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Forecasting Nutrient Concentration Dynamics in Hydroponic Lettuce Cultivation Using a Hybrid Fuzzy Time Series and Long Short-Term Memory Approach for Internet of Things–Based Systems

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Abstract

Proper nutrient management is crucial for the optimal growth and yield of hydroponically cultivated lettuce. This study proposes a hybrid time-series forecasting model that integrates Fuzzy Time Series (FTS) and Long Short-Term Memory (LSTM) networks to predict nutrient concentration dynamics in hydroponic lettuce cultivation within an Internet of Things–based environment. Experimental data from four lettuce plant samples with different nutrient treatments (control, 400 PPM, 600 PPM, and 1000 PPM) were analyzed for 26 days, with the prediction extended to 40 days, representing the complete growth cycle using a TDS Sensor as a PPM value reader and a Solenoid Valve to accurately control the PPM value via ESP32 with Internet of Things (IoT) communication. This hybrid model incorporates growth-stage awareness through an adaptive weighting mechanism, resulting in a superior forecasting accuracy. The results showed that the ensemble approach achieved a Mean Absolute Percentage Error (MAPE) of 2.43% for the control, 3.12% for the 400 PPM, 3.45% for the 600 PPM, and 3.78% for the 1000 PPM sample. The 600 PPM treatment showed optimal development with 82% compliance with the recommended PPM range (560-840 ppm). The proposed model provides actionable insights for precision nutrient management, potentially reducing fertilizer use by 23-35% while maintaining crop quality. This study contributes to hybrid intelligent systems and time-series forecasting by demonstrating an effective integration of rule-based fuzzy modeling and deep recurrent neural networks in Internet of Things–driven environments for hydroponic systems, supporting efficient resource utilization and increased crop productivity.

Keywords : *Fuzzy Time Series, Hybrid Intelligent Systems, Hydroponics Nutrient Forecasting, Internet of Things, Long Short-Term Memory, Precision Agriculture.*

1. INTRODUCTION

Hydroponic cultivation is a modern agricultural approach that enables efficient plant growth without soil by utilizing nutrient-rich water solutions. Lettuce (Lactuca sativa) is one of the most commonly cultivated hydroponic crops because of its rapid growth cycle and significant nutritional value [1]-[3]. The growth of hydroponic plants is influenced not only by lighting conditions but also by the accuracy of nutrient application. Therefore, nutrient formulation and concentration, commonly expressed in Parts Per Million (PPM), must be adjusted according to the specific requirements of each plant to ensure optimal growth [4]-[6]. The success of hydroponic lettuce production depends critically on the maintenance of optimal nutrient concentrations. An imbalance in nutrient intake can result in various growth-related complications, including obesity [7]. Concentrations below 559 ppm cause nutrient deficiency, resulting in stunted growth and pale leaf color. levels between 560-840 ppm represent the optimal range for vegetative growth and production, while concentrations exceeding 840 ppm risk over-fertilization, causing leaf burn and growth disruption [8], [9].

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Current monitoring methodologies in hydroponic systems frequently depend on periodic manual measurements, which are susceptible to human error and cannot provide continuous predictive insights [10]. Recent progress in precision agriculture has emphasized the significance of predictive analytics in optimizing resource utilization and maximizing crop yields [11]. Time-series forecasting methods have demonstrated particular potential in agricultural applications, with various approaches proposed for different crop parameters [12], [13].

Fuzzy Time Series (FTS) have emerged as a powerful forecasting technique for handling uncertainty and imprecision in time-series data. Its capacity to incorporate linguistic variables renders it especially suitable for agricultural data, which often contain vagueness and subjective measurements [14]. However, conventional FTS methods struggle to capture complex nonlinear patterns in time-series data. Conversely, Long Short-Term Memory (LSTM) networks, a recurrent neural network variant, excel at learning long-term dependencies and complex patterns in sequential data [15]-[17]. Their gating mechanisms effectively address the vanishing gradient problem common in traditional RNNs, making them ideal for time-series forecasting tasks [18], [19].

Recent investigations have explored hybrid methodologies that combine statistical methods with machine learning techniques to enhance forecasting accuracy [20], [21]. In agricultural applications, hybrid models have exhibited superior performance compared to individual methods for predicting c, soil moisture, and pest incidence [22], [23]. Nevertheless, limited research exists on hybrid approaches specifically designed for PPM-level forecasting throughout the complete growth cycle of hydroponic systems.

Despite the growing adoption of machine learning and deep learning techniques for agricultural time-series forecasting, several methodological limitations remain in the existing literature. Most existing studies rely on either standalone statistical models or single deep learning architectures without explicitly addressing uncertainty and growth stage variability. Recent studies employing Long Short-Term Memory networks primarily focus on nonlinear temporal modeling, whereas fuzzy-based approaches emphasize interpretability but lack the capability to capture complex long-term dependencies. Moreover, few studies have investigated hybrid forecasting frameworks that integrate fuzzy reasoning and deep recurrent neural networks within IoT–based hydroponic systems. In particular, growth-stage-aware ensemble strategies for nutrient concentration forecasting across the entire cultivation cycle remain underexplored.

This research addresses several critical gaps in the current literature: (1) insufficient hybrid FTS-LSTM models for hydroponic nutrient forecasting across complete growth cycles, (2) inadequate attention to growth stage-dependent nutrient requirements, and (3) limited implementation of ensemble methods that combine computational intelligence techniques for agricultural time-series data. The primary objective of this study was to develop and evaluate a hybrid forecasting model that integrates FTS and LSTM to predict the lettuce PPM levels over a 40-day growth cycle. Specific objectives encompass: (1) implementing and comparing individual FTS and LSTM models, (2) developing an ensemble model combining both approaches with growth stage awareness, (3) evaluating forecasting accuracy using multiple metrics, and (4) analyzing nutrient optimization strategies for practical agricultural decision-making.

The novelty of this study lies in the proposed hybrid architecture that leverages the complementary strengths of FTS and LSTM. While FTS provides interpretable linguistic rules and effectively handles uncertainty, LSTM captures complex temporal patterns and nonlinear relationships. The ensemble approach, which features dynamic weighting based on the growth stage, is an innovative solution for agricultural time-series forecasting. This study contributes to precision agriculture by providing a reliable tool for complete growth cycle nutrient management in hydroponic systems, potentially reducing fertilizer waste and improving the quality of crops.

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2. METHOD

2.1. Data Collection and Experimental Design

This study used experimental data obtained from four lettuce (Lactuca sativa var. crispa) samples were cultivated in individual hydroponic containers using a Deep Water Culture (DWC) system controlled by the Internet of Things (IoT). Each container was treated as an independent experimental unit to prevent cross-contamination between the nutrient treatments [24]. Sample A was used as the control group without nutrient supplementation, whereas Samples B, C, and D were supplied with nutrient solutions at concentrations of 400, 1000, and 600 ppm, respectively.

Nutrient concentration monitoring was performed using a Total Dissolved Solids (TDS) sensor installed in each hydroponic container and connected to an IoT-based ESP32 microcontroller, which sent sensor data to a database in real time [25]. The sensors measured the total dissolved solids in the nutrient solution, which were recorded as total parts per million (Tppm). As the TDS values represent the combined concentration of dissolved nutrients and the inherent mineral content of the water, the actual nutrient concentration (Nppm) was calculated by subtracting the baseline water ppm (Wppm) from the measured Tppm value. Wppm corresponds to the initial mineral content of the water prior to nutrient addition, enabling a consistent estimation of nutrient concentration across all samples.

Data collection was conducted daily at a fixed time to minimize diurnal variation. The ESP32 microcontrollers transmitted the collected sensor data to a cloud-based database, forming a structured time-series dataset for each nutrient treatment group [26], [27]. The experimental observation was performed for 20 consecutive days, and the collected data were subsequently used to extend the nutrient concentration forecasting up to 40 days to represent the complete lettuce growth cycle.

Throughout the experiment, environmental conditions were maintained under controlled settings, including a constant temperature of 22°C, relative humidity of 65%, photoperiod of 16 h light and 8 h dark, and nutrient solution pH of 5.8 ± 0.2. This controlled experimental design ensured that variations in nutrient concentration dynamics were primarily influenced by the applied nutrient treatment rather than external environmental factors.

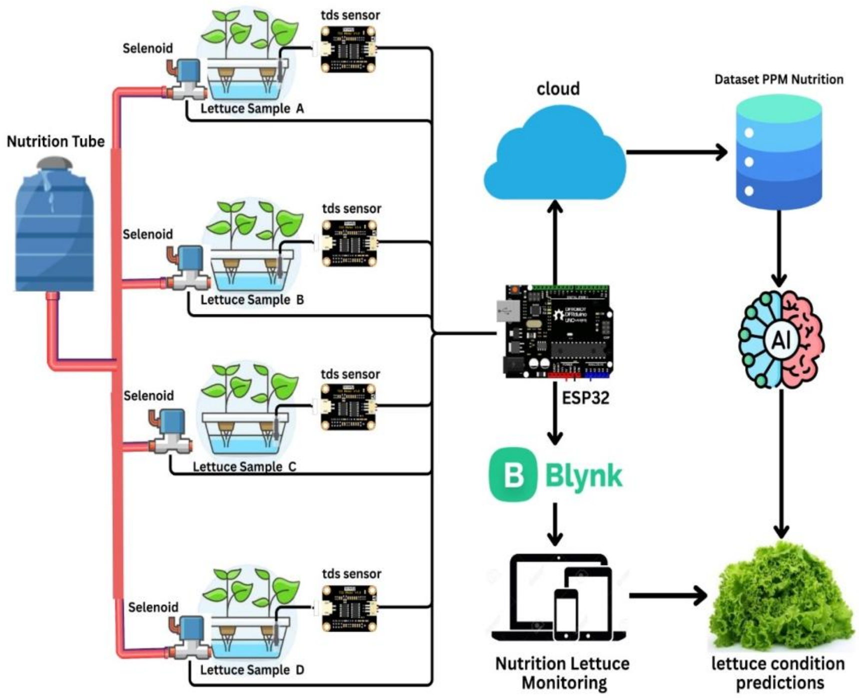

Figure 1. Architecture of the hydroponic lettuce nutrient monitoring system.

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The overall architecture of the hydroponic nutrient monitoring and data acquisition system is illustrated in Figure 1. Each lettuce sample was equipped with a TDS sensor connected to an ESP32 microcontroller, which functioned as the central unit for data acquisition and communication. The ESP32 collected the nutrient concentration data from all the containers and transmitted the information to a cloud server for storage and analysis. In addition, the system supports real-time monitoring through a mobile and web-based interface, and the collected dataset serves as the input for the proposed artificial intelligence–based nutrient prediction model [28], [29].

The daily nutrient concentration measurements obtained during the experimental period are presented in Table 1. The table presents the nutrient concentration values (Nppm), baseline water concentration (Wppm), and total dissolved solids (Tppm) for each lettuce sample over the 20-day observation period. These measurements provided the primary dataset used to analyze nutrient concentration dynamics and to train and validate the proposed hybrid Fuzzy Time Series–LSTM forecasting model.

Table 1. Daily nutrient concentration data of hydroponic lettuce samples

Day	Sample A (Without Nutrition)			Sample B (400PPM)			Sample C (1000PPM)			Sample D (600PPM)		
	Nppm	Wppm	Tppm	Nppm	Wppm	Tppm	Nppm	Wppm	Tppm	Nppm	Wppm	Tppm
1	0	93	93	395	87	482	933	94	1027	523	185	708
2	0	96	96	338	83	421	942	97	1039	502	188	690
3	0	96	96	408	90	498	917	95	1012	537	182	719
4	0	94	94	359	81	440	911	93	1004	512	189	701
5	0	96	96	388	88	476	945	96	1041	537	183	720
6	0	94	94	363	84	447	914	94	1008	508	186	694
7	0	97	97	406	89	495	925	97	1022	525	180	705
8	0	96	96	333	82	415	938	95	1033	501	187	688
9	0	90	90	383	85	468	921	96	1017	519	184	703
10	0	92	92	402	90	492	933	93	1026	529	189	718
11	0	91	91	347	86	433	915	94	1009	507	182	689
12	0	92	92	371	83	454	945	95	1040	527	185	712
13	0	96	96	399	89	488	935	97	1032	511	188	699
14	0	96	96	342	82	424	917	96	1013	502	181	683
15	0	95	95	364	87	451	912	93	1005	529	187	716
16	0	94	94	391	84	475	943	94	1037	509	183	692
17	0	97	97	409	90	499	925	95	1020	530	190	720
18	0	94	94	330	83	413	948	96	1044	503	182	685
19	0	96	96	395	87	482	933	97	1007	528	189	717
20	0	95	95	338	83	421	942	95	1007	523	185	708

2.2. Data Preprocessing and Feature Engineering

The raw nutrient concentration data collected from the hydroponic system were subjected to a preprocessing stage to ensure data quality, consistency, and suitability for time-series modeling. Preprocessing was required to reduce noise, handle missing values, and transform the data into a format compatible with both Fuzzy Time Series (FTS) and Long Short-Term Memory (LSTM) models [30].

Occasional missing values in the daily nutrient concentration measurements were handled using linear interpolation to preserve temporal continuity. For a missing observation at time t, the interpolated

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value was calculated as the average of the preceding and subsequent observations, as expressed in Equation (1). This approach is widely used for handling short gaps in time-series data due to its simplicity and effectiveness in maintaining local temporal trends [31], [32].

$$x_t = \frac{x_{t-1} + x_{t+1}}{2} \quad (1)$$

where x_t denotes the interpolated nutrient concentration value at time t, while x_{t-1} and x_{t+1} represent the observed values at the preceding and subsequent time steps, respectively.

To accommodate the different characteristics of the forecasting models, normalization was applied separately to each method. For the LSTM model, min-max normalization was employed to scale the nutrient concentration values into the range [0, 1], which improved the numerical stability and accelerated convergence during training. In contrast, the FTS model utilized partition-based normalization aligned with the defined universe of discourse for each growth stage, preserving the interpretability of fuzzy linguistic terms.

Feature engineering was performed to enhance the models' predictive capability. Temporal dependency was captured by constructing lag-based features, including nutrient concentration values at one, two, and three previous time points. In addition, short-term and medium-term trends were represented using moving average features with window sizes of three and seven days. The rate of change in nutrient concentration was computed to reflect the dynamic fluctuations in nutrient uptake.

Furthermore, growth stage information was incorporated into the dataset using categorical indicators representing the vegetative, maturation, and pre-harvest phases of the plants. These indicators were encoded as binary variables and integrated as additional inputs to the FTS and LSTM models. By embedding growth stage information into the feature set, the preprocessing stage enabled the forecasting models to account for physiological changes in the lettuce nutrient requirements throughout the growth cycle.

Overall, the preprocessing and feature engineering steps transformed the raw sensor measurements into a structured, informative time-series dataset. This dataset provides a reliable foundation for implementing the FTS, LSTM, and hybrid forecasting models described in the following sections.

2.3. Proposed Hybrid FTS–LSTM Framework

The overall workflow of the proposed hybrid forecasting framework is illustrated in Figure 2. The framework begins with the data collection stage, in which nutrient concentration data are acquired from hydroponic lettuce systems using total dissolved solids (TDS) sensors. The collected raw data were subsequently processed during the data preprocessing stage to handle missing values, normalize the feature scales, and construct time-series features suitable for the model input.

Following preprocessing, the processed dataset was fed into two complementary forecasting components: the Fuzzy Time Series (FTS) model and the Long Short-Term Memory (LSTM) network. The FTS component was designed to model the uncertainty and linguistic patterns in the nutrient concentration dynamics, whereas the LSTM component captured nonlinear temporal dependencies and long-term trends within the time-series data [33].

The outputs of both models were then combined within a hybrid learning framework to generate final nutrient-condition predictions. This hybrid approach enables the system to simultaneously leverage the interpretability of the FTS and the predictive power of the LSTM. The resulting predictions were used to estimate the lettuce nutrient conditions and support decision-making related to nutrient management and yield optimization. By integrating data-driven learning with fuzzy reasoning, the proposed framework provides a robust and adaptive solution for precision hydroponic agriculture.

Vol. 7, No. 3, June 2026, Page. 2277-2293
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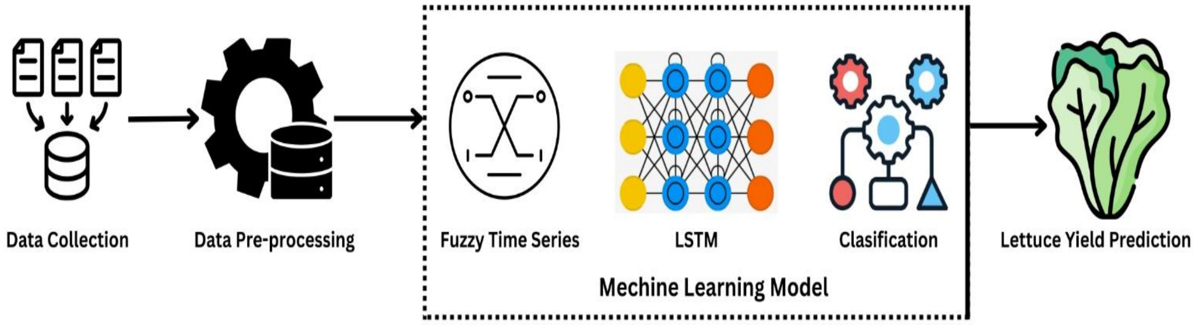

Figure 2. Overview of the proposed hybrid Fuzzy Time Series–LSTM framework for hydroponic lettuce nutrient prediction.

2.4. Fuzzy Time Series Implementation with Growth Stage Adaptation

The Fuzzy Time Series (FTS) approach was employed in this study to model nutrient concentration dynamics that exhibit uncertainty, gradual variation, and dependency on lettuce growth stages in hydroponic systems. Nutrient concentration data obtained from TDS sensors are inherently affected by measurement noise, biological variability, and nonlinear nutrient uptake behavior, making conventional crisp time-series models ineffective. FTS provides a suitable alternative by representing numerical data as fuzzy linguistic variables, allowing the model to capture imprecision and smooth transitions between nutrient states while preserving interpretability.

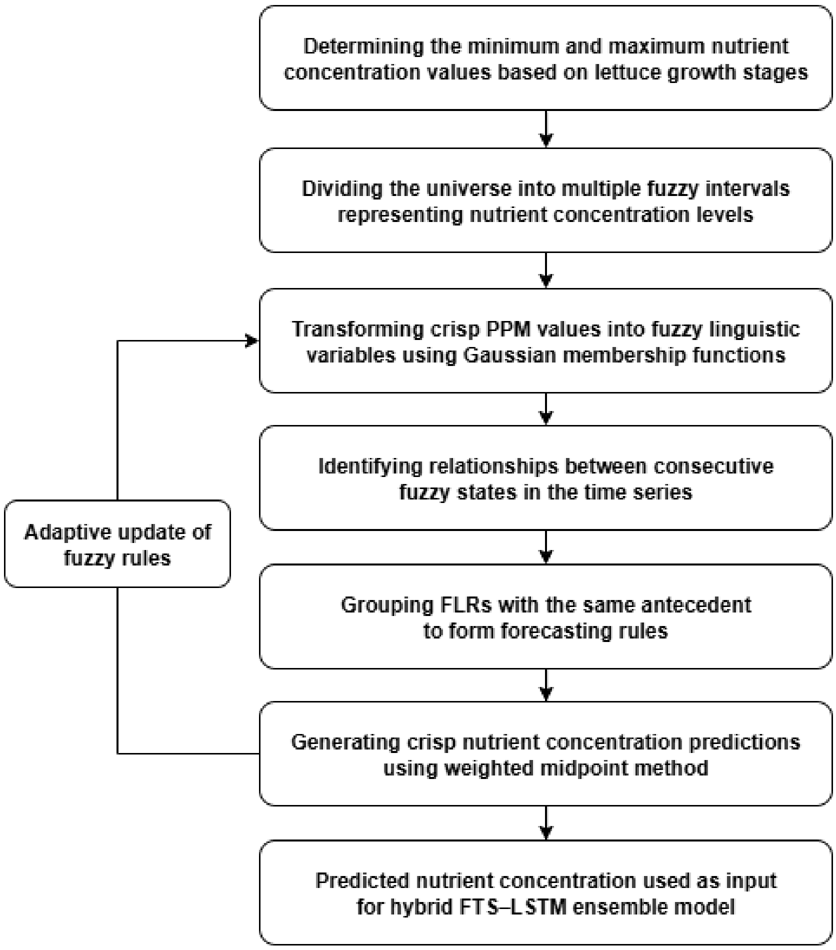

Figure 3. Fuzzy Time Series workflow for lettuce nutrient concentration forecasting

Vol. 7, No. 3, June 2026, Page. 2277-2293
https://jutif.if.unsoed.ac.id
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As illustrated in Figure 3, the FTS modeling process begins with the definition of the universe of discourse, which is determined based on the minimum and maximum observed nutrient concentrations corresponding to the different lettuce growth stages. This stage-aware universe definition ensures that nutrient dynamics during the vegetative, maturation, and pre-harvest phases are accurately. The universe is then partitioned into multiple fuzzy intervals that correspond to the linguistic nutrient levels, forming the basis of fuzzification [34].

Subsequently, crisp nutrient concentration values (PPM) were transformed into fuzzy linguistic variables using Gaussian membership functions, enabling a smooth overlap between adjacent fuzzy sets. The fuzzified time-series data were then used to establish fuzzy logical relationships (FLRs) by identifying the transitions between consecutive fuzzy states. These FLRs were grouped into fuzzy logical relationship groups (FLRGs), which served as forecasting rules for predicting future nutrient concentrations. The forecasting results were obtained through a defuzzification process using the weighted midpoint method to produce precise nutrient concentration estimates.

In addition, a feedback mechanism was incorporated into the FTS framework (Figure 1), allowing the fuzzy rules to be updated based on newly observed nutrient data. This adaptive process enables the FTS model to adjust its fuzzy sets and logical relationships over time, thereby enhancing its ability to track changes in nutrient dynamics throughout the lettuce growth cycle. The final output of the FTS model provides stage-aware nutrient concentration predictions, which are subsequently integrated into the hybrid FTS–LSTM ensemble framework, as described in the following sections.

2.5. Long Short-Term Memory (LSTM) Model Architecture

Long Short-Term Memory (LSTM) networks were utilized in this study to model nonlinear temporal patterns and long-term dependencies in hydroponic lettuce nutrient concentration data. Nutrient dynamics in hydroponic systems are influenced by cumulative nutrient uptake, plant growth stages, and gradual physiological changes, resulting in time-series behavior that cannot be effectively captured using conventional regression or shallow-learning models. LSTM, an advanced recurrent neural network architecture, is specifically designed to retain relevant historical information over long sequences through gated memory mechanisms, making it suitable for nutrient concentration forecasting [35]. Table 2. shows the parameters of the LSTM model used in this experiment.

Table 2. LSTM model parameters used in the experiments

Parameter	Value	Description
Input features	Nutrient concentration (PPM), growth stage indicators	Time-series input variables
Number of LSTM layers	2	Stacked LSTM architecture
Hidden units per layer	64	Number of neurons per LSTM layer
Activation function	Tanh	Default LSTM activation
Optimizer	Adam	Adaptive learning rate optimization
Learning rate	0.001	Initial learning rate
Batch size	16	Number of samples per batch
Number of epochs	100	Training iterations
Loss function	Mean Squared Error (MSE)	Training objective
Validation split	20%	Validation data portion
Framework	TensorFlow	Implementation platform

As illustrated in Figure 4, the proposed LSTM architecture receives historical nutrient concentration values (PPM) and growth stage indicators as input features. These input sequences were first processed through a temporal feature extraction stage, allowing the model to represent sequential nutrient patterns over saveral time steps. The extracted features are then passed to the stacked LSTM

Vol. 7, No. 3, June 2026, Page. 2277-2293
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5600

layers, where each LSTM cell learns long-term temporal dependencies by selectively retaining or discarding information through the forget, input, and output gates of the cells.

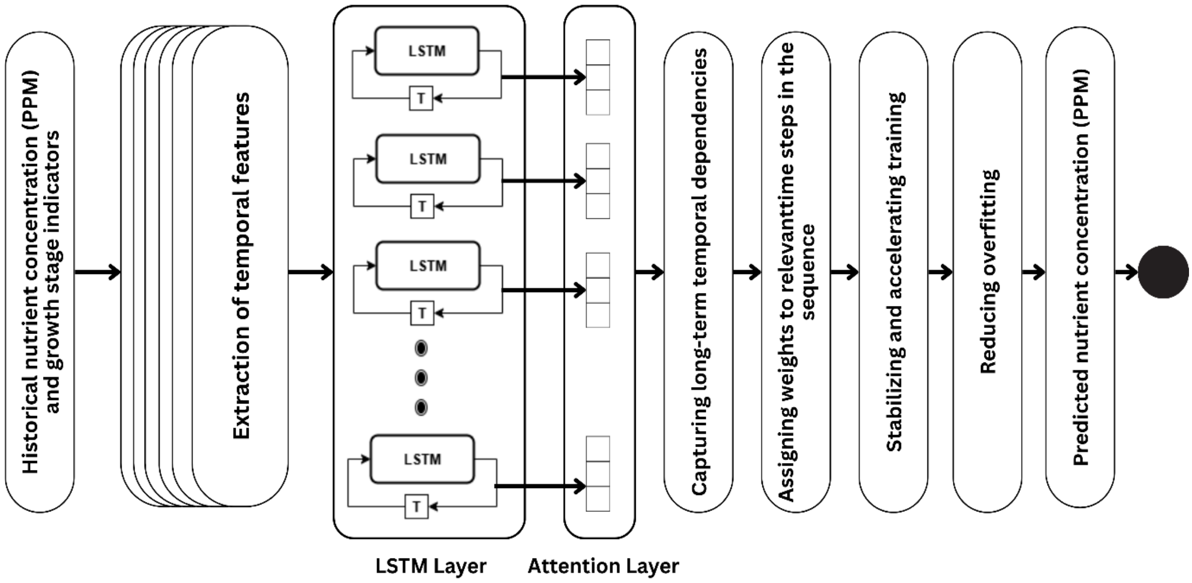

Figure 4. Attention-based LSTM architecture

Following the LSTM layers, an attention mechanism is applied to assign higher importance weights to the relevant time steps in the input sequence. This mechanism enables the model to focus on the critical periods that contribute most significantly to nutrient concentration predictions, particularly during the growth stage transition. The attention-enhanced representation is subsequently passed through normalization and regularization layers to stabilize training and reduce overfitting.

Finally, a fully connected output layer generated the predicted nutrient concentration values for the subsequent time steps. The complete LSTM with attention architecture, as shown in Figure 4, produces a data-driven nutrient concentration forecast that complements the rule-based prediction generated by the Fuzzy Time Series model. The output of this LSTM model was later combined with the FTS output within the proposed hybrid ensemble framework to improve the forecasting accuracy and robustness.

2.6. Hybrid Fuzzy Time Series–LSTM Ensemble Strategy

To improve forecasting accuracy and robustness, this study proposes a hybrid ensemble strategy that integrates a Fuzzy Time Series (FTS) model with a Long Short-Term Memory (LSTM) network. Each model possesses complementary strengths: the FTS provides interpretable rule-based forecasting and effectively handles uncertainty in nutrient concentration data, whereas the LSTM excels at capturing nonlinear temporal patterns and long-term dependencies. By combining both approaches, a hybrid model was designed to overcome the limitations of the individual methods and produce more reliable predictions of nutrient concentrations [36].

To combine the strengths of rule-based fuzzy reasoning and deep learning–based temporal modeling, a hybrid forecasting strategy was employed using a weighted ensemble mechanism. The final hybrid prediction was obtained by linearly combining the outputs of the FTS and LSTM models, as formulated in Equation (2). This weighted ensemble approach allows adaptive integration of complementary forecasting components and has been shown to improve prediction robustness in hybrid time-series models [37].

Vol. 7, No. 3, June 2026, Page. 2277-2293
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5600

$$\hat{Y}_{hybrid}(t) = \lambda(t)\, \hat{Y}_{LSTM}(t) + (1 - \lambda(t))\, \hat{Y}_{FTS}(t) \qquad (2)$$

where $\hat{Y}_{LSTM}(t)$ and $\hat{Y}_{FTS}(t)$ represent the predictions generated by the LSTM and FTS models, respectively, and $\lambda(t)$ denotes the weighting coefficient that controls the contribution of each model.

The weighting coefficient $\lambda(t)$ is defined dynamically to reflect the growth stage characteristics and prediction horizon requirements. During growth stages with complex and nonlinear nutrient dynamics, a higher weight was assigned to the LSTM component, whereas, during more stable stages, the contribution of the FTS model was increased. This adaptive weighting mechanism enables the hybrid model to adjust its behavior according to the physiological conditions of lettuce growth, thereby improving the forecasting throughout across the entire cultivation cycle.

The final output of the hybrid FTS–LSTM model represents an optimized nutrient concentration forecast that integrates both linguistic rule-based reasoning and deep learning-based temporal modeling. This hybrid prediction serves as the basis for nutrient management analysis and decision support in hydroponic lettuce cultivation, providing a more accurate and robust alternative to single-model forecasting approaches for lettuce cultivation.

2.7. Evaluation Metrics

The forecasting accuracy of the proposed models was evaluated using Mean Absolute Percentage Error (MAPE), which measures the average relative deviation between predicted and actual values. MAPE is commonly used in time-series forecasting because it provides an interpretable percentage-based error metric, making it suitable for performance comparison across different nutrient treatments, as defined in Equation (3) [38]. The MAPE is defined as:

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \qquad (3)$$

In addition to MAPE, Root Mean Square Error (RMSE) was used to quantify absolute prediction error and penalize larger deviations between predicted and observed values. RMSE is particularly sensitive to large errors, providing a complementary assessment of forecasting accuracy. The RMSE formulation is presented in Equation (4) and is widely adopted in hybrid forecasting model evaluations [39]. The MAPE is defined as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (Y_t - \hat{Y}_t)^2} \qquad (4)$$

where Y_t denotes the actual nutrient concentration at time step t, Y_t represents the predicted value, and n is the number of observations.

The selection of the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) as evaluation metrics was motivated by their complementary characteristics in time-series forecasting. MAPE provides a relative error measure expressed as a percentage, which is particularly suitable for comparing prediction accuracy across different nutrient concentrations in hydroponic systems. This metric enables an intuitive interpretation of the forecasting performance from a practical and decision-making perspective.

In contrast, the RMSE emphasizes the absolute error magnitude and penalizes larger prediction deviations more heavily. This property is essential for identifying substantial forecasting errors that may lead to incorrect nutrient-management decisions. By jointly employing MAPE and RMSE, this study ensured a balanced evaluation that captures both relative accuracy and absolute prediction reliability, making the evaluation suitable for nutrient concentration time-series forecasting in Internet of Things–based hydroponic environments.

Vol. 7, No. 3, June 2026, Page. 2277-2293
https://jutif.if.unsoed.ac.id
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3. RESULT

This section presents the results obtained from the implementation and evaluation of the proposed hybrid Fuzzy Time Series–Long Short-Term Memory (FTS–LSTM) model for forecasting nutrient concentration dynamics in hydroponic lettuce cultivation. The results were based on experimental nutrient concentration data collected from four different nutrient treatment levels over a 26-day observation period, with forecasting extended to 40 days to represent the complete lettuce growth cycle. The reported results include the descriptive characteristics of nutrient concentration behavior, forecasting accuracy evaluation, and prediction outcomes at the harvest stage.

3.1. Nutrient Concentration Characteristics

The observed nutrient concentrations exhibited distinct temporal patterns among the four treatments. The control sample (0 PPM), which did not receive nutrient supplementation, consistently showed low PPM values during the observation period. These values primarily reflect the baseline mineral content of the water and show minimal temporal variation.

The 400 PPM treatment demonstrated moderate nutrient concentrations with noticeable daily fluctuations. Although nutrient levels increased compared to the control, the observed values remained below the recommended optimal range for hydroponically cultivated lettuce.

The 600 PPM treatment showed relatively stable and balanced nutrient concentration dynamics. Nutrient levels gradually increased during the early growth stage and remained within or close to the recommended optimal range during subsequent stages, indicating consistent nutrient availability throughout the growth cycle of the plant.

In contrast, the 1000 PPM treatment consistently produced high nutrient concentrations. The observed PPM levels frequently exceeded the recommended upper limit, indicating excessive nutrient availability during most of the observation periods.

3.2. Forecasting Accuracy Results

The forecasting performance of the proposed hybrid FTS–LSTM model was evaluated using the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) as accuracy metrics.

Table 3. Forecasting accuracy of the hybrid FTS–LSTM model

Nutrient Treatment	MAPE (%)	RMSE (ppm)
Control (0 PPM)	2.43	1.98
400 PPM	3.12	9.87
600 PPM	3.45	15.23
1000 PPM	3.78	28.67

The results in Table 3 indicate that the hybrid model achieved low error values for all nutrient treatments, demonstrating high forecasting accuracy. Lower error values were observed for treatments with minimal nutrient variation, whereas higher error values were observed for treatments exhibiting greater concentration fluctuations.

3.3. Forecasting Results of Standalone Models

This subsection presents the forecasting performance of the standalone FTS and LSTM models to establish the baseline accuracy prior to evaluating the effectiveness of the proposed hybrid approach.

The standalone FTS model demonstrated stable performance for nutrient treatments with relatively smooth temporal patterns, particularly in the control and 400 PPM treatments. However, its accuracy decreased for treatments with higher variability, especially at 600 and 1000 PPM treatment groups, where nonlinear nutrient dynamics were more pronounced.

Jurnal Teknik Informatika (JUTIF) Vol. 7, No. 3, June 2026, Page. 2277-2293
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The standalone LSTM model showed improved performance for treatments with higher variability owing to its ability to capture nonlinear temporal dependencies. Nevertheless, the model exhibited sensitivity to short-term fluctuations, resulting in less stable predictions during certain growth-stage transitions.

3.4. Performance of the Hybrid FTS–LSTM Model

The performance of the proposed hybrid FTS–LSTM model was evaluated for all nutrient treatments using standard forecasting accuracy metrics. By integrating fuzzy rule-based reasoning with deep learning-based temporal modeling, the hybrid model generated stable nutrient concentration forecasts throughout the lettuce growth cycle.

Figure 5 illustrates the combined actual and predicted nutrient concentration trends over a 40-day growth cycle. The curves demonstrate a smooth transition between the measured data during the observation phase and the predicted values during the forecasting phase. Distinct nutrient dynamics were observed across the treatments, with the 600 PPM treatment approaching and remaining within the recommended optimal range during the later growth stages. In contrast, the 400 PPM treatment remained below the optimal threshold, whereas the 1000 PPM treatment exceeded the upper limit, indicating potential overfertilization.

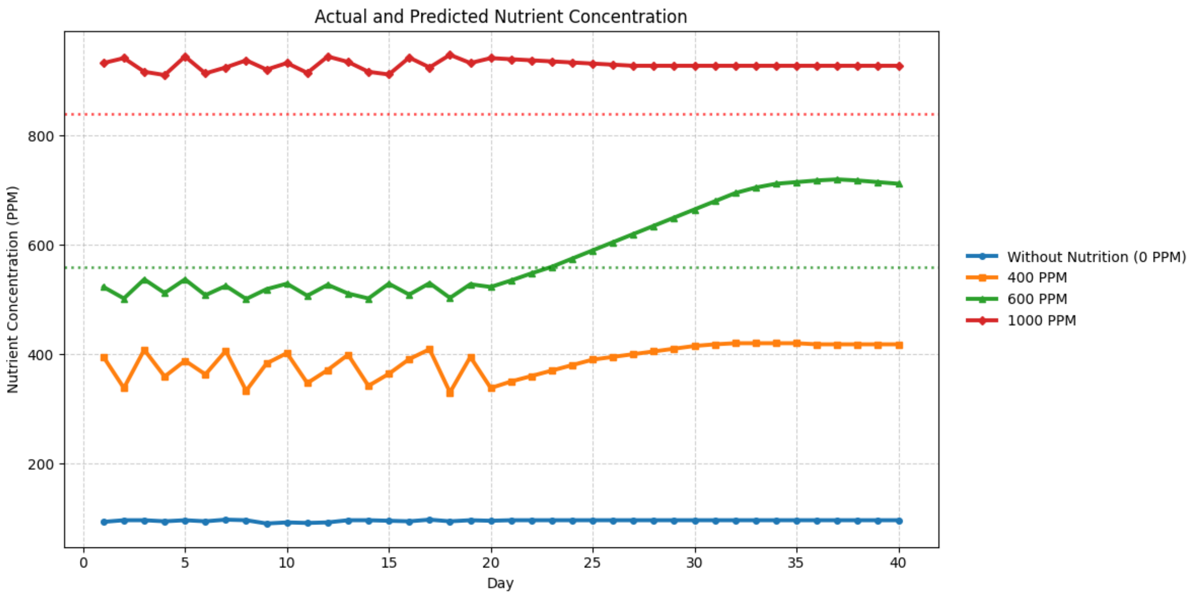

Figure 5. Actual and predicted nutrient concentration

To further examine the nutrient conditions at the harvest stage, the predicted nutrient concentration values on day 40 are summarized in Table 4.

Table 4. Predicted nutrient concentration at day 40

Nutrient Treatment	Predicted PPM	Nutrient Category
Control (0 PPM)	96.2	Low
400 PPM	418.5	Low
600 PPM	712.4	Optimal
1000 PPM	927.8	High

The observed nutrient concentration patterns reflect the interaction between nutrient supply levels and plant uptake capacity during the growth cycle. Treatments with insufficient nutrient input resulted

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in consistently low concentrations, whereas excessive input led to nutrient accumulation beyond the recommended range. The 600 PPM treatment exhibited a balanced nutrient profile at the harvest stage, indicating an equilibrium between nutrient supply and plant demand during the later growth stages.

3.5. Forecasting Performance Comparison

To validate the effectiveness of the proposed hybrid approach, a quantitative comparison was conducted between the standalone FTS model, standalone LSTM model, and hybrid FTS–LSTM model. The comparison results are listed in Table 5.

Table 5. Performance comparison of forecasting models

Model	0 PPM (MAPE/RMSE)	400 PPM (MAPE/RMSE)	600 PPM (MAPE/RMSE)	1000 PPM (MAPE/RMSE)
FTS	3.18 / 2.64	4.27 / 13.92	5.01 / 21.87	5.62 / 34.11
LSTM	2.91 / 2.31	3.89 / 11.45	4.12 / 18.96	4.76 / 30.42
Hybrid FTS-LSTM	2.43 / 1.98	3.12 / 9.87	3.45 / 15.23	3.78 / 28.67

As shown in Table 5, the hybrid FTS–LSTM model achieved lower MAPE and RMSE values across all nutrient treatments than the standalone models, indicating improved forecasting accuracy and robustness.

3.6. Analysis of Hybrid Model Performance

The observed performance advantages of the hybrid model can be attributed to its ability to leverage the complementary strengths of the FTS and LSTM. The FTS component contributes to the stability and interpretability through fuzzy linguistic rules, whereas the LSTM component effectively captures the nonlinear temporal dependencies in the nutrient concentration dynamics. The adaptive weighting mechanism further enhances the prediction stability by adjusting the model contributions according to the growth stage characteristics.

3.7. Optimal Nutrient Range Compliance

An additional evaluation was conducted to assess the compliance with the recommended nutrient concentration range for hydroponically cultivating lettuce. The 600 PPM treatment achieved the highest compliance rate, with 82% of the predicted values falling within the optimal range throughout the growth cycle. Lower compliance rates were observed for the 400 PPM and 1000 PPM treatments owing to nutrient deficiency and excess conditions, respectively.

4. DISCUSSIONS

This study demonstrates that integrating Fuzzy Time Series (FTS) and Long Short-Term Memory (LSTM) models provides a robust approach for forecasting nutrient concentration dynamics in hydroponic lettuce cultivation. The discussion focuses on interpreting the obtained results, explaining the observed model behavior, and highlighting the practical implications for precision nutrient management.

The observed performance advantages of the hybrid FTS–LSTM model can be attributed to the complementary characteristics of both the approaches. The FTS component effectively handles uncertainty and gradual changes in nutrient concentration using fuzzy rules, whereas the LSTM component captures complex nonlinear temporal patterns associated with plant growth and nutrient uptake. This combination allows the hybrid model to maintain a stable prediction accuracy across different growth stages, particularly during transitions, where the nutrient dynamics tend to change rapidly.

Vol. 7, No. 3, June 2026, Page. 2277-2293
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The results indicate that the 600 PPM treatment provides the most balanced nutrient conditions for hydroponic lettuce. Unlike the 400 PPM treatment, which consistently remained below the optimal nutrient range, the 600 PPM treatment gradually approached and maintained concentrations within the recommended range during the later growth stages. This finding aligns with the principles of hydroponic cultivation, where moderate nutrient availability supports efficient uptake and minimizes physiological stress. In contrast, the 1000 PPM treatment exceeded the optimal threshold, suggesting that excessive nutrient concentrations do not necessarily improve nutrient availability and may lead to inefficiencies or potential toxicity.

The smooth transition between the actual measurements and predicted values observed in the hybrid model indicates good generalization capability. This behavior suggests that the model does not merely memorize historical data but learns the underlying patterns of nutrient dynamics. Such stability is essential for real-world deployment, where forecasting models must reliably extend beyond observed data to support proactive decision-making.

When compared with recent studies on agricultural time-series forecasting, the accuracy achieved by the proposed hybrid FTS–LSTM model is competitive and, in several cases, superior. Previous research employing standalone deep learning models or conventional hybrid approaches has typically reported MAPE values above 4–6% for nutrient or environmental parameter predictions. In contrast, the hybrid model proposed in this study achieved MAPE values as low as 2.43%, indicating improved forecasting precision. This performance gain can be attributed to the integration of fuzzy rule-based uncertainty handling with deep recurrent temporal modeling, which enables a more accurate representation of complex nutrient dynamics across different growth stages.

From an error analysis perspective, larger prediction deviations were primarily observed during growth-stage transitions, where the nutrient uptake behavior changed more rapidly. During these phases, nutrient demand increases or stabilizes at different rates, leading to abrupt variations in the concentration trends. Standalone models exhibit reduced accuracy under such conditions owing to their limited capacity to simultaneously capture uncertainty and nonlinear temporal dependencies. In contrast, the hybrid FTS–LSTM model maintained a stable performance by dynamically balancing the contributions of the FTS and LSTM components, thereby reducing the error amplification during the transition periods.

Beyond its agricultural applications, this study contributes to the field of computer science, particularly in time-series forecasting and hybrid intelligent systems. The proposed framework demonstrates how rule-based fuzzy inference and deep learning architectures can be effectively integrated to overcome the limitations of single-model approaches. The adaptive ensemble strategy introduced in this study provides a generalizable methodology for IoT–based forecasting problems, including environmental monitoring, energy demand prediction, and smart city analytics. This contribution highlights the relevance of the proposed model for broader data-driven computing applications.

Despite these promising results, this study had several limitations. The current study focused primarily on nutrient concentration dynamics without explicitly incorporating other environmental factors such as light intensity, temperature fluctuations, or dissolved oxygen levels. Additionally, the experiment was conducted on a single lettuce variety under controlled conditions, which may limit its generalizability. Future research should explore multivariable integration, real-time implementation, and validation across various crops and hydroponic configurations.

Overall, the discussion confirms that the hybrid FTS–LSTM approach is well-suited for modeling nutrient dynamics in hydroponic systems. By combining accuracy, stability, and interpretability, the proposed model bridges the gap between advanced machine learning techniques and practical agricultural decision-making.

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In the control treatment (0 PPM), nutrient availability was limited to the baseline mineral content of the water, which is insufficient to support normal lettuce growth and may result in severe nutrient deficiency or plant failure if sustained throughout the entire growth cycle of the plant. The 400 PPM treatment provided additional nutrients; however, the concentration remained below the optimal range, which may have led to suboptimal growth and reduced biomass accumulation in the present study. In contrast, the 600 PPM treatment supplied sufficient nutrients to support balanced uptake, allowing plants to maintain nutrient concentrations within the recommended range and supporting healthy growth and development. Conversely, the 1000 PPM treatment resulted in nutrient concentrations exceeding the optimal threshold, which may have induced osmotic stress or nutrient toxicity, potentially inhibiting nutrient absorption efficiency and overall plant performance.

5. CONCLUSION

This study successfully developed and evaluated a hybrid forecasting model that combines Fuzzy Time Series (FTS) and Long Short-Term Memory (LSTM) networks to predict nutrient concentration dynamics in hydroponic lettuce cultivation. The proposed model was designed to address the limitations of individual forecasting approaches by integrating fuzzy rule-based reasoning with deep learning-based temporal pattern recognition.

The experimental results demonstrated that the hybrid FTS–LSTM model achieved superior forecasting performance compared to the standalone models, as indicated by lower prediction errors for all nutrient treatments. Among the evaluated treatments, the 600 PPM nutrient concentration consistently exhibited the most balanced and stable nutrient dynamics, achieving predicted values within the recommended optimal range (560–840 ppm) at the harvest stage. In contrast, the 400 PPM treatment remained below the optimal threshold, whereas the 1000 PPM treatment exceeded the upper limit, indicating potential under-fertilization and over-fertilization conditions, respectively.

The integration of growth stage awareness and adaptive weighting mechanisms enabled the hybrid model to maintain stable predictions throughout the 40-day growth cycle. These results confirm that the proposed approach provides reliable and actionable insights into precision nutrient management in hydroponic systems. These findings suggest that optimal nutrient regulation, supported by predictive modeling, can contribute to improved crop productivity while reducing excessive fertilizer use.

From an informatics and computer science perspective, this research contributes to the development of hybrid intelligent systems for time-series forecasting in Internet of Things environments. The proposed hybrid FTS–LSTM framework demonstrates how interpretable fuzzy inference mechanisms can be effectively integrated with deep learning architectures to overcome the limitations of single-model approaches. The adaptive ensemble strategy introduced in this study provides a generalizable computational framework that can be applied to a wide range of IoT-driven predictive analytics problems, beyond agriculture.

Future research may extend this study by incorporating multivariate environmental factors, such as temperature, light intensity, pH, and dissolved oxygen, to enhance the robustness of nutrient forecasting. From a computational perspective, further investigations may explore alternative deep learning architectures, including Gated Recurrent Units (GRU) and Transformer-based models, as comparative benchmarks to evaluate scalability and predictive performance. Additionally, real-time implementation and validation across different crop types and hydroponic configurations will further strengthen the the proposed framework's applicability.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest between the authors or with the research object in this paper.

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REFERENCES

[1] G. Kudirka, R. Sutulienė, A. Viršilė, K. Laužikė, and G. Samuolienė, "Precise Management of Hydroponic Nutrient Solution pH: The Effects of Minor pH Changes and MES Buffer Molarity on Lettuce Physiological Properties," *Horticulturae*, vol. 9, no. 7, pp. 837–850, 2023, doi: 10.3390/horticulturae9070837.

[2] A. B. Kaswar, R. D. Mahande, and J. D. Malago, "A New Model For Hydroponic Lettuce Nutrition Adaptive Control System Based On Fuzzy Logic Sugeno Method Using ESP32," *Jurnal Teknik Informatika (Jutif)*, vol. 4, no. 2, pp. 391–400, 2023, doi: 10.52436/1.jutif.2023.4.2.626.

[3] B. Ikiz, H. Y. Dasgan, and N. S. Gruda, "Utilizing The Power of Plant Growth Promoting Rhizobacteria on Reducing Mineral Fertilizer, Improved Yield, and Nutritional Quality of Batavia Lettuce in a Floating Culture," *Sci Rep*, vol. 14, no. 1, pp. 16–27, 2024, doi: 10.1038/s41598-024-51818-w.

[4] B. İkiz, H. Y. Dasgan, S. Balik, S. Kusvuran, and N. S. Gruda, "The Use of Biostimulants as a Key to Sustainable Hydroponic Lettuce Farming Under Saline Water Stress," *BMC Plant Biol*, vol. 24, no. 1, p. 808, 2024, doi: 10.1186/s12870-024-05520-8.

[5] Muh. Agus, A. T. P. D. Akhsa, and S. R. Yunus, "Perancangan Sistem Pemberian Nutrisi Tanaman Sayuran Hidroponik Otomatis Berbasis Arduino," *Jurnal Fokus Elektroda: Energi Listrik, Telekomunikasi, Komputer, Elektronika dan Kendali*, vol. 8, no. 4, pp. 248–258, 2023.

[6] S. Sharmin, M. T. Hossan, and M. S. Uddin, "A Review of Machine Learning Approaches for Predicting Lettuce Yield in Hydroponic Systems," *Smart Agricultural Technology*, vol. 11, pp. 100925–100937, 2025, doi: 10.1016/j.atech.2025.100925.

[7] S. L. Perez *et al.*, "Enhanced Vegetable Production in Hydroponic Systems Using Decontamination of Closed Circulating Fluid," *Sci Rep*, vol. 14, no. 1, pp. 602–611, 2024, doi: 10.1038/s41598-023-50974-9.

[8] C. N. Harsela, "Sistem Hidroponik Menggunakan Nutrient Film Technique Untuk Produksi dan Hasil Tanaman Selada (Lactuca sativa L.)," *Syntax Literate ; Jurnal Ilmiah Indonesia*, vol. 7, no. 11, pp. 17136–17144, 2022, doi: 10.36418/syntax-literate.v7i11.11983.

[9] M. Marisa, C. Carudin, and R. Ramdani, "Otomatisasi Sistem Pengendalian dan Pemantauan Kadar Nutrisi Air menggunakan Teknologi NodeMCU ESP8266 pada Tanaman Hidroponik," *Jurnal Teknologi Terpadu*, vol. 7, no. 2, pp. 127–134, 2021, doi: 10.54914/jtt.v7i2.430.

[10] D. Lim, K. Keerthi, S. Perumbilavil, C. S. Suchand Sandeep, M. M. Antony, and M. V. Matham, "A Real-time On-site Precision Nutrient Monitoring System for Hydroponic Cultivation Utilizing LIBS," *Chemical and Biological Technologies in Agriculture*, vol. 11, no. 1, pp. 111–120, 2024, doi: 10.1186/s40538-024-00641-6.

[11] R. Manimozhi and G. Krishnamoorthy, "Innovative Techniques in Agriculture: Transitioning From Traditional Farming to Precision and Hydroponic Agriculture," *Environmental Quality Management*, vol. 34, no. 3, pp. 70074–70084, 2025, doi: 10.1002/tqem.70047.

Vol. 7, No. 3, June 2026, Page. 2277-2293
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5600

[12] F. Al Faris *et al.*, "Comparative Analysis of LSTM and GRU for River Water Level Prediction," *Jurnal Teknik Informatika (Jutif)*, vol. 6, no. 5, pp. 3481–3494, 2025, doi: 10.52436/1.jutif.2025.6.5.5054.

[13] Y.-M. Qin, Y. Ni, T. Li, H. Wang, Y.-H. Tu, and R.-F. Wang, "Deep Learning for Sustainable Agriculture: A Systematic Review on Applications in Lettuce Cultivation," *Sustainability*, vol. 17, no. 7, pp. 3190–3222, 2025, doi: 10.3390/su17073190.

[14] S. Ashraf, S. Askar, N. Jabbar, and M. S. Chohan, "q-Rung Orthopair Fuzzy Time Series Forecasting Technique: Prediction Based Decision Making," *AIMS Mathematics*, vol. 9, no. 3, pp. 5633–5660, 2024, doi: 10.3934/math.2024272.

[15] I. G. S. Mahendra *et al.*, *Snart Computing IoT & Machine Learning*. PT. Sonpedia Publishing Indonesia, 2025.

[16] T.-W. Yoo and I.-S. Oh, "Time Series Forecasting of Agricultural Products' Sales Volumes Based on Seasonal Long Short-Term Memory," *Applied Sciences*, vol. 10, no. 22, pp. 8169–8173, 2020, doi: 10.3390/app10228169.

[17] O. Orojo, J. Tepper, T. M. Mcginnity, and M. Mahmud, "The Multi-Recurrent Neural Network for State-Of-The-Art Time-Series Processing," *Procedia Comput Sci*, vol. 222, pp. 488–498, 2023, doi: 10.1016/j.procs.2023.08.187.

[18] W. A. Pratiwi, I. M. Sumertajaya, and K. A. Notodiputro, "Stacking Ensemble RNN-LSTM Models for Forecasting the IDR/USD Exchange Rate with Nonlinear Volatility," *Jurnal Teknik Informatika (Jutif)*, vol. 6, no. 4, pp. 2331–2347, 2025, doi: 10.52436/1.jutif.2025.6.4.5057.

[19] X. Zou, D. Wu, K. Wang, and J. Lu, "Time Series Forecasting of Emission Trends Using Recurrent Neural Networks," *Computer Life*, vol. 12, no. 3, pp. 12–18, 2024, doi: 10.54097/ezvnav34.

[20] M. Rafrin, M. Agus, and P. A. Maharani, "IoT-Based Irrigation System Using Machine Learning for Precision Shallot Farming," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 8, no. 2, pp. 216–222, 2024, doi: 10.29207/resti.v8i2.5579.

[21] F. Yasin, M. R. Firmansyah, M. A. Amrustian, and D. Aldo, "Multivariate Forecasting of Paddy Production: A Comparative Study of Machine Learning Models," *Jurnal Teknik Informatika (Jutif)*, vol. 6, no. 3, pp. 1431–1442, 2025, doi: 10.52436/1.jutif.2025.6.3.4681.

[22] M. Taheri, H. Imanian, M. Bigdeli, and A. Mohammadian, "An Overview of Machine-Learning Methods for Soil Moisture Estimation," *Water (Basel)*, vol. 17, no. 11, pp. 1638–1672, 2025, doi: 10.3390/w17111638.

[23] F. Schneider, J. Swiatek, and M. Jelali, "Detection of Growth Stages of Chilli Plants in a Hydroponic Grower Using Machine Vision and YOLOv8 Deep Learning Algorithms," *Sustainability*, vol. 16, no. 15, pp. 6420–6448, 2024, doi: 10.3390/su16156420.

[24] M. Alimussadad, D. Lestari, and W. Mulyo Utomo, "Smart Hydroponic Nutrient Monitoring and Control System Using Fuzzy Logic and IoT," *Teknologi Informasi dan Komputer*, vol. 115, no. 2, pp. 115–129, 2025, doi: 10.31961/eltikom.v9i2.1494.

[25] Muh. Agus, P. Ayu Maharani, and M. Rafrin, "Perancangan Sistem Pemantauan Kelembaban Tanah,Udara dan Suhu pada Tanaman Bawang Merah Menggunakan IoT," *Prosiding Seminar Nasional SISFOTEK*, 2023, vol. 7, no. 1, pp. 102–108.

[26] L. Judijanto, V. Wiliyanti, W. Sahusilawane, M. Agus, E. Efitra, and N. Dihniah, *Teknologi Pembelajaran: Inovasi Pembelajaran di Masa Depan*, PT. Sonpedia Publishing Indonesia, 2025.

[27] M. Itasari *et al.*, *Elektronika Dasar (Teori dan Praktik)*, PT. Sonpedia Publishing Indonesia, 2025.

[28] Muh. Agus, M. Rafrin, S. R. Yunus, N. R. Sulnas, and N. Aulia, "Perancangan Prototype Sistem Rekomendasi Tempat Parkir Berbasis IoT dan AI (Studi Kasus: Mall Panakkukang)," *JURNAL IT Media Informasi IT STMIK Handayani*, vol. 15, no. 3, pp. 153–161, 2024, doi: https://doi.org/10.37639/jti.v15i3.382.

[29] M. Syafaat, R. B. Syafiun, A. N. Ramadhan, and D. A. Haerunnisa, "IoT-Based Smart Garden Using MQTT Protocol with Adafruit IO App," *Jurnal Teknik Informatika (Jutif)*, vol. 4, no. 4, pp. 723–732, 2023, doi: 10.52436/1.jutif.2023.4.4.636.

[30] S. Zhou, J. Guo, S. Huang, S. Guo, and B. Du, "A Hybrid Framework for Multivariate Time Series Forecasting of Daily Urban Water Demand Using Attention-Based Convolutional Neural Network and Long Short-Term Memory Network," *Sustainability*, vol. 14, no. 17, pp. 11086–11107, 2022, doi: 10.3390/su141711086.

[31] H. Kang, "The Prevention and Handling of the Missing Data," *Korean J Anesthesiol*, vol. 64, no. 5, pp. 402–406, 2013, doi: 10.4097/kjae.2013.64.5.402.

[32] M. J. Azur, C. Frangakis, P. J. Leaf, and E. A. Stuart, "Multiple Imputation by Chained Equations: What is it and How Does it Work?," *Int J Methods Psychiatr Res*, vol. 20, no. 1, pp. 40–49, 2011, doi: 10.1002/mpr.329.

[33] K. Yemets, I. Izonin, and I. Dronyuk, "Enhancing the FFT-LSTM Time-Series Forecasting Model via a Novel FFT-Based Feature Extraction–Extension Scheme," *Big Data and Cognitive Computing*, vol. 9, no. 2, pp. 35–50, 2025, doi: 10.3390/bdcc9020035.

[34] T. Cansu, E. Egrioglu, E. Bas, and T. Akkan, "Intuitionistic Fuzzy Time Series Forecasting Method Based on Dendrite Neuron Model and Exponential Smoothing," *Granular Computing*, vol. 9, no. 2, pp. 49–57, 2024, doi: 10.1007/s41066-024-00474-6.

[35] O. Eraliev and C.-H. Lee, "Performance Analysis of Time Series Deep Learning Models for Climate Prediction in Indoor Hydroponic Greenhouses at Different Time Intervals.," *Plants*, vol. 12, no. 12, pp. 2316–2328, 2023, doi: 10.3390/plants12122316.

[36] H.-Y. Lin and B.-W. Hsu, "Application of Hybrid Fuzzy Interval-based Machine Learning Models on Financial Time Series - A Case Study of Taiwan Biotech Index During the Epidemic Period.," *Front Artif Intell*, vol. 6, no. 1, pp. 1–17, 2024, doi: 10.3389/frai.2023.1283741.

[37] D. Phamtoan, N. Vothihang, and B. Phamthi, "Improving Forecasting Model for Fuzzy Time Series Ysing the Self-updating Clustering and Bi-directional Long Short Term Memory Algorithm," *Expert Syst Appl*, vol. 241, p. 122767, 2023, doi: 10.1016/j.eswa.2023.122767.

[38] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, "The M4 Competition: Results, Findings, Conclusion and Way Forward," *Int J Forecast*, vol. 34, no. 4, pp. 802–808, 2018, doi: 10.1016/j.ijforecast.2018.06.001.

[39] S. Kim and H. Kim, "A New Metric of Absolute Percentage Error for Intermittent Demand Forecasts," *Int J Forecast*, vol. 32, no. 3, pp. 669–679, 2016, doi: 10.1016/j.ijforecast.2015.12.003.