE was used to measure the accuracy of hybrid LSTM, ARIMA, and Prophet models in predicting future GDP, showing that RMSE was highly effective in identifying significant differences between predictions and actual data over certain periods. Similarly, Mokhtar et al. (2022) applied RMSE to predict hydroponic yields, revealing that RMSE is more sensitive to outliers than MAE, making it an important evaluation metric when dealing with highly variable data [13], [34].

Using both RMSE and MAE together provides a more comprehensive picture of model performance. While MAE gives a general overview of the average error, RMSE emphasizes larger errors, which can be crucial in applications where minimizing extreme errors is important. Therefore, in many studies, these two metrics are often used together to evaluate time-series predictive models, including in hydroponic farming and energy prediction applications [12].

This combined approach allows for a better understanding of model behavior under various conditions, ensuring that both overall performance and outlier sensitivity are addressed. By evaluating models using MAE and RMSE, researchers can fine-tune predictions to optimize both short-term and long-term outcomes

F. *Dataset Preparation Description*

In the process of preparing the dataset for machine learning modeling, the first step involved collecting data from the hydroponic system. The dataset includes several critical environmental and growth metrics to ensure that the information fed into the models is relevant and accurate.

TABLE II. INITIAL DATASET SHOWING ENVIRONMENTAL CONDITIONS AND PLANT GROWTH METRICS

	day	hole	time	temperature	humidity	light	pH	Ec	TDS	WaterTemp	LeafCount
0	1	1	09:19:00	26.8	72	17820	7.2	677	340	26.1	3
1	1	2	09:23:00	26.6	72	16490	7.2	677	338	26.1	3
2	1	3	09:27:00	26.4	72	15160	7.2	678	334	26.1	3
3	1	4	09:31:00	26.2	72	13830	7.2	677	338	26.1	3
4	1	5	09:35:00	26.2	72	12500	7.2	673	340	26.1	3

The Table II, summarizes the primary data columns that were included in the dataset. This data was collected at specific time intervals from each plant hole in the hydroponic system.

- Day: Represents the day number during the data collection process, crucial for understanding time-based trends and growth patterns in the plants [12].
- Hole: This refers to the individual plant hole in the hydroponic system. Each hole corresponds to a plant, and this column ensures that the data collected is specific to each plant [35].
- Time: Indicates the exact time the data was recorded. Time tracking is crucial for analyzing daily patterns in plant growth [36].

- Temperature (°C): Records the temperature of the growing environment. Maintaining optimal temperature is vital for plant growth, with prior studies suggesting its significance in hydroponic systems [20].
- Humidity (%): This column records the humidity levels in the environment, an important factor affecting plant water intake and overall health [37].
- Light (lux): Measures the intensity of light, which directly influences photosynthesis and plant growth. The importance of this factor is well-documented in the works of Lontsi Saadio et al. (2022) [14].
- pH: Captures the pH level of the nutrient solution. Balanced pH levels ensure optimal nutrient absorption [8].
- EC (mS/cm): Electrical Conductivity measures the concentration of nutrients in the solution. The correct EC level ensures that plants receive the necessary nutrients for growth [37].
- TDS (ppm): Total Dissolved Solids measure the concentration of dissolved substances, including essential nutrients. This helps monitor nutrient levels in the solution, as supported by Schwartz et al. (2019) [1].
- WaterTemp (°C): This column represents the temperature of the water or nutrient solution, which is crucial for maintaining healthy root systems [36].
- LeafCount: Records the number of leaves on each plant, serving as a metric for plant growth and overall health. Studies show that an increasing leaf count indicates good plant health [34].

This dataset provides comprehensive data necessary for analyzing environmental conditions and their impact on plant growth in a hydroponic system. Each column represents a critical factor in understanding and optimizing plant development, making it a solid foundation for further data processing and modeling.

G. *CRISP-DM Methodology*

CRISP-DM (Cross Industry Standard Process for Data Mining) is a widely used methodology for structuring data mining projects. Developed in the late 1990s, it provides a systematic and flexible approach applicable across industries, particularly in projects involving complex data analysis. This methodology is commonly applied in various machine learning applications, including hydroponic farming, to guide the entire development process, from the initial stages to deploying a fully functional predictive model [38].

The first phase of CRISP-DM is business understanding, which is crucial for identifying the project's business goals. This phase involves defining the business problems clearly and determining how data mining can provide actionable solutions. In the context of agricultural research, such as yield prediction using environmental data, this stage helps shape the problem and goals, such as optimizing crop yields in hydroponic systems [9].

After establishing the business goals, the next phase is data understanding. This phase focuses on gathering and exploring relevant data to gain an initial insight into the structure and characteristics of the dataset. Data exploration aims to identify patterns, outliers, and relationships between variables. For example, in machine learning studies related to hydroponics, data could include temperature, humidity, and nutrient levels, which would be further analyzed for patterns [4].

The third phase is data preparation, where the collected data is cleaned and prepared for analysis. This involves various steps such as handling missing values, transforming data, and selecting relevant features for the model. The quality of the data is crucial, as cleaner and more relevant data directly impact the model's performance [38].

Once the data is prepared, the next phase is modeling. This is where machine learning algorithms or data mining techniques are applied to the dataset. Depending on the objectives, different algorithms, such as regression or classification, may be used. For agricultural yield prediction, models like Random Forest or Neural Networks are often employed to predict critical variables affecting plant growth. Each model is evaluated to ensure it accurately predicts outcomes according to the predefined goals [9].

Following modeling, the evaluation phase assesses the performance of the model. Here, various evaluation metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to measure the accuracy and reliability of the model on both training and unseen test data. This ensures that the model is robust and reliable for real-world applications [4].

The final phase of CRISP-DM is deployment, where the evaluated model is integrated into an operational system. At this stage, the model is embedded into broader business processes to provide real-world benefits. For example, in an IoT-based hydroponic system, the developed model can be used by farmers to monitor environmental conditions in real-time and make decisions based on the model's predictions [39].

The usefulness of CRISP-DM lies in its structured and organized approach to managing data mining projects. Each phase can be revisited or refined as needed, ensuring that the desired outcomes are systematically achieved. In the context of machine learning research for hydroponics, CRISP-DM allows for the development of accurate and relevant models that optimize agricultural yields under dynamic environmental conditions [40].

Fig. 1 below illustrates a conceptual framework that combines exploratory data science activities, goal-directed CRISP-DM phases, and core data management activities. The outer circle represents broader exploration activities, while the inner circle shows the structured steps of the CRISP-DM process. At the center are essential data management activities such as data acquisition, simulation, and preparation, which are critical for the success of any data mining project [41].

To effectively address the complexities of managing hydroponic systems in Indonesia's unique climatic conditions, the CRISP-DM methodology was adopted and adapted to the specific needs of this research. The proposed methodology integrates the structured phases of CRISP-DM, such as data collection, modeling, and deployment, while incorporating tailored adjustments for hydroponic farming. The figure below illustrates the proposed methodology, which includes detailed steps drawn from the CRISP-DM framework, optimized for the implementation of ARIMA and Prophet models in the context of hydroponic lettuce growth during the rainy season.

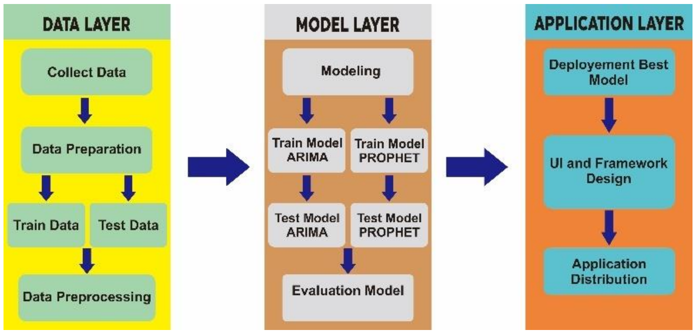

Fig. 1. Proposed methodology based on CRISP-DM framework.

The proposed methodology, as shown in Fig. 1, follows the CRISP-DM framework to provide a systematic approach for predictive modeling in hydroponic farming. ARIMA and Prophet were chosen as the primary models due to their strengths in handling time-series data. ARIMA is effective for stationary data with linear trends but is limited in managing irregular seasonal patterns. Prophet, on the other hand, excels in handling non-stationary data, incorporating flexible seasonalities, and managing missing data, making it more suitable for the dynamic nature of hydroponic systems.

Compared to traditional regression models, which lack temporal dependency analysis, and advanced machine learning methods, which demand larger datasets and computational resources, ARIMA and Prophet offer an optimal balance of accuracy, efficiency, and practicality. This methodology ensures each phase, from data preparation to model deployment, is rigorously executed, creating a scalable framework that can be expanded to other crops or environmental conditions in future research.

The Data Layer represents the initial phases of CRISP-DM, namely Data Understanding and Data Preparation. According to CRISP-DM, understanding and preparing data are foundational to successful modeling. In this research, the data collected includes key environmental parameters such as temperature, humidity, light, pH, Electrical Conductivity (EC), Total Dissolved Solids (TDS), and water temperature— all critical for hydroponic plant growth. The data preparation process involves splitting the dataset into training and test sets, ensuring that both the training data and the test data undergo preprocessing to eliminate noise, handle missing values, and standardize formats.

Data preprocessing is vital because the quality of the input data directly influences the performance of machine learning models. According to Schwartz et al. (2019), high-quality data preparation significantly improves the accuracy of predictive models, especially in controlled environments like hydroponics, where multiple variables can affect plant growth.

The Model Layer corresponds to the Modeling phase in CRISP-DM, where machine learning algorithms are applied to the prepared dataset. This layer includes the training and testing of both ARIMA and Prophet models, which are widely used for time-series forecasting.

1) Training the ARIMA model: The ARIMA model is trained on the dataset to capture time-series patterns that influence plant growth under various environmental conditions. ARIMA has been employed in agriculture for its effectiveness in forecasting time-series data, though it often requires stationary data and is sensitive to outliers.

2) Training the prophet model: Developed by Facebook, Prophet is more flexible than ARIMA and can handle missing data, seasonality, and trends more efficiently. It is particularly effective in capturing the irregular trends often seen in agricultural environments, such as during unpredictable weather patterns like Indonesia’s rainy season.

3) Model evaluation: The models are tested on unseen test data, and their performance is evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These metrics provide insight into how well each model predicts the key environmental variables that affect lettuce growth. Comparative evaluations ensure that the best model—Prophet in this case—is identified for deployment.

The Application Layer reflects the Deployment phase in CRISP-DM. After evaluating the models, the best-performing model (Prophet) is deployed into a user-friendly web application designed for practical use by hydroponic farmers. This phase involves integrating the trained model into an operational system that can deliver real-time predictions, which allows farmers to make data-driven decisions.

4) UI and framework design: The model is integrated into an intuitive user interface, ensuring that farmers can interact with the application easily. This user interface is designed to simulate plant growth automatically and adjust to real-time data inputs, offering farmers actionable insights into optimizing their hydroponic systems.

5) Application distribution: The final step is distributing the application, making it accessible to users for real-time hydroponic growth simulations. This practical deployment ensures that the model's predictions are embedded into daily decision-making processes, improving efficiency and crop yields in dynamic environments like Indonesia’s rainy season

III. Results and Discussion

A. Data Preparation

In this study, data preparation is a crucial step performed before the modeling process. This phase involves data collection and exploratory data analysis (EDA) to ensure that the processed data is of high quality, leading to the development of accurate models. Previous research highlights that data preparation is vital in machine learning and data mining projects, as errors in this stage can significantly reduce model performance [24]. In this research, data was gathered from a Nutrient Film Technique (NFT) hydroponic system used for growing lettuce (Lactuca sativa) during the rainy season in Indonesia. The system involved monitoring various environmental variables and plant growth [8]. The collected data included temperature, humidity, light intensity, pH, total dissolved solids (TDS), electrical conductivity (EC), water temperature, and the number of leaves. Fig. 2 illustrates the NFT hydroponic system used for data collection, along with the measurement tools employed to capture environmental and plant growth variables.

Fig. 2. Lettuce in the NFT hydroponic system and the calibration equipment.

Fig. 2 shows the lettuce plants grown in the NFT system, where environmental and growth data were collected starting from the first day after planting until harvest on day 40. In the NFT system, plant roots continuously receive nutrients and oxygen through a thin film of flowing solution, enabling optimal plant growth. As noted by Abioye et al. (2022), the NFT system offers advantages in efficient use of nutrients and water in hydroponic crop production [42].

Also shown in the figure are several measurement tools used to collect data on environmental variables, such as a Hygrometer to measure temperature and humidity, and a Lux Meter to measure light intensity. These measurements are crucial for monitoring environmental conditions that affect plant growth. As noted by Sundari et al. (2022), even small changes in light intensity can have a significant impact on the photosynthesis process [43]. Additionally, a pH-TDS-EC meter was used to measure pH, TDS, EC, and water temperature, all of which are key variables in ensuring plants receive sufficient nutrients. Data on the number of leaves, used as a growth variable, was collected through direct observation by counting the number of new leaves each day.

By conducting this thorough data collection process, the study follows a detailed methodology to maximize hydroponic crop yields, particularly during the challenging rainy season [24], [42].

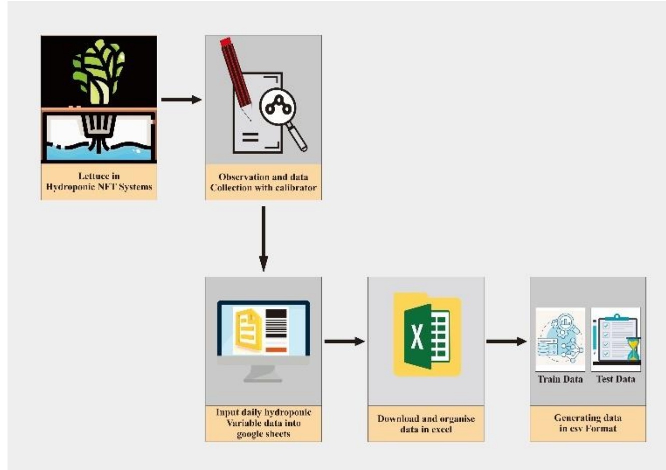

Fig. 3. Stages in the data preparation phase.

The data preparation phase begins after daily data collection from hydroponic variables and lettuce growth in the NFT system. As shown in Fig. 3, data from environmental variables and lettuce growth are manually inputted into Google Sheets each day. This data collection involves the use of various measurement instruments, such as a Hygrometer for temperature and humidity, a Lux Meter for light intensity, and a pH-TDS-EC meter for measuring pH, TDS, and water conductivity (EC), in accordance with standard hydroponic data collection protocols (Sambo et al., 2019).

After collecting data over the 40-day period, from planting to harvest, the data is downloaded from Google Sheets and organized in Excel for further validation and processing, such as formatting adjustments and data cleaning. This step is crucial to ensure there are no outliers or input errors that could impact the predictive model’s results (Abioye et al., 2022). The data is then divided into training and testing datasets as required for the machine learning model's training and testing phases (Menculini et al., 2021). In the final stage, the data is saved in CSV format, ready to be used for modeling.

This process enables researchers to maintain data integrity and optimize the quality of the dataset before using it in predictive models. These steps align with methods commonly used in the CRISP-DM (Cross-Industry Standard Process for Data Mining) approach, which emphasizes the importance of proper data preparation to achieve optimal results in machine learning projects (Ayele et al., 2020).

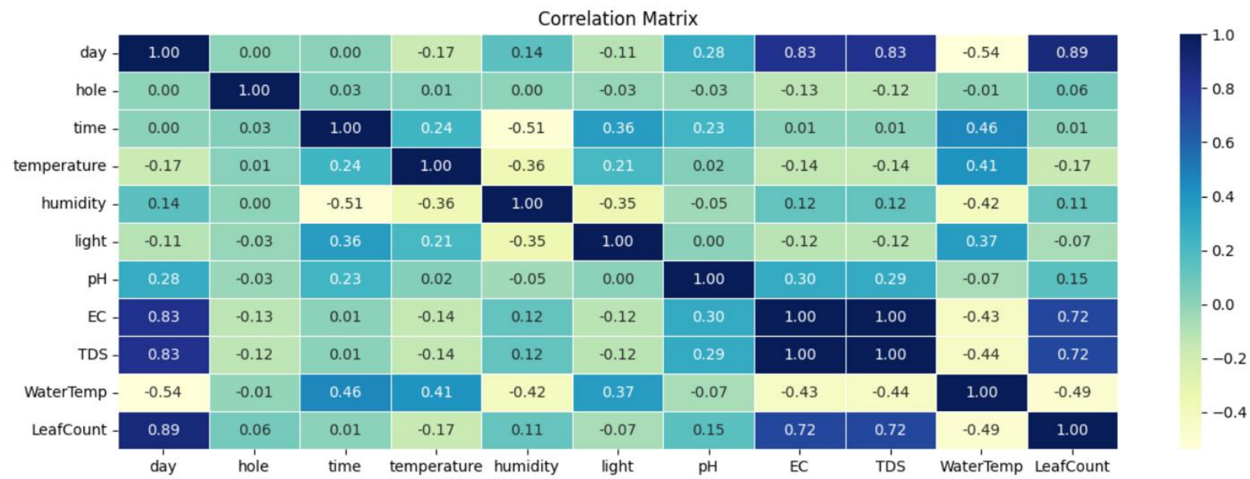

Fig. 4. Correlation matrix.

The correlation matrix is a table that displays the linear relationships between variables in a dataset. Correlation values range from -1 to 1, where a value of 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no correlation. In data analysis, a correlation matrix helps to understand how variables influence one another and how they might affect the predictive model being developed (Chopra & Khurana, 2023).

From Fig. 4, it is evident that some variables show strong correlations with each other. One of the most prominent examples is the relationship between EC (Electrical Conductivity) and TDS (Total Dissolved Solids), with a correlation value of 1.00. This perfect correlation indicates that EC and TDS are directly related, meaning any change in one variable is always accompanied by the same change in the other. This makes sense in the context of a hydroponic system, where EC measures the concentration of dissolved ions in water, while TDS measures the total amount of dissolved solids. Since EC and TDS essentially measure almost the same aspect of water nutrition, these variables move in tandem.

Additionally, a strong correlation is observed between EC and Leaf Count, with a correlation of 0.72. This suggests that the nutrient concentration (measured by EC) has a significant impact on the number of leaves produced. This aligns with findings from other studies, which highlight that balanced nutrient levels in hydroponics play a crucial role in maximizing plant growth (Sambo et al., 2019).

Another noteworthy correlation is between Day and Leaf Count (0.89), showing that as time progresses (in days), the number of leaves on the plants increases, reflecting a consistent growth process over time. This relationship is important for understanding plant growth patterns, particularly in a hydroponic system, where growth is highly influenced by time and nutrient levels.

However, there are some variables that do not show significant correlations with each other. For instance, Humidity and Water Temperature have a negative correlation (-0.42), indicating that as water temperature increases, humidity tends to decrease. This relationship, however, may not be entirely linear and may require further analysis to understand its impact on plant growth.

Overall, this correlation matrix provides valuable insights into the relationships between variables in the hydroponic system under study. Understanding these relationships will help in building more accurate predictive models by focusing on variables with significant correlations to key outcomes, such as leaf count and nutrient effectiveness in the water.

A correlation matrix is a numerical representation used to describe the linear relationships between two or more variables in a dataset. In the context of machine learning, the correlation matrix is crucial for understanding how variables relate to each other. Strong positive or negative correlations between variables can influence the model's outcomes, as a well-built model should account for inter-variable relationships to avoid redundancy or excessive bias in predictions [18].

In Fig. 5, histograms of key variables in this study such as temperature, humidity, light, pH, EC, TDS, and leaf count are presented to provide an overview of the distribution and variation patterns of each measured variable in the hydroponic system. These histograms help to understand the basic characteristics of the collected data and to identify potential outliers or abnormal distributions.

The temperature distribution ranges from 24°C to 32°C, with the highest frequency between 26°C and 28°C. This pattern indicates that the temperature in the hydroponic environment remains fairly stable within the optimal range for lettuce growth, with extreme temperatures rarely occurring. The humidity distribution shows significant variation, ranging from 40% to 100%, with the highest frequency around 70%, indicating relatively high humidity during most of the measurement period.

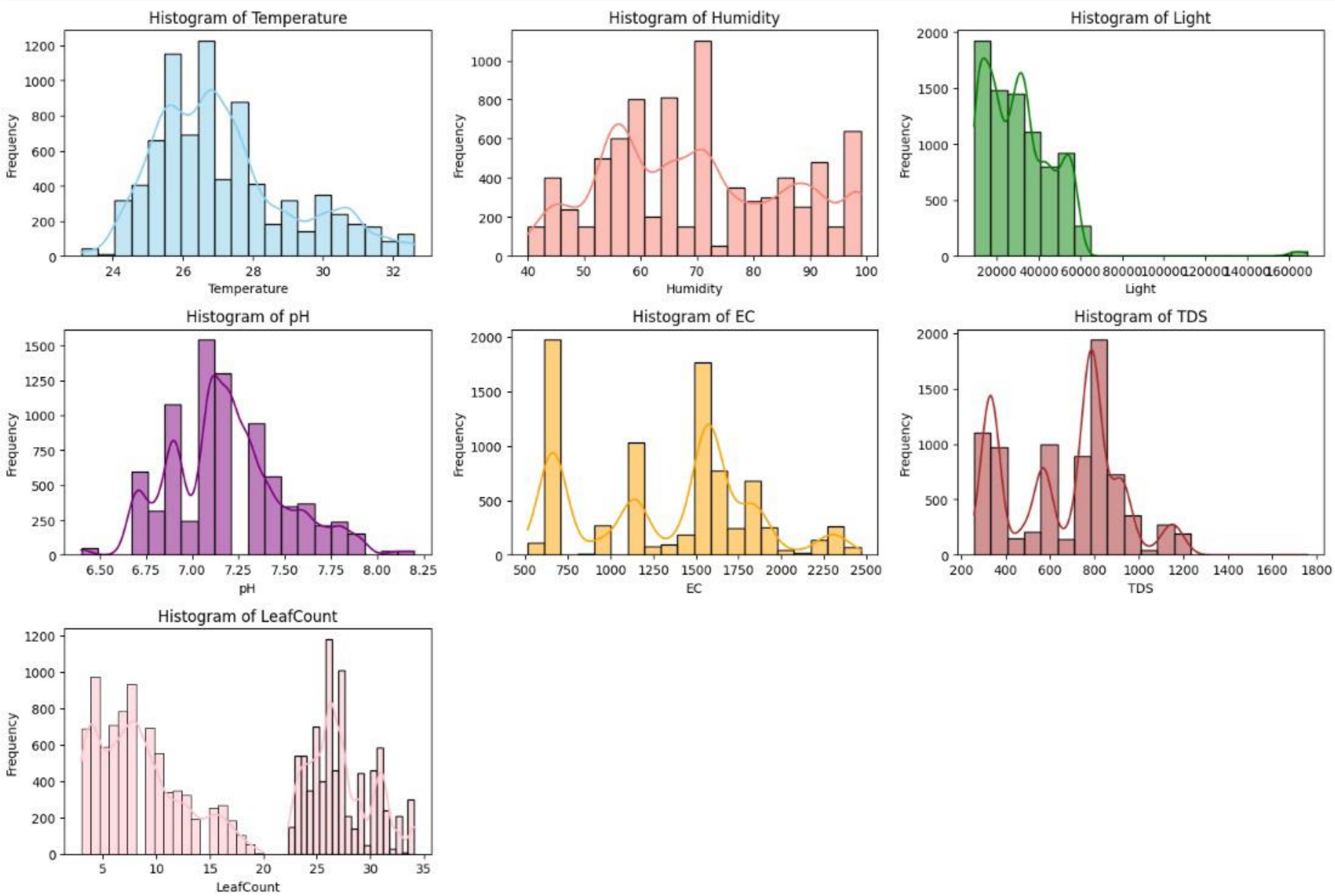

Fig. 5. Histogram of all variables.

The light variable shows a wide range of light intensity values, from 20,000 to over 60,000 lux. The peak distribution occurs between 20,000–30,000 lux, which is considered optimal for photosynthesis in a hydroponic system. The pH distribution also follows a near-normal pattern, with values ranging from 6.5 to 8.0, and the highest frequency around pH 7.2. This suggests that the hydroponic system tends to maintain an optimal acidity level for plant nutrient absorption.

Next, EC (Electrical Conductivity) varies between 500 and 2500 µS/cm, with several peaks reflecting fluctuations in nutrient concentration during the growth cycle. This range is critical to ensure that plants receive sufficient minerals without causing an oversupply. The TDS (Total Dissolved Solids) variable shows a similar pattern, with values ranging from 200 to 1800 ppm, with the highest frequency around 800–1000 ppm. This indicates varying levels of nutrient solubility in the water throughout the observation period.

Finally, the leaf count distribution shows significant variation in the number of leaves, with the highest frequency occurring between 15 and 25 leaves. This variable reflects fairly stable plant growth, while also showing some variation among the plants measured during the hydroponic cycle.

Overall, these histograms provide initial insights into how each variable functions within the hydroponic system and offer important information for the next stage—predictive modeling. The data will be used to build simulations for lettuce growth under Indonesia's rainy season conditions.

Fig. 6 illustrates the changing patterns of various environmental and hydroponic variables over time (in days) as measured throughout the study. In this graph, variables such as EC (Electrical Conductivity), TDS (Total Dissolved Solids), Temperature, Water Temperature, pH, and Light are visualized in relation to days, allowing us to understand the trends and fluctuations of each variable.

It is clear that EC and TDS follow almost identical patterns, with their values gradually increasing over time. This aligns with the findings shown in the correlation matrix, where these two variables have a very high correlation (close to 1), indicating a strong relationship. The increase in EC corresponds with the rising nutrient concentration in the hydroponic solution, which is directly measured by TDS. Over time, the hydroponic system shows a controlled increase in nutrient concentration in the water [8].

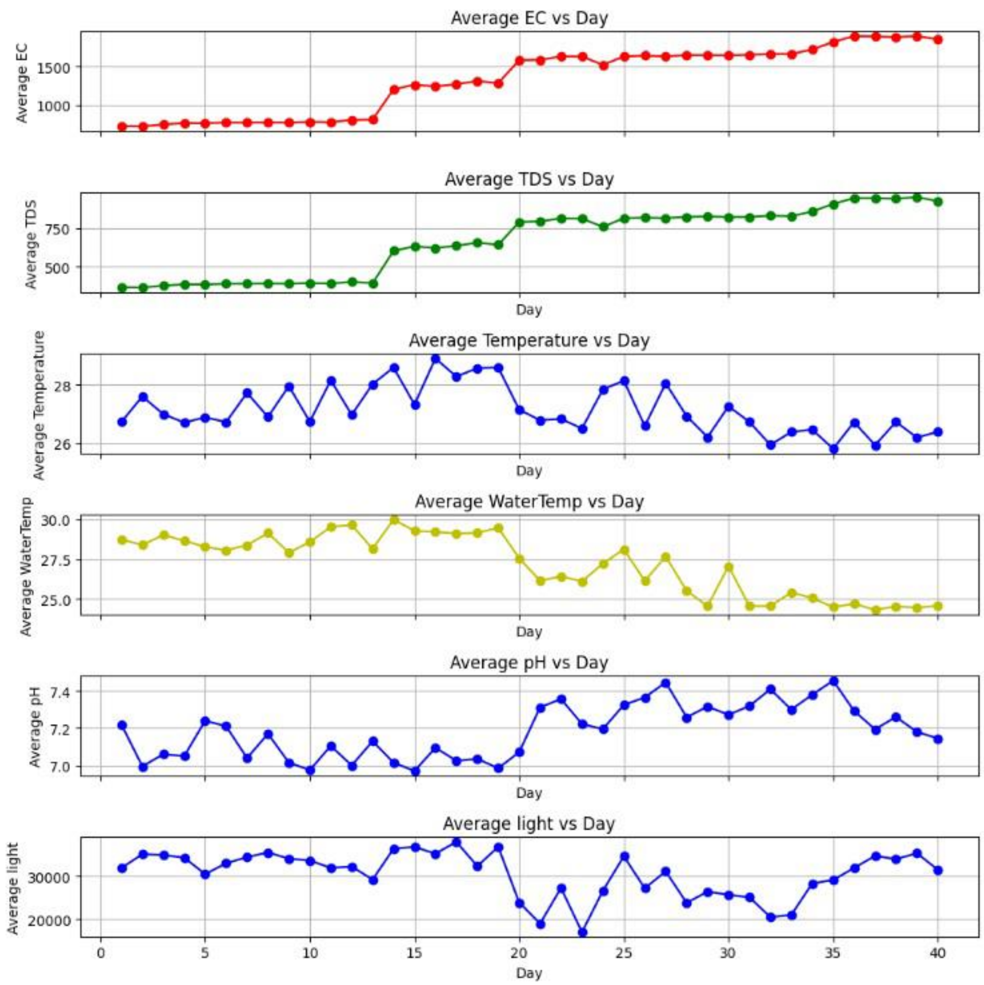

Fig. 6. Visualization of all variables over time.

For the Temperature and Water Temperature variables, the patterns show more irregular fluctuations compared to EC and TDS. Air temperature exhibits more dynamic variation, with several peaks and troughs, though it generally remains within a stable range. This is important because temperature plays a direct role in photosynthesis and plant growth [42]. Water temperature, on the other hand, shows smaller fluctuations, although some sudden drops were recorded on certain days. Maintaining stable water temperature is crucial for keeping the plant roots healthy and ensuring effective nutrient absorption.

The pH graph shows that pH values remain relatively stable with slight fluctuations, tending towards 7.2, which is the optimal pH for lettuce growth in a hydroponic system. This stability is essential to ensure that plants can absorb nutrients effectively [44].

Meanwhile, the Light variable exhibits more regular daily fluctuations. Light intensity greatly influences photosynthesis and plant growth, and the variability in the light pattern may be caused by external factors such as weather changes during the data collection period.

Overall, this visualization provides a clear picture of how each variable contributes to plant growth in the hydroponic system, with EC and TDS being the most closely related variables in influencing nutrient conditions. Understanding these patterns is critical for developing predictive models for future automated simulations of hydroponic plant growth.

B. Data Preprocessing

Data preprocessing is a crucial step in data handling before modeling or further analysis. This phase involves various tasks such as data cleaning, transformation, and formatting adjustments to ensure that the data is optimally prepared for use by modeling algorithms. In the context of machine learning, data preprocessing aims to ensure that the data is clean, free from noise, and ready for modeling purposes, as explained by Kramar and Alchakov (2023) [28]. By undergoing data preprocessing, the data becomes more consistent and structured, ultimately improving the performance of the model being developed. During this phase, several important steps are carried out. For instance, the 'time' column is adjusted by adding digits before and after to ensure that the time format aligns with the standards used in time-series analysis. Additionally, unnecessary columns, such as labels that contain only one type of value, are removed to prevent them from affecting the prediction outcomes.

TABLE III. DATA ADJUSTMENT

	day	hole	time	temperature	humidity	light	pH	Ec	TDS	WaterTemp	LeafCount
0	1	1	09:19:00	26.8	72	17820	7.2	677	340	26.1	3
1	1	2	09:23:00	26.6	72	16490	7.2	677	338	26.1	3
2	1	3	09:27:00	26.4	72	15160	7.2	678	334	26.1	3
3	1	4	09:31:00	26.2	72	13830	7.2	677	338	26.1	3
4	1	5	09:35:00	26.2	72	12500	7.2	673	340	26.1	3

Table III illustrates this data adjustment process, where each column is reviewed and reformatted as needed. For example, the 'time' column had zeros added in front of single-digit hours to follow the standard time format, ensuring that the data could be correctly processed by the model. Furthermore, this process also involves removing irrelevant columns or those containing only one type of label, allowing the data to focus on the variables that influence the forecasting process.

Subsequent processing involves merging the day and time columns to create a new column called datetime. This column serves to provide the appropriate time series format, making it usable in future modeling and prediction processes. This step is crucial because data structured in a time series format allows algorithms like ARIMA and Prophet to recognize patterns and trends that occur over time [28]. The merging of these columns is a key step in data preprocessing, ensuring the data is ready to be used in machine learning modeling.

```
df_model after merge:
   day  hole      time  temperature  humidity  light   pH   EC  TDS  \
0    1     1  09:19:00         26.8        72  17820  7.2  677  340
1    1     1  09:19:00         26.8        72  17820  7.2  677  340
2    1     2  09:23:00         26.6        72  16490  7.2  677  338
3    1     2  09:23:00         26.6        72  16490  7.2  677  338
4    1     3  09:27:00         26.4        72  15160  7.2  678  334

   WaterTemp  LeafCount            datetime
0       26.1          3 2024-07-01 09:19:00
1       26.1          3 2024-07-01 09:19:00
2       26.1          3 2024-07-01 09:23:00
3       26.1          3 2024-07-01 09:23:00
4       26.1          3 2024-07-01 09:27:00
```

Fig. 7. Dataset after preprocessing.

In Fig. 7, the results after the preprocessing stage are shown, where the datetime column has been combined with the main dataset. This new dataset not only includes information about hydroponic variables such as temperature, humidity, light, pH, EC, TDS, and LeafCount, but also includes datetime as a crucial time marker in the time series analysis.

Once the datetime column is added and the dataset updated, the dataset is then saved in csv format. Saving in csv format aims to create a new, more ready-to-use database for the modeling and forecasting process. Data preprocessing like this is essential to ensure that the data is in optimal condition before being input into predictive models, as without this process, the data might be poorly structured or not aligned with the desired format [28].

C. Modeling

In the modeling phase, two time-series models were used: ARIMA and Prophet, each with its own strengths in forecasting time-series data. The ARIMA model operates through three key components: autoregressive (AR), differencing (I), and moving average (MA). To begin with, the stationarity of the data is tested using the Augmented Dickey-Fuller (ADF) test. If the data is found to be non-stationary, differencing is applied to address trends and seasonality, as proposed by Menculini et al. (2021) [24].

Once the data becomes stationary, the parameters p, d, and q are determined to build the ARIMA model. This model is used to predict environmental variables such as EC (Electrical Conductivity) and TDS (Total Dissolved Solids), which are crucial for hydroponic plant growth. On the other hand, Prophet is a flexible model that automatically handles trends and seasonal components, as described by Satrio et al. (2021) [30]. Prophet works by separating data components into trend, seasonality, and residuals, making it well-suited for predicting dynamic weather conditions.

In this study, both models were evaluated using the MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error) metrics. The results showed that Prophet outperformed in handling seasonal trends, especially during Indonesia's rainy season, while ARIMA produced better results for more stationary data [22].

```
                               SARIMAX Results
==============================================================================
Dep. Variable:              LeafCount   No. Observations:                 5282
Model:                 ARIMA(1, 1, 1)   Log Likelihood              -10246.137
Date:                Tue, 12 Nov 2024   AIC                          20498.274
Time:                        11:17:32   BIC                          20517.990
Sample:                             0   HQIC                         20505.165
                               - 5282
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.1913      0.012    -16.310      0.000      -0.214      -0.168
ma.L1         -0.9682      0.003   -314.518      0.000      -0.974      -0.962
sigma2         2.8346      0.051     55.715      0.000       2.735       2.934
===================================================================================
Ljung-Box (L1) (Q):                   0.14   Jarque-Bera (JB):               242.43
Prob(Q):                              0.71   Prob(JB):                         0.00
Heteroskedasticity (H):               8.45   Skew:                            -0.40
Prob(H) (two-sided):                  0.00   Kurtosis:                         3.68
===================================================================================
```

Fig. 8. SARIMAX results.

SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors) is a popular method for time series data analysis that takes into account both seasonal and non-seasonal components [45]. In the SARIMAX results shown in Fig. 8, it is clear that the ARIMA (1,1,1) model has been used to predict the variable LeafCount with 5282 observations. According to the reference by Pindiga (2022), SARIMAX is utilized because it can capture fluctuations and seasonal patterns, providing more comprehensive results in time series forecasting [25].

From the SARIMAX results, the AR.L1 coefficient has a value of -0.1913 with a p-value of less than 0.05, indicating that this parameter is significant in the model. The MA.L1 value is also significant, with a coefficient of -0.9682, meaning that the moving average model plays an important role in predicting LeafCount. The sigma2 value (2.8346) represents the variability in the model's residuals, which affects the accuracy of the predictions. Additionally, the AIC (20498.274) and BIC (20517.990) values provide indicators of how well the model fits the data, where lower values suggest a better-fitting model.

Moreover, the Jarque-Bera (JB) statistical test resulted in a value of 242.43 with a p-value of 0.00, indicating that the residual distribution does not follow a normal distribution. This is important in time series model evaluation as it can impact prediction accuracy.

	ds	y	hole	temperature	humidity	light	pH	EC	TDS	WaterTemp
0	2024-07-01 08:55:00	3	1	25.3	92	21910	7.0	660	330	23.1
1	2024-07-01 08:57:00	3	2	25.3	92	21910	7.0	660	330	23.1
2	2024-07-01 08:59:00	3	3	25.5	92	21060	7.8	984	492	26.1
3	2024-07-01 08:59:00	4	3	25.5	92	21060	7.0	652	326	23.1
4	2024-07-01 09:02:00	3	4	25.7	92	28330	7.0	656	328	23.1
...	...	...	...	...	...	...	...	...	...	...
5278	2024-08-09 16:44:00	18	9	25.6	44	12820	7.5	1851	930	26.3
5279	2024-08-09 16:44:00	16	9	25.6	44	12820	7.5	1851	930	23.9
5280	2024-08-09 16:45:00	15	10	25.4	44	16810	7.5	1886	943	23.9
5281	2024-08-09 16:45:00	18	10	25.4	44	16810	7.5	1886	943	23.9
5282	2024-08-09 16:45:00	19	10	25.4	44	16810	7.5	1886	943	26.3

Fig. 9. Preparing data for the prophet model.

Fig. 9 shows the dataset prepared for modeling using Prophet. The dataset includes key columns such as time (ds), the target variable (y), plant hole (hole), and various environmental factors like temperature, humidity, light, pH, EC, TDS, and water temperature (WaterTemp). This data is structured to help predict lettuce leaf growth (LeafCount) based on these factors. Each row in the dataset represents a single point in time, with data collected periodically during the observation period from July 1, 2024, to August 9, 2024. This ensures that the Prophet model can accurately capture any temporal patterns. The data serves as the training set for the Prophet model to predict the target variable, which is the number of lettuce leaves (LeafCount).

D. Evaluation

Evaluation is a crucial stage in the modeling process to assess the performance of the model that has been developed. The goal of evaluation is to determine how well the model predicts the observed data and to ensure that the prediction results are relevant to the research objectives.

To ensure reliable model performance, this study emphasizes the importance of validation measures. We used two key evaluation metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These metrics are essential for assessing prediction accuracy and understanding how well the models perform in forecasting hydroponic growth. MAE shows the average error magnitude, while RMSE highlights larger errors by squaring the differences. Together, they provide a comprehensive view of model accuracy.These two metrics are commonly used in time series modeling because they provide insight into the magnitude of the model's prediction error compared to the actual data (Sushma Niveni, 2022).

MAE measures the average absolute error between the predicted and actual values. It helps in understanding the extent of the prediction error without considering its direction (positive or negative). The smaller the MAE value, the more accurate the model is in making predictions. Meanwhile, RMSE gives more weight to larger errors by squaring them, which is useful for detecting predictions with large deviations from the actual values. A model with a smaller RMSE is considered better at capturing trends and patterns in the data (Lorenzo Menculini, 2021).

Based on the evaluation of the ARIMA and Prophet models, the following table summarizes the performance comparison of the two models:

TABLE IV. PERFORMANCE COMPARISON OF ARIMA AND PROPHET MODELS BASED ON MAE AND RMSE METRICS

Model	MAE	RMSE
ARIMA	8.17	8.97
Prophet	1.475	1.808

From the evaluation Table IV, it is evident that the Prophet model has much lower MAE and RMSE values compared to ARIMA. The MAE value for Prophet is 1.475, indicating that the average prediction error from this model is much smaller compared to ARIMA, which has an MAE of 8.170. This indicates that Prophet is able to provide more accurate predictions. Additionally, the RMSE value for Prophet, which is 1.808, also shows that this model has fewer large errors, whereas ARIMA, with an RMSE of 8.970, indicates that it tends to make larger errors.

The Prophet model outperformed ARIMA in both MAE and RMSE. Prophet’s ability to handle non-stationary data and complex seasonal patterns made it more suitable for hydroponic forecasting compared to ARIMA, which assumes that data is stationary. Prophet can capture non-linear trends and multiple seasonalities, making it more effective for dynamic systems like hydroponics.

Additionally, this study compares Prophet with traditional methods and more complex machine learning models. Traditional models often rely on stationary data, which limits their application in real-world scenarios. Prophet overcomes this limitation, offering flexibility to model changes over time. Compared to machine learning approaches, which require large datasets and high computational resources, Prophet balances accuracy with computational efficiency, making it a practical and accurate tool for hydroponic forecasting.

Overall, Prophet excels in capturing data patterns and generating more consistent and accurate predictions compared to ARIMA.

Fig. 10 shows the evaluation of the Prophet model's performance in predicting the number of lettuce leaves in an NFT hydroponic system, using two key evaluation metrics: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). In the graph on the left, we can see that the RMSE value obtained is 1.82, while the MAE is 1.49. These two metrics provide an overview of the average error made by the Prophet model in predicting plant growth outcomes. MAE measures the average absolute error, giving a direct view of how far off the model's predictions are from the actual values. Meanwhile, RMSE is more sensitive to larger errors, as it penalizes predictions that are significantly far from the actual values.

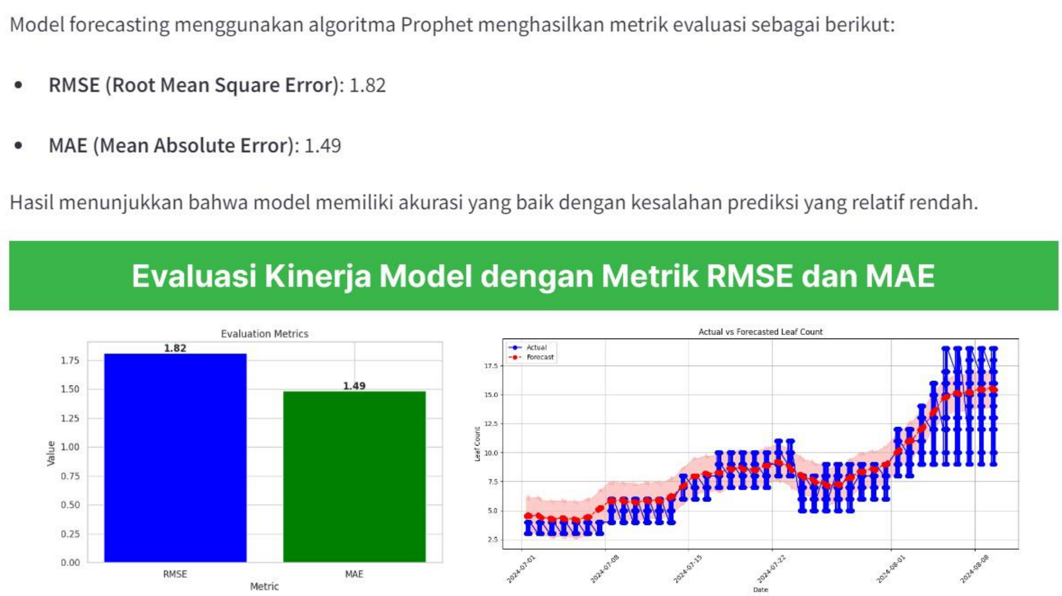

Fig. 10. Model performance evaluation using MAE and RMSE.

The graph on the right in Fig. 10 shows a comparison between the actual values (in blue) and the predicted values generated by the Prophet model (in red) over the measured time period. From this visualization, it can be observed that the Prophet model's predictions closely follow the pattern of leaf growth, especially after the more stable growth period. The range of prediction errors (shaded area) narrows over time, indicating that the model is learning well from historical data and providing more accurate predictions in the later stages.

Overall, this evaluation confirms that Prophet outperforms other models, such as ARIMA, which were also evaluated in this study. As a result, the Prophet model was chosen to move forward to the deployment stage, where it will be used in a web-based automated growth simulation, helping hydroponic farmers monitor and predict their crop yields more accurately and effectively.

E. Comparison to Existing Study

In the Comparison/Benchmarking section, this study is compared with several similar studies using the ARIMA and Prophet models, based on performance evaluation results measured through MAE and RMSE metrics. The findings of this study, where the Prophet model achieved an MAE of 1.475 and an RMSE of 1.808, are compared to similar studies from academic literature. Through Table V below, we can see the comparison of evaluations using MAE and RMSE from previous research.

TABLE V. COMPARISON OF MAE AND RMSE VALUES

	Purnama, 2023		**Elseidi, 2024**		**Pindiga, 2022**		**Rahmadi, 2024**	
	MAE	***RMSE***	***MAE***	***RMSE***	***MAE***	***RMSE***	***MAE***	***RMSE***
Prophet	2.51	2.89	1.78	2.12	2.65	3.15	1.475	1.808

Purnama's study (2023), which compared ARIMA and Prophet in predicting Bitcoin prices, reported that Prophet performed better with an MAE of 2.51 and an RMSE of 2.89, compared to ARIMA, which had an MAE of 3.12 and an RMSE of 3.58. Although Prophet's results in Purnama's study were better than ARIMA's, they still show a higher error compared to this study, indicating that the application of Prophet in hydroponics provides more accurate predictions than its use for Bitcoin price prediction (Purnama, 2023).

Furthermore, the study by Elseidi (2024), which utilized a combined ARIMA-Prophet framework to predict high-frequency temperature data, reported results similar to this study. Elseidi's study achieved an MAE of 1.78 and an RMSE of 2.12, which are slightly higher than Prophet's results in this study. This indicates that Prophet is highly suitable for short-term predictions, such as temperature and plant growth in hydroponics (Elseidi, 2024).

Another study by Pindiga (2022), which predicted stock indices using ARIMA and Prophet, reported that Prophet performed better with an MAE of 2.65 and an RMSE of 3.15, compared to ARIMA, which had an MAE of 3.24 and an RMSE of 3.67. These findings still show that the Prophet model in this study provides more accurate predictions compared to stock index predictions by Pindiga (Pindiga, 2022).

Overall, the evaluation results demonstrate that Prophet excels in environments requiring predictions of variables with consistent change patterns, such as plant growth in hydroponic systems, compared to its application to more volatile data such as stock prices and temperature data. The benchmarking results reinforce the study's findings that Prophet is a more suitable model for predictions in hydroponic farming systems

F. Deployment

The deployment phase of this study entailed turning the Prophet model into a fully functional web-based application for simulating hydroponic lettuce growing. This approach was carried out on the Streamlit platform, which was chosen for its ease of use and versatility when developing interactive online apps [46]. The major purpose of this deployment was to give users, primarily hydroponic farmers and academics, with a simple tool for simulating lettuce growth in real time using environmental data. The following Fig. 11 shows the homepage of the HydroSim application resulting from the model deployment using the Streamlit platform.

The Prophet model, which has demonstrated the best performance in predicting lettuce growth during the rainy season, has been integrated into Streamlit, allowing users to input important hydroponic variable data such as temperature, humidity, light intensity, water quality indicators, and the number of lettuce leaves. After receiving the data, the program runs the Prophet model in the background to forecast, simulate growth patterns, and provide estimates in a simple and user-friendly interface. Key performance parameters, such as the number of leaves and harvest time, are provided, offering actionable information to users. In addition, interactive elements are included, allowing users to modify factors and quickly observe how these changes affect the expected outcomes, making this application not only informative but also instructive for understanding the dynamics of hydroponic agriculture.

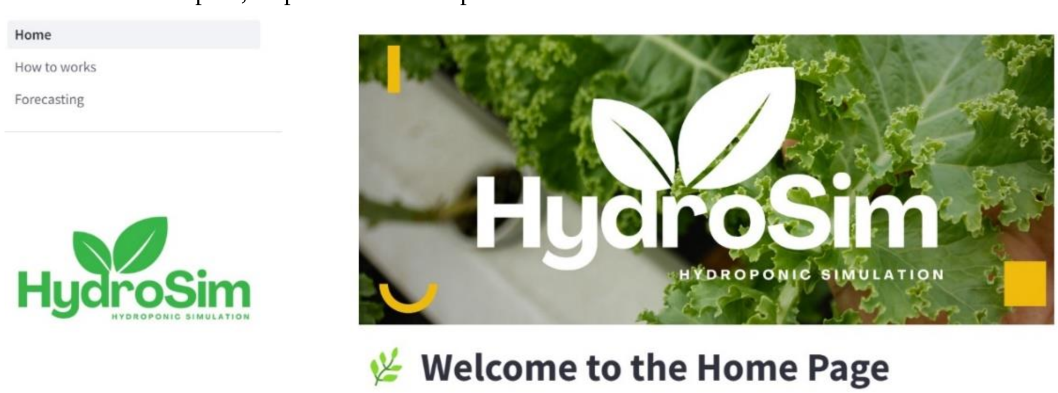

Fig. 11. Homepage HydroSim.

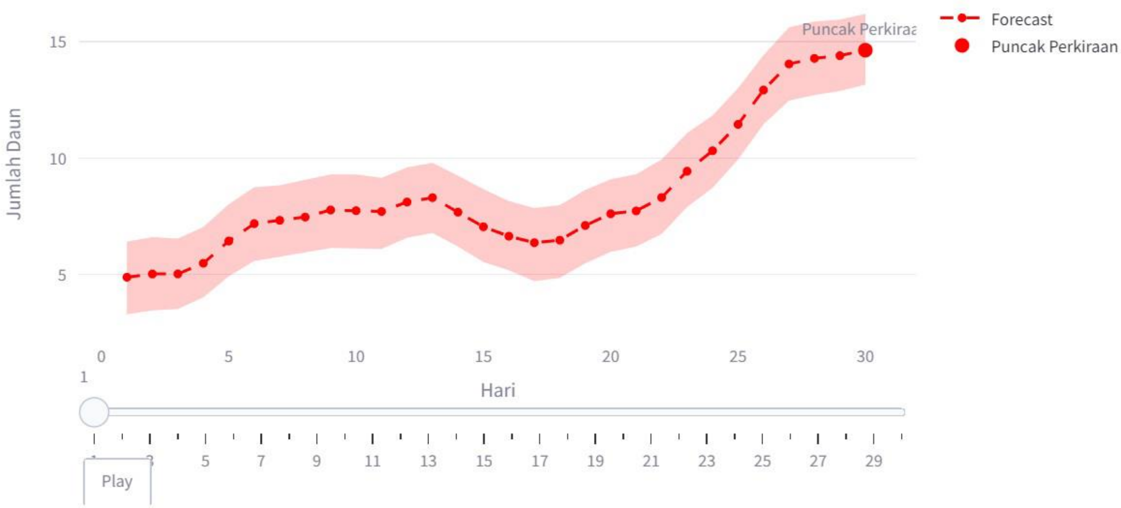

Fig. 12. Simulation forecasting results based on days.

Referring to Fig. 12, the forecast results produced by the model are displayed after the user submits their data. Users can choose how many days ahead they would like to simulate the growth. Additionally, they can press the play button to see an animated, interactive graph of the growth simulation over time. Users also have the flexibility to select a specific day for simulation by dragging the marker to their preferred point on the timeline, offering an interactive and customizable way to visualize the predicted growth.

Tabel Prediksi

	ds	yhat	yhat_lowe
0	2024-07-10 16:35:00	4.8747	3.2826
1	2024-07-11 16:35:00	5.0147	3.4513
2	2024-07-12 16:35:00	5.0194	3.5124
3	2024-07-13 16:35:00	5.4764	4.0104
4	2024-07-14 16:35:00	6.4307	4.9116
5	2024-07-15 16:35:00	7.1793	5.5737
6	2024-07-16 16:35:00	7.3208	5.7771
7	2024-07-17 16:35:00	7.4599	5.9398
8	2024-07-18 16:35:00	7.7657	6.1295
9	2024-07-19 16:35:00	7.7349	6.0957

Fig. 13. Forecasting table and lettuce illustration.

Apart from the animated growth chart, a dynamic illustration of a lettuce plant is included, changing according to the day being predicted on the graph above. This allows users to visually see how the plant may develop over time. Additionally, a forecasting table is presented, which provides detailed daily predictions. The table includes columns like "ds," which displays the forecast date, and "yhat," which shows the primary predicted value for leaf count. The "yhat_lower" column gives the lower limit of the prediction range, representing the minimum likely estimate, while the "yhat_upper" column indicates the upper limit, showing the maximum expected leaf count for each prediction. Fig. 13 shows forecasting table and lettuce illustration.

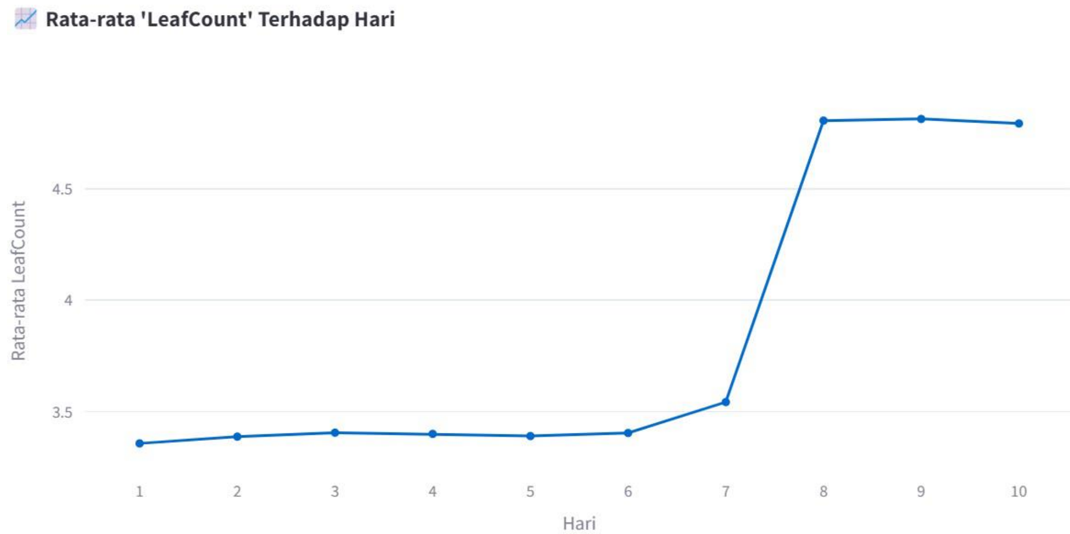

Fig. 14. Average value growth variable.

Fig. 14 explains the average value feature of each leaf count variable, allowing users to select which variable they want to see the average value of. The HydroSim application also includes a variety of features designed to assist both users and farmers in interpreting the data for practical use. One key feature is the ability to visualize average growth variable charts, particularly the Leaf Count. This chart allows users to observe how different growth variables behave over time, offering a detailed perspective on the factors influencing lettuce development. By providing a graphical representation of this data, the feature helps users better understand the dynamics of plant growth, such as how environmental conditions or nutrient levels impact leaf production. These insights can be crucial for making informed adjustments to hydroponic systems, ensuring that optimal growing conditions are maintained.

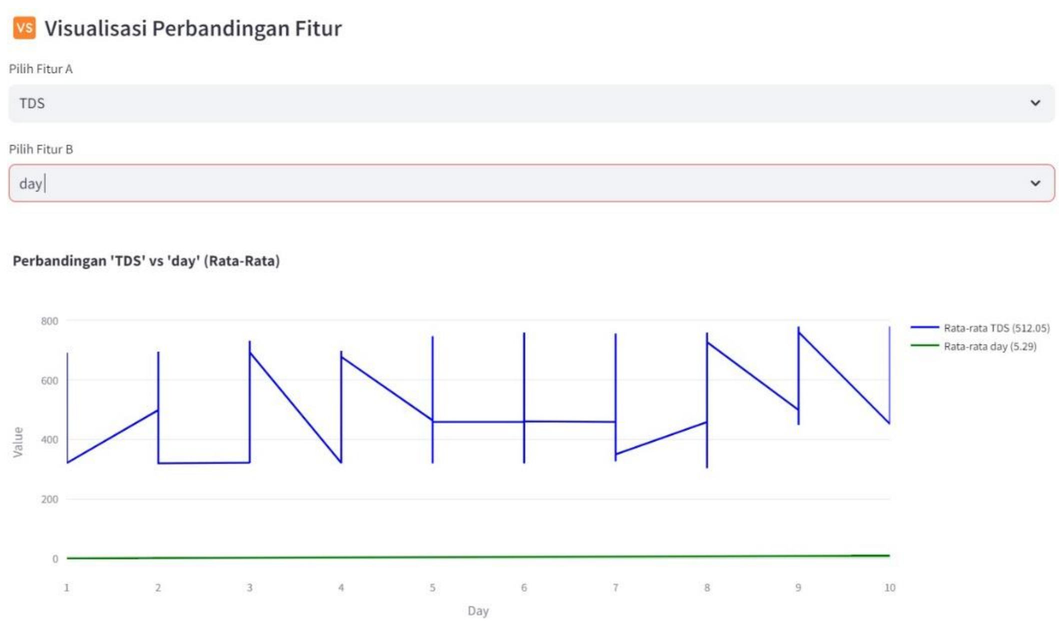

Fig. 15. Comparison between variable.

The variable comparison feature can be seen in Fig. 15, where users can compare two selected variables to observe the graphical pattern comparison of both variables. Another valuable feature integrated into HydroSim is the variable comparison tool, designed to provide users with insights into how different environmental and growth variables correlate with one another. As demonstrated in Fig. 15, users can choose which variables they would like to compare, such as water temperature, nutrient levels, and light intensity, and the application will generate a detailed comparative graph. This helps users better understand how environmental factors and growth metrics interact, making it easier to identify patterns or anomalies. The comparison tool empowers users to make more informed decisions about optimizing their hydroponic systems based on the relationships between key variables, ultimately improving plant growth outcomes.

Fig. 16. Conclusion information.

Fig. 16 shows the summary information display from the HydroSim application, which provides information on the percentage increase in the number of leaves simulated according to the selected number of days and information on the number of leaves that increased after simulation. This implementation represents a substantial improvement in precision agricultural technology by providing a real-time, data-driven solution for improving lettuce growth and resource management while remaining cost-effective and user-friendly. The use of Streamlit in model deployment provides a lightweight and scalable solution that is easily accessible via web browsers, without requiring substantial technical knowledge, making it suitable for widespread adoption by a variety of user groups from small-scale farmers, major research institute, to commercial hydroponic farmers.

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IV. Conclusion

This research concluded with the successful implementation of real-time automatic hydroponic growth simulation for lettuce using ARIMA and Prophet models, specifically designed for the rainy season in Indonesia. Through meticulous data collection using calibrated instruments, this study captures crucial environmental variables, providing an accurate foundation for model development. The Prophet model has proven to be superior, achieving a Mean Absolute Error (MAE) of 1.475 and a Root Mean Square Error (RMSE) of 1.808, highlighting its effectiveness in managing time series data to simulate plant growth. The integration of models into a web-based platform provides practical and user-friendly tools for predicting lettuce growth, enhancing the decision-making process for researchers and farmers by offering data-driven insights into environmental management. The contribution of this study lies in its focus on tropical climates and the use of real-time data for automation in hydroponic systems.

Future research will prioritize expanding the model by incorporating data from other seasons, particularly the dry season, to address environmental challenges and enhance its robustness across diverse climatic conditions. Furthermore, datasets from other hydroponic crops, such as spinach, bok choy, water spinach, and tomatoes, will be integrated to extend the model's applicability. This direction aligns with prior studies, such as Smith et al. (2022) [47], who emphasized multi-crop modeling for resource optimization, and Lee et al. (2023) [48], who demonstrated improved system adaptability in diverse hydroponic conditions. Hybrid modeling approaches will also be explored, combining techniques like ARIMA, Prophet, and advanced machine learning algorithms such as LSTM and Random Forest. Zhang et al. (2021) [49] highlighted the effectiveness of hybrid methods in improving simulation accuracy for complex environments, making this a promising avenue for further enhancement. These efforts aim to develop a more versatile, scalable, and high-performing hydroponic automation system to support sustainable agricultural practices. By addressing these aspects, future studies can enhance the precision, scalability, and reliability of automated hydroponic growth simulations.

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