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Optimized ensemble framework for predicting hydroponic stock and sales using machine learning

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ABSTRACT

The increasing global demand for food necessitates the adoption of sustainable agricultural practices. Hydroponic farming, while efficient in resource utilization, faces challenges in accurately predicting stock levels and sales due to dynamic, ever-changing factors. This research presents an optimized ensemble framework for forecasting hydroponic stock levels and sales by integrating linear regression (LR), random forest (RF), and XGBoost, further enhanced through an evolutionary algorithm (EA). The proposed framework is evaluated using root mean square error (RMSE) and mean absolute error (MAE), demonstrating significant accuracy improvements over individual models. The ensemble model achieves an RMSE reduction of 43.82% for stock prediction and 55.3% for sales forecasting compared to the best-performing individual model. Additionally, local interpretable model-agnostic explanations (LIME) are employed to offer stakeholders clear insights into decision-making processes, such as identifying "number of harvested crops" and "sales data" as key drivers of prediction outcomes. This framework supports sustainable development goals (SDGs) 9.3, 12.3, and 12.C by promoting resource efficiency, reducing food waste, and improving small-scale farmer market access. Future research will explore real-time data integration for dynamic adaptation and further model enhancements.

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1. INTRODUCTION

The increasing demand for sustainable agriculture has led to the rise of hydroponic farming, a resource-efficient cultivation method. However, hydroponic farms face significant challenges in stock management, including overstocking, understocking, and food waste [1]. Studies indicate that improper forecasting leads to up to 30% of produce spoilage in urban hydroponic farms due to inaccurate demand prediction and supply chain inefficiencies [2]. These inefficiencies highlight the critical need for advanced predictive analytics to optimize production and reduce losses.

Existing forecasting models often struggle with the unique complexities of hydroponic farming, such as dynamic plant growth cycles, fluctuating weather conditions, and resource constraints [3], [4]. These challenges make it difficult to maintain optimal stock levels, often resulting in inefficiencies and financial losses. Traditional statistical models and single-machine learning approaches fail to capture the intricate, nonlinear relationships in hydroponic data, leading to inaccurate predictions [5], [6].

To address this research gap, this study proposes an optimized ensemble framework that integrates linear regression (LR), random forest (RF), and XGBoost. These models complement each other by leveraging their unique strengths: LR captures linear trends in stock movement [7]. RF enhances robustness by handling nonlinear interactions and feature importance [8]. XGBoost improves accuracy through gradient boosting techniques [6].

The integration of an evolutionary algorithm (EA) optimizes model weighting to enhance predictive performance [9]. This method dynamically adjusts model contributions, reducing forecasting errors and improving adaptability. Additionally, the adoption of local interpretable model-agnostic explanations (LIME) enhances transparency by identifying key predictive factors, enabling stakeholders to make informed decisions regarding inventory control and demand forecasting [10], [11]. This research aligns with sustainable development goals (SDGs) by supporting SDG 12.3 (reducing food waste), SDG 9.3 (enhancing market access for small-scale farmers), and SDG 12.C (optimizing resource allocation). The proposed ensemble framework enhances prediction accuracy, helping farmers make data-driven decisions to minimize waste and optimize resources. Additionally, the interpretability provided by LIME improves transparency, ensuring that stakeholders can effectively manage production cycles for a more sustainable and efficient hydroponic farming ecosystem.

The remainder of this paper is organized as: section 2 outlines the proposed methodology, including data acquisition, preprocessing, and model development. Section 3 presents the results and discussion, evaluating the performance of the proposed framework. Section 4 concludes with key insights, implications, and potential future research directions.

2. METHOD

This research consists of four main steps: data acquisition, model development, model evaluation, and interpretability. Figure 1 provides additional details on the process. Further explanations are available in the subsequent subsections.

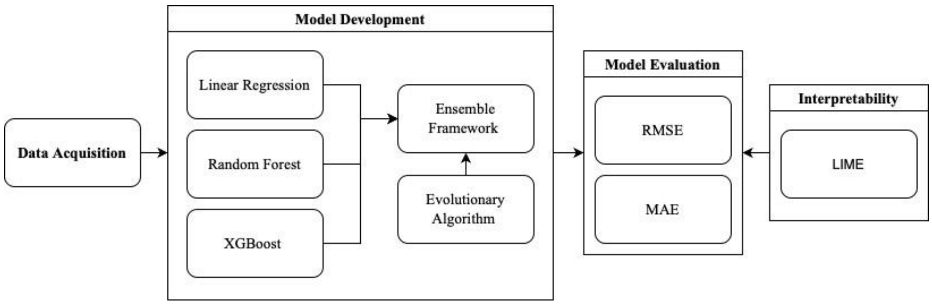


Figure 1. The development of an ensemble framework

2.1. Data acquisition

The dataset used in this study was collected from a hydroponic farm over a span of 28 weeks. It includes key variables such as the number of crops planted, the number of crops harvested, and sales records. Data preprocessing involved handling missing values by calculating the remaining stock based on available data, such as harvest and sales quantities, and adding it to the stock for the following week, and splitting the dataset into an 80% training set and a 20% testing set to ensure the reliability of the model [12], [13].

2.2. Model development

The EA used in this study adjusts the weights of individual models-LR [14], RF [15], and XGBoost [16] to minimize prediction errors. Rather than assigning equal weights to these models, the EA dynamically optimizes their contributions based on their performance. The goal is to find the optimal weight for each model by minimizing prediction errors using performance metrics such as root mean square error (RMSE) and mean absolute error (MAE). This approach ensures that models with higher individual accuracy have a greater influence on the final prediction while maintaining the robustness of the ensemble.

The optimization process begins by initializing a population of 100 individuals, each representing a unique combination of weights. Fitness evaluation is conducted to assess each individual's performance based on RMSE and MAE, allowing the algorithm to identify the most effective weight assignments. Once the optimal weight combination is found, the ensemble model is evaluated using various performance metrics. Additionally, LIME is applied to explain the model's predictions, providing stakeholders with actionable insights into the factors driving stock and sales forecasts.

The selection mechanism retains the top 50% of individuals with the best performance for the next generation. To maintain diversity and avoid premature convergence, crossover and mutation operations are employed to introduce genetic variations. Crossover occurs with a probability of 50%, allowing weight combinations to share information, while mutation occurs with a 20% probability, introducing small variations to explore new potential solutions. The optimization process runs iteratively for 50 generations, gradually refining weight distributions until convergence is achieved. Through this iterative approach, the model dynamically adjusts the contributions of each algorithm to minimize prediction errors [9], [17]. The optimized weight assignments enhance the model's adaptability, improving forecasting accuracy and decision-making efficiency.

2.3. Model evaluation

The models were evaluated using RMSE and MAE scores. A comparative analysis was conducted to measure the differences in performance between individual models and the optimized ensemble. This analysis aimed to assess improvements in predictive accuracy and reliability [18]–[20].

2.4. Interpretability with local interpretable model-agnostic explanations

To ensure transparency, LIME was employed to analyze feature importance such as number harvested, sales data, remaining stock, and number of plants planted. This method helps explain prediction outcomes by illustrating the influence of key variables. By providing clearer insights, LIME enhances stakeholder trust in stock and sales predictions [21], [22].

3. RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed ensemble framework, its interpretability, comparisons with prior research, and its implications for sustainable agricultural practices. The findings demonstrate the effectiveness of EA-based optimization in improving the predictive accuracy of hydroponic stock and sales forecasting. Additionally, the integration of LIME enhances the model's transparency, making it more actionable for stakeholders.

3.1. Model performance evaluation

Model performance was evaluated using RMSE and MAE to assess the accuracy of stock and sales predictions. Table 1 shows the RMSE and MAE values for each individual model and the ensemble model. The ensemble approach consistently outperforms LR, RF, and XGBoost in both metrics, demonstrating its ability to handle the complexities of hydroponic sales forecasting. Figure 2 visualizes the predicted versus actual remaining stock levels, highlighting the model's accuracy. Overall, the ensemble model provides more consistent predictions that are closer to the actual values.

Table 1. Model performance comparison

Model	Remaining stock		Sales	
	RMSE	MAE	RMSE	MAE
LR	1.78	1.04	5.39	2.17
RF	2.89	1.49	6.53	2.12
XGBoost	4.27	1.19	16.60	3.32
Ensemble model	1.00	0.93	2.41	1.66

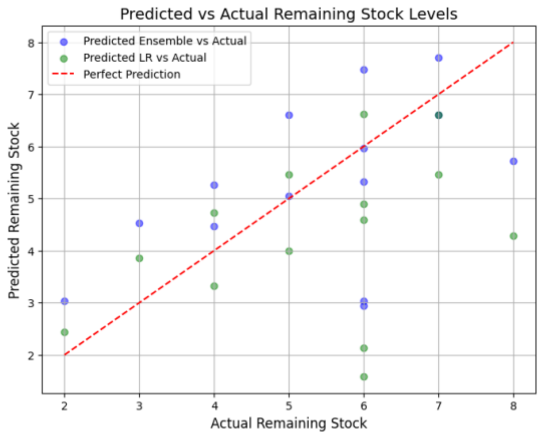


Figure 2. The predicted versus actual remaining stock levels

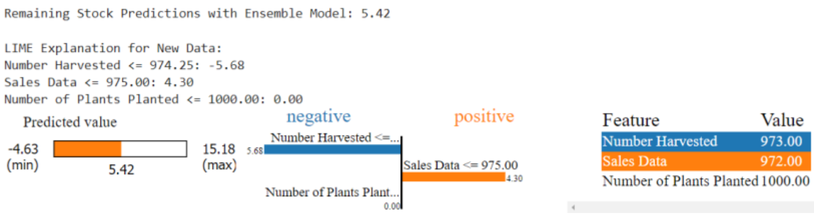
The ensemble model, optimized using an EA for weight adjustment, significantly reduces both RMSE and MAE values. This improvement demonstrates the effectiveness of combining multiple models through optimized weighting, leading to more reliable predictions. These enhancements are particularly valuable for small-scale hydroponic farmers, as they improve inventory management and sales forecasting, ultimately minimizing waste and optimizing resources [23]–[25]. For stock prediction, the optimized weights are 0.92 for LR, 0.52 for RF, and -0.26 for XGBoost. For sales prediction, the weights are 0.03 for LR, 0.72 for RF, and 0.26 for XGBoost. The weight optimization process improves prediction accuracy, supporting more efficient stock management and reducing food waste.

The ensemble model handles non-linearity and feature interactions by utilizing the strengths of RF and XGBoost. While LR captures only linear relationships, RF and XGBoost are capable of modeling complex, non-linear patterns and interactions between features. Therefore, even though LR does not account for feature interactions, the ensemble model combines the benefits of all three models, enabling it to capture both non-linearity and feature interactions effectively.

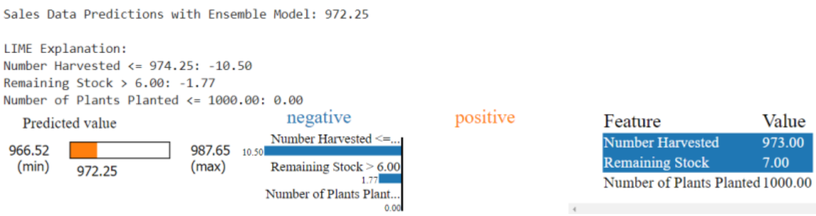
3.2. Interpretability of predictions

To enhance the transparency of model decisions, LIME was employed to analyze the impact of various features on prediction outcomes as shown in Figure 3. The results indicate that "number harvested" and "sales data" are the most influential factors in determining remaining stock Figure 3(a), while "number harvested" and "remaining stock" play a crucial role in predicting sales Figure 3(b). For remaining stock predictions Figure 3(a), if the number of harvests is less than or equal to 974.25, the prediction decreases by 5.68 units, indicating a strong negative impact. Conversely, if sales data is less than or equal to 975.00, the predicted stock increases by 4.30 units, suggesting that stock levels are expected to be higher when recent sales stay within this threshold. The number of plants planted has a negligible effect on this prediction. These findings highlight those fluctuations in harvest size and recent sales trends significantly influence stock availability, allowing farmers to better anticipate inventory levels.

For sales predictions Figure 3(b), when the number of harvests is less than or equal to 974.25, the predicted sales decrease by 10.50 units, confirming the direct correlation between harvest size and sales volume. Additionally, if remaining stock exceeds 6.00 units, the prediction drops by 1.77 units, indicating that surplus inventory does not necessarily translate to higher sales. Similar to the stock prediction, the number of plants planted has an insignificant influence on the sales forecast. These insights demonstrate that maintaining an optimal harvest size and managing inventory effectively are critical for maximizing sales. By interpreting predictions through LIME, the framework provides actionable insights that enable farmers to make data-driven adjustments in production strategies. Understanding these feature contributions helps optimize inventory control, improve demand forecasting, and enhance resource allocation, leading to more efficient and sustainable hydroponic farming [26], [27].



(a)



(b)

Figure 3. LIME analysis for (a) remaining stock prediction and (b) sales prediction

3.3. Comparison with previous studies

Previous research on hydroponic forecasting has predominantly utilized single machine learning models or statistical methods, which often struggle to adapt to diverse environmental conditions and market fluctuations. These methods often lack generalizability and robustness, limiting their effectiveness in real-world hydroponic systems. Idoje *et al*. [28] emphasize the limitations of traditional machine learning algorithms when applied to hydroponic data, highlighting the need for more adaptive and optimized approaches.

In contrast, our proposed EA-optimized ensemble framework overcomes these limitations by dynamically adjusting model weights, resulting in higher predictive accuracy, robustness, and interpretability. The improvements are supported by the lower RMSE and MAE scores, demonstrating the effectiveness of the optimization process. Compared to conventional approaches, our method optimally integrates multiple models, ensuring greater stability and improved generalization across diverse datasets [29].

Additionally, explainability has been largely overlooked in previous hydroponic forecasting research. Unlike earlier studies that focused solely on prediction accuracy, our work incorporates LIME to enhance model transparency. Razak *et al*. [30] highlighted, explainable artificial intelligence (XAI) is crucial for agricultural decision-making, as it allows stakeholders to understand the rationale behind predictions. Our framework ensures that model outputs are not only accurate but also interpretable, making it practical for real-world implementation.

3.4. Implications for sustainable practices

The proposed framework contributes to sustainable agricultural practices by utilizing advanced predictive analytics. Improved forecasting capabilities enable better stock management, waste reduction, and support small-scale hydroponic farmers in making informed decisions. By integrating machine learning and EA-based optimization, the framework enhances efficiency and adaptability in agricultural operations. A key contribution of this framework is its alignment with SDGs. It supports SDG 12.3 (reducing food waste) by optimizing stock management, which minimizes overproduction and spoilage. By providing more accurate predictions of supply and demand, the system helps reduce unnecessary resource consumption and financial losses.

Furthermore, the framework contributes to SDG 9.3 (supporting small-scale farmers) by providing data-driven decision-making tools. These tools empower farmers with actionable insights, allowing them to make more strategic decisions and compete more effectively in the market. With improved forecasting and inventory control, small-scale hydroponic farmers can enhance productivity and reduce operational risks.

Additionally, the framework advances SDG 12.C (improving resource efficiency) by fostering efficient resource use. By optimizing agricultural processes, it ensures that resources such as water, nutrients, and energy are utilized effectively. This contributes to a more sustainable approach to hydroponic farming, reducing environmental impact while enhancing productivity. Overall, the proposed framework promotes data-driven agriculture by improving efficiency, productivity, and sustainability. By minimizing inefficiencies and facilitating better decision-making, it benefits individual farmers and contributes to broader sustainability efforts in agricultural practices [31].

4. CONCLUSION

This study demonstrates the effectiveness of an optimized ensemble framework combining LR, RF, and XGBoost models, refined through EA-based weight optimization, for accurately forecasting hydroponic stock and sales. By integrating LIME, the framework also enhances model interpretability, empowering informed decision-making. The improved predictive accuracy has significant implications for small-scale hydroponic farmers, supporting better inventory management, waste reduction, and resource optimization, which align with sustainable agriculture practices and contribute to achieving the SDGs. Future work will focus on incorporating real-time data and adaptive modeling techniques to further improve forecasting performance, responsiveness, and the overall effectiveness of the system in dynamic agricultural environments.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Ressa Priskila	✓	✓							✓	✓	✓		✓	
Putu Bagus Adidyana Anugrah Putra	✓	✓	✓	✓		✓	✓							
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C : **C**onceptualization
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

INFORMED CONSENT

There were no human subjects.

ETHICAL APPROVAL

There were no animal subjects.

DATA AVAILABILITY

The dataset utilized in this study can be accessed at: https://drive.google.com/drive/folders/1-FnIbXqmkBFCrR1SLlFmINjDaRFx04Od?usp=sharing.

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