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Enhanced Prediction of Jasmine 105 Rice Growth with RC-ELM and Slow-Release Organic Fertilizers

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ABSTRACT

This study explores the use of a Residual Compensation Extreme Learning Machine (RC-ELM) to predict the growth of Jasmine 105 rice, specifically in the context of slow-release organic fertilizers (SROFs). The experiment involved four types of fertilizers: Cow Manure, Filter Cake, Aerated Compost, and a standard chemical control (27-12-6). The macronutrient content of each fertilizer was used as key input variables in the RC-ELM model, with real-time field sensor data providing insights. After extensive preprocessing through normalization and feature engineering, RC-ELM demonstrated superior performance compared to traditional models, such as Linear Regression, Support Vector Machines (SVM), and standard ELM variants. In particular, RC-ELM achieved an $R^2 = 0.9609$, $Y=14.982x - 103.58$ for Aerated Compost, reducing the Mean Squared Error (MSE) by 30%. The results indicate that while organic fertilizers like Aerated Compost may incur higher costs, they offer long-term sustainability benefits, including improved soil fertility. The study further highlights the importance of adopting organic agricultural practices, which align with internationally recognized standards, such as Organic Thailand and IFOAM, for food safety and environmental preservation. These findings underscore the potential of RC-ELM in enhancing crop yield predictions while supporting sustainable farming practices.

Article information:

Keywords: Residual Compensation-ELM, Correlation-Based Feature Selection, Kernel Function, Jasmine Rice Khao Dawk Mali 105, Slow-Release Organic Fertilizers

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1. INTRODUCTION

The cultivation of Thailand's Jasmine Rice, Khao Dawk Mali 105, plays a crucial role in the country's agricultural sector, contributing significantly to domestic consumption and export revenue. Known for its distinct aroma and high quality, KDML 105 has become a global favorite. [1] The growing need for sustainable agricultural practices in the cultivation of Jasmine 105 rice is critical due to challenges in optimizing yield and quality while minimizing environmental impacts. Traditional farming techniques, including conventional fertilizer application and statistical models, have often led to inconsistent outcomes, such as nutrient leaching and suboptimal growth rates. Although historically utilized, these methods lack the precision and adaptability required for dynamic agricultural environments [2]. Given the increasing global demand for food and the environmental risks associated with inefficient fertilizer use, there is a critical need for innovative solutions such as slow-release organic fertilizers (SROFs) and advanced machine learning models. These tools aim to enhance growth prediction accuracy and resource utilization, thus improving both crop yield and sustainability [3].

Recent research has investigated machine learning algorithms and fertilizer management techniques in rice cultivation, but challenges persist. Support Vector Regression and Artificial Neural Networks have shown limited success in capturing the complex, nonlinear interactions between growth factors and yield [4, 5]. Furthermore, conventional fertilizers are often

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used without considering the benefits of slow-release organic fertilizers [6], which offer better nutrient efficiency. Studies, such as Li *et al.* (2024), examined SROFs across crops but failed to integrate them with machine learning models for rice, highlighting a gap in enhancing both nutrient management and predictive accuracy [7].

Our research aims to address current limitations by developing a model that integrates the Residual Compensation Extreme Learning Machine [8] with slow-release organic fertilizers for Jasmine 105 rice cultivation. Previous models like Support Vector Regression and Artificial Neural Networks have shown potential but lack the predictive accuracy needed for complex agricultural systems. By combining RC-ELM with SROFs, we can enhance nutrient management and increase the precision of rice growth prediction, thereby improving yield, promoting sustainability, and minimizing environmental impact [9]. This integrated approach enhances precision agriculture and contributes to sustainable farming practices.

2. RELATED WORKS

The use of Machine Learning in optimizing agricultural practices has gained significant traction in recent years. This section reviews the existing literature on integrating ML with slow-release organic fertilizers, with a specific focus on applications in Thailand.

2.1 Agricultural Photoperiod Sensitivity of The Thai Jasmine Rice Variety Khao Dawk Mali 105

Photoperiod sensitivity plays a crucial role in cultivating The Thai Rice variety Khao Dawk Mali 105 (KDML105). This variety's flowering and maturation are highly influenced by changes in day length, aligning with optimal climatic conditions such as sufficient rainfall and moderate temperatures. Traditional agricultural practices in Thailand have leveraged this sensitivity to maximize yields. However, these methods often encounter significant limitations in dynamic and complex environments [10].

Conventional techniques such as direct seeding and transplanting have been integral to rice cultivation for decades. These methods depend heavily on historical knowledge and the intuitive experience of farmers. While effective in stable conditions, they often lack the precision to handle the intricate interactions between various environmental factors. This can lead to inconsistent yields and inefficient resource use, particularly when unexpected weather changes disrupt the timing of flowering in photoperiod-sensitive rice varieties [11].

Traditional statistical models, such as linear regression, have been widely applied to predict crop yields and optimize farming practices. However, these models rely on simplifying assumptions, such as linear relationships between variables, which often fail to capture the complexity of agricultural systems [12]. Factors like soil composition, weather variability, and plant genetics interact in non-linear ways, making it difficult for traditional models to deliver accurate predictions under changing environmental conditions [13]. Recent advancements in slow-release fertilizers offer a solution by providing a sustained nutrient supply over time, improving nutrient use efficiency, and reducing application frequency [14]. This approach supports the photoperiod-sensitive growth of KDML 105 rice, enhancing yield and sustainability. Integrating slow-release fertilizers with advanced predictive models optimizes fertilizer use and boosts rice productivity in Thailand.

2.2 Slow-Release Organic Fertilizers in Agriculture

Slow-release organic fertilizers (SROFs) provide a controlled nutrient release that matches the crop's growth requirements, reducing nutrient losses and improving use efficiency. These fertilizers enhance soil health, increase crop yields, and minimize environmental impacts compared to conventional fertilizers. Integrating SRFs with predictive models can further improve their effectiveness in agricultural practices [15]. The SROFs typically consist of organic materials such as Compost, manure, and biochar, which decompose slowly [16]. This gradual decomposition ensures a steady supply of nutrients, improving soil health and promoting sustainable agricultural practices. Key benefits include improved nutrient efficiency, enhanced soil structure, and reduced environmental pollution [11, 16-17]. Some common SROFs include:

Manure-Based Fertilizers: Animal manure, often combined with straw or other organic matter, provides a slow-release source of nitrogen, phosphorus, and potassium.

Compost: Compost made from plant residues, food waste, and manure offers a balanced mix of nutrients and improves soil structure.

Biochar: Biochar, produced from the pyrolysis of organic material, enhances nutrient retention and soil health by providing a stable habitat for beneficial microorganisms.

The study [18] assessed the effects of slow-release and controlled-release urea fertilizers on rice yield and environmental impact. The research found that slow-release urea fertilizers increased rice grain yield by 10% compared to conventional urea. Additionally, ammonia volatilization was significantly reduced by 30-50%, depending on the type of controlled-release fertilizer used. The study also noted a 20-30% reduction in greenhouse gas emissions, including methane and nitrous oxide, showcasing the ecological benefits [19]. These findings highlight the dual advantages of enhanced agricultural productivity and reduced environmental footprint using advanced urea fertilizers.

2.3 Extreme Learning Machine

An Extreme Learning Machine (ELM) is a feedforward neural network specifically designed explicitly for single-hidden layer feedforward networks (SLFNs). It is known for its rapid learning capabilities and high generalization performance. Unlike traditional neural networks that require iterative parameter tuning, ELM assigns input weights and biases randomly and keeps them constant throughout training [20]. The output weights are determined analytically, significantly speeding up the training process.

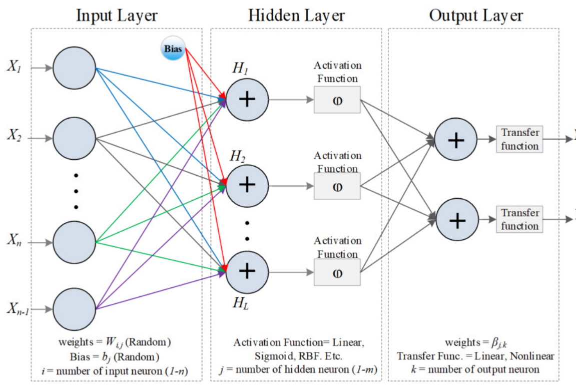

Fig.1: *The structure of Extreme Learning Machine.*

Random Initialization: The input weights a_i, and biases b_i of the hidden layer neurons are randomly assigned and remain fixed throughout training.

Linear Parameter Solution: Given N training samples (x_i, t_i), where x_i is the input vector, and t_i is the target output, the hidden layer output matrix H is computed as:

$$H = \begin{bmatrix} G(a_l, b_l, x_l) & \cdots & G(a_L, b_L, x_l) \\ \vdots & \vdots & \vdots \\ G(a_l, b_l, x_N) & \ldots & G(a_L, b_L, x_N) \end{bmatrix} \quad (1)$$

Where G is the activation or transfer function, and L is the number of hidden nodes.

Output Weights Calculation: The output weights β are determined using the Moore-Penrose generalized inverse of H:

$$\beta = H^{\dagger} T \quad (2)$$

Where T is the matrix of target outputs, and $H^{\dagger}$ is the Moore-Penrose inverse of H.

A comprehensive review of the Extreme Learning Machine, emphasizing its rapid learning speed and low computational costs, making it highly effective for classification, regression, and feature selection tasks. The authors explore ELM's wide applications across multimedia analysis, agriculture, and industrial process control [21]. They highlight the growing trend of using hybrid ELM models, which integrate optimization algorithms to improve performance [22]. In agriculture, hybrid ELM models show promise in enhancing crop yield prediction and resource optimization, particularly when combined with sustainable practices like slow-release fertilizers.

2.4 Advanced Predictive Models: Residual Compensation Extreme Learning Machine

The Residual Compensation Extreme Learning Machine (RC-ELM) is an advanced variant of the Extreme Learning Machine (ELM) designed to improve prediction accuracy by iteratively compensating for residual errors. This method integrates additional layers that iteratively refine the initial predictions made by the base ELM model, enhancing its performance in capturing complex data relationships [23].

Residual Calculation: The residuals e_1 from the initial ELM predictions are calculated:

$$e_1 = y - \tilde{y} = y - H_1\beta_1. \quad (3)$$

First Compensation Layer: A secondary ELM to predict these residuals. The hidden layer output matrix for this layer H_2 in a similar manner and adjusts the residuals accordingly:

$$\begin{aligned} \hat{e}_1 &= H_1\beta_1 \\ e_2 &= e_1 - \hat{e}_1 \end{aligned} \quad (4)$$

Iterative Residual Compensation: This process is iteratively applied, where each subsequent layer compensates for the residual errors of the previous layer.

$$e_{i+1} = e_i - H_i\beta_{i+1} \quad (5)$$

Consequently, RC-ELM can be employed to predict the optimal environmental and soil conditions required for cultivating KDML105. By analyzing historical data on temperature, humidity, soil nutrients, and water availability, RC-ELM can model the complex, nonlinear relationships between these variables and the growth outcomes of the rice. The model's Multi-Layer structure allows it to capture residual errors and iteratively improve predictions, ensuring that farmers receive highly accurate guidance on the best times and conditions for planting [24].

2.5 Kernel Function in ELM and RC-ELM

Kernel Function is a mathematical function used that transform data from a lower-dimensional space to a higher-dimensional space without directly computing the transformation. This approach enables the

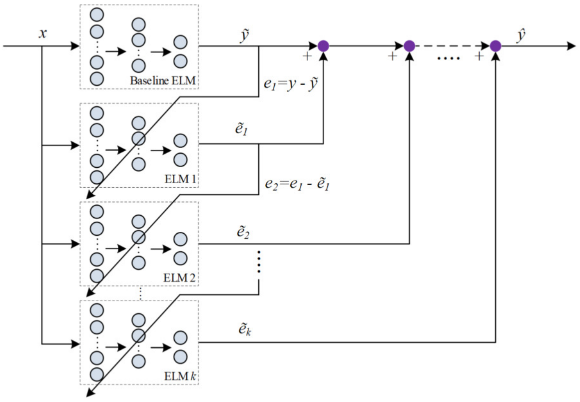

Fig.2: *Training phase of RC-ELM.*

separation of data groups that cannot be linearly separated in the original space using linear methods. In ELM and RC-ELM, Kernel Functions to handle nonlinear data. The Kernel Trick allows computations in the higher-dimensional space directly using the Kernel Function instead of performing complex feature transformations.

2.5.1 Linear Kernel Function [20, 24]

$$G(a, b, x) = (x_i, x_j) = x_i^T x_i \quad (6)$$

Linear Kernel Function compute the dot product between two data vectors x_i and x_j, where: x_i and x_j are vectors in the original space. x_i^T is the transpose of vector x_i.

2.5.2 Sigmoid Kernel Function [20, 24]

$$G(a, b, x) = \tanh(\alpha x_i^T + c) \quad (7)$$

Sigmoid Kernel Function consists of the following steps: (1) compute the dot product between x_i and x_j, i.e. $x_i^T x_j$; (2) Multiply the result by the parameter α; and (3) add the constant c. Apply the hyperbolic tangent function to the result using the equation $\tanh(z)$.

2.5.3 Radial Basis Function Kernel Function [20, 24]

$$G(a, b, x) = \exp\left(-\gamma \|x_i - x_j\|^2\right) \quad (8)$$

Radial Basis Function the Kernel Function involves the following steps: $\|x_i - x_j\|^2$ is the squared Euclidean distance between vectors x_i and x_j, calculated by summing the squared differences of each component in the vectors. γ is a parameter that controls the spread of the Kernel, where a higher value of γ makes the Kernel more focused on nearby points.

2.6 Purpose integration of RC-ELM with SROFs

Integrating advanced predictive models like RC-ELM with slow-release organic fertilizers (SROFs) marks a notable advancement in agricultural yield prediction. RC-ELM excels in managing nonlinear data and large datasets, enhancing predictive accuracy by addressing residual errors often neglected by traditional models [11, 12]. This study highlights that combining SROFs with biochar and Compost improves nitrogen use efficiency in wetland rice paddies, reducing ammonia emissions by 15% and increasing soil bacterial populations by 20% [16-17, 19]. Moreover, nutrient synchronization achieved through SROFs resulted in a 10% rise in rice yields [25], demonstrating their potential to enhance sustainable agriculture and productivity.

Recent studies have showcased the effectiveness of RC-ELM in integrating diverse data sources such as remote sensing, meteorological data, and soil health metrics to improve crop yield predictions [27]. For instance, combining. Hyperspectral Imaging and Machine Learning for Crop Stress Detection and Management reported a 95% accuracy in detecting crop stress [26]. conducted a study on Controlled-Release Nitrogen Fertilizer (CRNF) and its impact on microbial community symbiosis, published in Field Crop Research [19]. The results showed that CRNF significantly enhanced nitrogen use efficiency by 25%, increased microbial biomass by 18%, and improved crop yield by 15% compared to conventional fertilizers. These findings underscore the potential of CRNF to promote sustainable agriculture.

Utilizing multi-spectral and hyper-spectral imaging as high-resolution inputs for RC-ELM models has improved yield estimation accuracy by 20% and achieved an R^2 of 0.85 when integrating satellite data [28]. RC-ELM offers advantages such as faster training times and reliable performance on limited datasets, making it well-suited for scenarios involving sporadic agricultural data collection. Studies confirm RC-ELM's superior accuracy in predicting crop yields, outperforming traditional models like SVM and random forests [27, 29].

3. MATERIALS AND METHODS

The procedures and methodologies employed in this research encompass the entire process from data collection and preprocessing through to the selection of significant features, training and testing of various models, and ultimately, the evaluation of the model outcomes for predicting the growth of KDML 105.

The study used Jasmine rice seeds (KDML 105) – 50 kg, Cow Manure – 17 kg, Filter Cake – 17 kg, Aerated Compost – 17 kg, and Chemical Fertilizer (27-12-6) – 30 kg. Equipment included a mixing tub, 1000 mL beaker, 200-cell seedling trays, high-precision scale (NBL 254i), ruler, measuring tape, moisture meter (Dickey-john 46233-1223A), and weighing scales (100 kg capacity and SUNFORD ACS-30-ZC41). This setup ensured accuracy in material preparation and data collection.

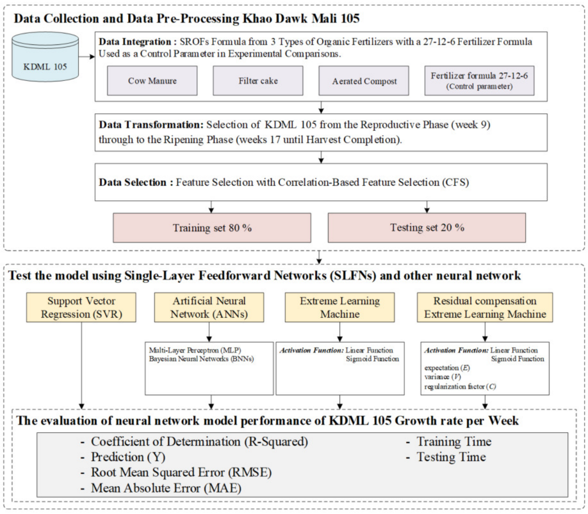

Fig.3: The Conceptual Framework of this study.

3.1 Data Collection and Data Preparation

The cultivation of KDML 105 rice involves key growth stages, starting from transplanting and progressing through the initiation of panicle primordia (IPP). By the 9^{th} Week, the rice enters the reproductive phase, marked by morphological changes as the stem transitions from flat to cylindrical. These morphological changes lead to the booting stage, marked by stem swelling and flag leaf emergence, signaling the beginning of panicle formation. The ripening phase occurs between the 17^{th} and 21^{st} weeks, culminating in full-grain maturation. The development of slow-release organic fertilizers (SROFs) for KDML 105 utilized three agricultural by-products: Cow Manure, Filter Cake, and Aerated Compost. These were combined with urea and additives to create three distinct formulations. Each 5-gram fertilizer was coated with 10 grams of clay, embedding three rice seeds. The experiment employed a Randomized Complete Block Design (RCBD) in 2×2 meter plots, with nine plots comprising three replications per treatment, and each replication containing five plants [30].

The researchers installed temperature and humidity data collectors in the experimental plots. A 27-12-6 fertilizer served as the control for comparison, detailed in Table 1.

The nutrient content analysis of three slow-release fertilizer formulations, as shown in Table 1, highlights Aerated Compost as having the highest levels of nitrogen and phosphate, making it highly effective for promoting strong plant growth. Cow Manure stands out for its rich potassium content, which is vital for plant health and disease resistance. Cow Manure and Filter Cake are rich in organic matter, which is essential for improving soil structure and fertility. Aerated Compost contains significantly higher moisture, which may influence its application and nutrient release rate. The pH levels across all formulations are slightly alkaline, making them suitable for most soil types. Electrical conductivity is highest in Filter Cake, reflecting a higher concentration of soluble salts. Moreover, the favorable carbon-to-nitrogen ratio in Cow Manure supports a slow release of nutrients, contributing to improved soil fertility and sustained plant growth.

Table 1: *The analysis of nutrients in slow-release fertilizers developed into planting blocks.*

Macronutrients	Cow Manure	Filter Cake	Aerated Compost
Nitrogen (Total N; %)	5.22	5.79	5.96
Phosphate (P2O5; %)	0.03	0.08	0.25
Potassium (K2O; %)	0.44	0.11	0.16
Organic matter	9.45	9.44	7.69
Moisture by weight	14.38	10.07	20.11
pH Value 1:2	7.34	7.39	7.47
EC 1:10; ds/m	0.42	0.54	0.39
Organic carbon	5.48	5.47	4.46
Carbon/Nitrogen ratio	1.05	0.94	0.75

3.2 Correlation-Based Feature Selection

Correlation-Based Feature Selection (CFS) is a vital method for enhancing regression models by selecting features that are highly correlated with the target variable but have low inter-correlation among themselves [31]. The effectiveness of CFS in improving model accuracy by focusing on relevant features while eliminating redundancy [32]. This method is advantageous in regression analysis, where feature selection directly impacts predictive performance, making CFS a robust tool for researchers in machine learning and data analysis.

Data collection on the cultivation of photoperiod-sensitive KDML 105 using slow-release organic fertilizer from planting to harvesting consists of 59 data types, consisting of 16 Nominal, 7 Nominal (Date), 9 Discrete, and 27 Continuous. In the process of selecting factors using the CFS method for predicting the growth rate of KDML 105, the merit of a feature subset [31, 32] is calculated using the formula: (9)

$$Marit(S) = \frac{k \cdot \overline{r_{cf}}}{\sqrt{k + k \cdot (k-1) \cdot \overline{r_{ff}}}} \tag{9}$$

Where k is the number of features in the subset (S)

$\overline{r_{cf}}$ is the average correlation between the features in subset (S) and the target variable Y

$\overline{r_{ff}}$ denotes the average correlation between features in the subset (S) Evaluate the feature subsets using the formula above and select the one with the highest merit score.

3.2.1 Calculate the Correlation between Factors and Target Variable [31, 32]:

Compute the Pearson Correlation coefficient between each feature $X_1, X_2, \ldots, X_n$. The target variable Y is Growth rate (Week), The formula is:

$$\overline{r_{cf}} = \frac{\sum(X_i - \bar{X}_i)(Y - \bar{Y})}{\sqrt{\sum(X_i - \bar{X}_i)^2 \sum(Y - \bar{Y})^2}} \quad (10)$$

The result is $\overline{r_{cf}}$. will use Pearson Correlation values with a score of 0.70 or higher. Features with lower scores will be removed as they may introduce errors that are not important. Table 2 is used as the criteria for significant correlation between all features and the target variable.

Features: X_{Temp}, $X_{Humidity}$, $X_{Chlorophyll}$, $X_{Riceearclump}$, $X_{Plant\ weight(fresh)}$, $X_{Seed\ weight}$, $X_{Ricegrains(ear)}$, $X_{Total\ grain}$, $X_{Plant\ Height(cm)}$, $X_(Yield(kg/plot))$

Target Variable: $Y_{Growth\ rate(week)}$

$$\overline{r_{cf}} = \frac{0.85 + 0.75 + 0.80 + 0.72 + \cdots + 0.87}{10}$$

$$\overline{r_{cc}} = \frac{0.08}{10} = 0.808$$

Table 2: *Result of Correlation between Factors and Target Variable.*

No	Features	Description	Values	Correlation
1	Temp	Temperature (°C)	28.2 c	0.85
2	Humidity	Humidity within the rice field (%)	62	0.75
3	Chlorophyll	Chlorophyll content in rice leaves (%)	33.9	0.80
4	Rice ear clump	Total number of rice ears per clump	40.34	0.72
5	Plant weight (fresh)	Fresh plant weight per clump (g)	3.5	0.88
6	Seed weight	Weight of 100 rice seeds per clump (g)	Week 9	0.76
7	Rice grains (ear)	Number of rice grains per ear	35 cm	0.74
8	Total grain	Total grain weight for 1000 rice seeds (g)	25 kg	0.82
9	Growth rate (Week)	Week number indicating the growth stage of the Rice	Week 9, day 2	1.00
10	Plant Height (cm)	Height of the rice plants in centimeters	16	0.89
11	Yield (kg/plot)	Yield of Rice in kilograms per plot	145	0.87

3.2.2 Calculate the Correction between Features:

Calculate the average correlation between features and the target variable [31, 32]. The formula for the Pearson Correlation Coefficient between features X_i and X_j is.

$$\overline{r_{ff}} = \frac{\sum(X_i - \bar{X}_i)(X_j - \bar{X}_j)}{\sqrt{\sum(X_i - \bar{X}_i)^2 \sum(X_j - \bar{X}_j)^2}} \quad (11)$$

$rX_1, X_2 = 0.06$ (X_{Temp} and $X_{Humidity}$)
$rX_1, X_3 = 0.05$ (X_{Temp} and $X_{Chlorophyll}$)
$rX_{10}, X_9 = 0.85$ ($X_{Yield(kg/plot)}$ and $X_{PlantHeight(cm)}$)
The result is $\overline{r_{ff}}$ which indicates the correlation between the features.

$$\overline{r_{ff}} = \frac{0.60 + 0.55 + 0.40 + 0.70 + \cdots + 0.85}{45} \approx 0.65$$

3.2.3 Calculate the Merit of the Feature Subset [31, 32]

We use the Merit formula (9) to evaluate the feature subset:

$$Merit_s = \frac{10 \cdot 0.808}{\sqrt{10 + 10(10-1) \cdot 0.65}}$$

$$Merit_s = \frac{8.08}{\sqrt{10 + 58.5}} = \frac{8.08}{\sqrt{68.5}} = \frac{8.08}{8.28} = 0.976$$

Therefore, the Merit value of this Feature Subset is 0.976, which reflects the average correlation between all the selected factors and the target (Growth rate per Week). Generally, a high Pearson Correlation value indicates that the factors are closely related to the target variable, which in turn enhancing the accuracy of predictive modeling.

When conducting experiments with KDML 105 rice using the four sets of planting blocks, we transplanted seedlings during the Reproductive Phase. During this period, rice reaches full growth, forming young panicles, and the stems change from a flattened to a round shape between weeks 10^{th} and 17^{th}. This continues into the Ripening Phase, during which the rice flowers pollinate, and the grains, initially resembling milky liquid, turn into complex starch and eventually mature, ready for harvest by week 16^{th} onwards. Following the completion of the rice planting process, we divided the data into training and testing sets using an 80:20 ratio, as show in Table 3.

Table 3: *Training and Testing datasets in the experiment..*

Experimental	Training set	Testing set	Total
Cow Manure	327	81	405
Filter Cake	318	79	397
Aerated Compost	340	85	415
Control (27-12-6)	353	89	443
Total	1,338	334	1,660

3.3 Performance Evaluation

Performance Evaluation is a critical process in assessing the effectiveness of predictive models, particularly in forecasting the growth of KDML 105. This process involves using various metrics to evaluate how well the model can predict the target variable, in this case, the growth rate of the Rice over a specified period [33]. By applying suitable performance metrics, researchers can assess the model's accuracy, reliability, and generalizability.

3.3.1 Mean Absolute Error (MAE) [33]

Measures the average magnitude of the errors between the predicted and actual values without considering their direction. It provides a straightforward interpretation of the average prediction error.

$$MAE = \frac{1}{n}\sum\nolimits_{i=1}^{n} |y_i - \hat{y}_i| \qquad (12)$$

3.3.2 Mean Squared Error (MSE) [33]

Is the average of the squared differences between the predicted and actual values. By squaring the errors, MSE places greater emphasizes on larger errors, making it helpful in highlighting significant deviations in predictions.

$$MSE = \frac{1}{n}\sum\nolimits_{i=1}^{n} (|y_i - \hat{y}_i|)^2 \qquad (13)$$

3.3.3 Root Mean Squared Error (RMSE) [33]

Is the square root of MSE, providing an error metric in the same units as the target variable. Researchers often prefer this metric due to its interpretability and sensitivity to significant errors.

$$RMSE = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n} (y_i - \hat{y}_i)^2} \qquad (14)$$

3.3.4 R-squared (Coefficient of Determination) [33]

Measures the extent to which the model accounts for variability in the target variable. It ranges from 0 to 1, with values closer to 1 indicating a better fit.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \qquad (15)$$

Where y represents the mean of the actual growth rates observed in the dataset.

4. RESULTS AND DISCUSSION

4.1 Results of General Rice Cultivation with SROFs

The experimental results from the cultivation of KDML 105 using various slow-release organic fertilizers, although promising, reveal that optimal growth conditions have not yet been fully reached. Despite notable improvements in growth rates with different fertilizer treatments, the overall growth remains moderate. For instance, the Cow Manure treatment exhibited growth ranging from 43.33 cm at week 10$^{\text{th}}$ to 59.01 cm at week 17$^{\text{th}}$, yet its $R^2 = 0.6415$ indicates only a moderate correlation in predicting growth trends. Similarly, although the Filter Cake and Aerated Compost treatments showed better results, with higher growth rates and stronger correlations (R^2 values of 0.8064 and 0.8465, respectively), the growth performance, especially during the early stages, remained inconsistent. The control group using the 27-12-6 fertilizer demonstrated the most substantial and consistent growth with an $R^2 = 0.8659$, suggesting a better fit for the predictive model. Aerated Compost demonstrated the highest growth performance among natural slow-release fertilizers, with an $R^2 = 0.8465$. While the chemical fertilizer control 27-12-6 outperformed in growth, this study emphasizes the potential of sustainable, natural fertilizers for agriculture.

Table 4: *Growth Results of KDML 105 Rice Cultivation Using a Developed SROFs Formula.*

Organic Fertilizer	Maximum-Minimum Height (cm)		R^2	Y
	Week 10	Week 17		
Cow Manure	43.33±50.20	59.01±85.09	0.6415	4.1931x + 5.9591
Filter Cake	45.06±61.23	75.85±89.04	0.8064	4.3248x + 13.018
Aerated Compost	**48.04±54.21**	**83.05±99.76**	**0.8465**	**8.896x - 53.146**
Control 27-12-6	60.22±67.30	92.02±104.00	0.8659	6.7113x - 18.317

To enhance the accuracy of rice growth predictions, advanced models like the Extreme Learning Machine (ELM) and its variant, Residual Compensation ELM (RC-ELM), offer significant advantages. These models capture the nonlinear and complex growth patterns characteristic of rice cultivation. By applying regression techniques and neural network-based approaches, such as RC-ELM, these models effectively account for subtle variations in growth rates under different fertilizer treatments. This precision is critical for optimizing fertilizer strategies and enhancing crop yield. Compared to traditional linear regression methods, ELM and RC-ELM provide more reliable predictions by handling the complexities of agricultural data, making them ideal for improving decision-making in dynamic environmental conditions.

4.2 The experimental results of Support Vector Regression (SVR)

The results presented in Table 5, using the Support Vector Regression (SVR) model, show varying degrees of predictive accuracy as reflected by the R^2 values and corresponding regression equations Y. The R^2 values for the Cow Manure, Filter Cake, and Aerated Compost fertilizers were 0.8316, 0.8339, and 0.8632, respectively, indicating a moderate to strong correlation between the predicted and observed growth rates. However, the predictive models did not achieve a sufficiently high R^2 to be considered highly accurate predictors of rice growth. The regression equations Y also suggest that while the models captured some growth patterns, they may still lack the precision required to fully model the complexities of rice growth under varying fertilization conditions. Notably, these results exclude the control group, focusing solely on the experimental treatments.

Table 5: *Growth Results of Support Vector Regression.*

Organic Fertilizer	Maximum-Minimum Height (cm)		R^2	Y
	Week 10	Week 17		
Cow Manure	35.09±39.32	72.51±85.06	0.8316	5.8076x - 24.508
Filter Cake	45.06±61.23	75.85±89.00	0.8339	2.2409x - 27.449
Aerated Compost	48.04±54.21	83.02±99.76	0.8632	5.3927x - 24.025
Control 27-12-6	40.30±42.18	82.05±95.51	0.8961	2.4452x - 34.4513

4.3 The experimental results of Artificial Neural Networks (ANNs)

We analyzed the growth prediction of KDML 105 rice using Multi-Layer Perceptron (MLP) and Bayesian Neural Networks (BNNs), with performance metrics (R^2 values and regression equations) detailed in Table 6.

Table 6: *Growth Results of Artificial Neural Network.*

Models	Organic Fertilizer	Maximum-Minimum Height (cm)		R^2	Y
		Week 10	Week 17		
MLP	Cow Manure	35.09± 39.32	72.51± 85.06	0.8316	5.8076x – 24.508
	Filter Cake	45.06± 61.23	75.85± 89.00	0.8339	2.2409x – 27.449
	Aerated Compost	**48.04± 54.21**	**83.02± 99.76**	**0.8632**	**5.3927x – 24.025**
	Control 27-12-6	40.30± 42.18	82.05± 95.51	0.8961	2.4452x – 34.4513
BNNs	Cow Manure	**28.07± 50.21**	**59.01± 85.09**	**0.7632**	**2.2409x + 7.4492**
	Filter Cake	25.02± 46.18	42.24± 60.12	0.7316	1.3927x + 7.7025
	Aerated Compost	32.23± 50.25	71.06± 84.25	0.7351	2.4452x + 4.4513
	Control 27-12-6	24.37± 44.29	80.18± 90.23	0.8462	5.044x – 13.9688

The results in Table 6 highlight the predictive performance of the MLP algorithm in modeling the growth of KDML 105 rice with various organic fertilizers. The MLP achieved R^2 values between 0.8316 and 0.8632, indicating a strong correlation between predicted and actual growth. For example, the regression equation for Cow Manure ($Y = 5.8076x - 24.508$) shows a positive relationship between time and development, with MLP refining predictions through backpropagation by iteratively adjusting network weights.

Conversely, the BNNs algorithm demonstrated lower R^2 values, from 0.7316 to 0.7632, reflecting moderate accuracy. BNNs account for uncertainty by modeling weights as distributions rather than fixed values, as shown in the regression equation $Y = 2.2409x + 7.4492$ for cow manure. While both models provided useful predictions, their limitations suggest exploring more advanced approaches, such as the ELM, which offers more efficient handling of nonlinear data and faster training times.

Table 7: *Growth Results of Experiments Using Advanced Predictive Models: RC-ELM.*

Models	Organic Fertilizer	Max-Min Height (cm)		R^2	Y
		Week 10	Week 17		
ELM (Linear Kernel)	Cow Manure	41.06± 55.22	53.30± 81.12	0.8079	5.1212x – 47.4478
	Filter Cake	34.25± 44.53	58.22± 74.44	0.8776	8.896x – 43.146
	Aerated Compost	**38.82± 47.72**	**60.16± 92.50**	**0.8906**	**8.7982x – 48.893**
	Control 27-12-6	40.12± 51.11	60.18± 90.23	0.9121	10.223x – 59.3652
ELM (Sigmoid Kernel)	Cow Manure	50.00± 57.30	92.02± 104.04	0.7932	6.2247x – 27.415
	Filter Cake	42.12± 61.23	72.34± 88.51	0.7671	6.8758x – 23.8232
	Aerated Compost	**42.71± 53.14**	**80.76± 102.84**	**0.8041**	**6.7123x – 25.5456**
	Control 27-12-6	41.04± 56.33	92.00± 106.73	0.8185	6.962x – 29.1234
ELM (RBF Kernel)	Cow Manure	39.17± 47.28	101.18± 124.47	0.7532	12.198x – 89.0987
	Filter Cake	30.34± 41.21	98.69± 120.85	0.7104	11.284x – 98.0192
	Aerated Compost	**40.23± 46.93**	**104.36± 126.22**	**0.7844**	**12.348x – 100.237**
	Control 27-12-6	41.25± 48.44	105.52± 128.94	0.8276	13.120x – 101.132
RC-ELM (Linear Kernel)	Cow Manure	43.34± 52.41	115.32± 128.12	0.9265	12.143x – 107.39
	Filter Cake	40.11± 51.23	101.23± 130.29	0.9121	12.873x – 100.949
	Aerated Compost	**45.31± 54.45**	**127.66± 140.03**	**0.9609**	**14.982x – 103.58**
	Control 27-12-6	45.21± 57.21	133.12± 148.12	0.9645	15.416x – 108.02
RC-ELM (Sigmoid Kernel)	Cow Manure	40.15± 56.09	117.08± 140.01	0.9176	10.896x – 100.146
	Filter Cake	38.33± 41.18	92.39± 109.33	0.9012	12.8384x – 95.923
	Aerated Compost	**45.31± 54.45**	**127.66± 140.03**	**0.9309**	**14.982x – 103.58**
	Control 27-12-6	42.45± 53.12	121.12± 158.08	0.9238	15.044x – 103.96
RC-ELM (RBF Kernel)	Cow Manure	39.05± 42.28	113.11± 131.64	0.8948	12.143x – 100.31
	Filter Cake	35.35± 48.54	119.12± 129.09	0.8862	10.145x – 102.732
	Aerated Compost	40.58± 45.12	120.12± 141.47	0.9057	13.764x – 94.708
	Control 27-12-6	43.65± 50.62	121.36± 147.42	0.9101	11.377x – 106.999

4.4 Results of Experiments Using Advanced Predictive Models: RC-ELM.

The application of ELM and RC-ELM in predictive modeling for the growth of KDML 105 rice involved a systematic hyperparameter optimization process. We tested the number of hidden nodes (L) with values ranging from 10, 30, 50 up to 1,000, and so on. We varied the Regularization Factor (C) across $2^{-12}, 2^{-10}, 2^{-8}, \ldots, 2^{12}$. We made comparisons using three activation functions: Linear, Sigmoid, and Radial Basis Function (RBF). We identified the optimal configuration as L=700 for ELM and $L = 500$, $C = 2^6$ for RC-ELM, with Linear activation yielding the best performance for the predictive task. These results, visualized in Fig. 4

RC-ELM outperformed linear regression in forecasting growth rates under diverse conditions and fertilizer treatments in Table 7.

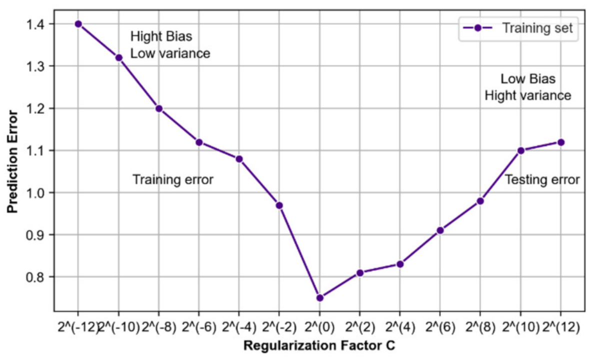

Fig.4: *Regularization Factor C.*

The ELM algorithm, when applied with different activation functions—Linear, Sigmoid, and RBF Kernels—demonstrates varying degrees of predictive performance for KDML 105 growth using slow-release organic chemical fertilizers: Cow Manure, Filter Cake, and Aerated Compost. The Linear Kernel generally exhibits the highest R^2 values among the three, indicating a strong linear relationship between time and growth. For instance, using Aerated Compost with the Linear Kernel yields an $R^2 = 0.8906$ and a regression equation of $Y = 8.7982x - 48.893$, indicating that the model effectively captures linear growth patterns. The high R^2 demonstrates a strong fit, explaining most of the variance in rice growth. In contrast, the Sigmoid Kernel, which introduces nonlinearity into the model, has lower R^2 values, such as 0.8041 for Aerated Compost, with a Corresponding equation $Y = 6.7123x - 25.5456$. The lower R^2 indicates that while the Sigmoid Kernel captures some nonlinear relationships, it may not fully account for the complexity of growth patterns in the rice data. The RBF Kernel, known for its ability to handle more complex, nonlinear data, also shows moderate predictive capability, but with R^2=0.7844 for Aerated Compost. The regression equation $Y = 12.348x - 100.237$ suggests that the RBF Kernel attempts to model growth with more aggressive parameter shifts. However, it may overestimate the variability in the data, leading to less precise predictions.

The RC-ELM algorithm, designed to enhance ELM's predictive performance by compensating for residual errors, significantly improves the accuracy of growth predictions for KDML105. When applied with the Linear Kernel, RC-ELM achieves an R^2=0.9609 for Aerated Compost, with the regression equation $Y = 14.982x - 103.58$, indicating a near-perfect fit and highly accurate predictions. The Linear Kernel in RC-ELM captures the linear growth dynamics of rice with remarkable precision, explaining nearly all the variance in growth. Similarly, the RC-ELM with Sigmoid and RBF Kernels outperforms their ELM counterparts. For example, the Sigmoid Kernel in the RC-ELM model combined with Aerated Compost achieves an R^2= 0.9309 and a regression equation of Y=13.112x-103.84, indicating its superior capability to capture complex nonlinear growth patterns. The RBF Kernel in RC-ELM also shows significant improvement, with an $R^2 = 0.9057$ for Aerated Compost and a regression equation $Y = 13.764x - 94.708$. These results indicate that RC-ELM possesses superior capabilities for handling the intricacies of rice growth data, providing more accurate and stable predictions across all kernel types.

The RC-ELM consistently delivers superior results to other algorithms due to its unique ability to correct residual errors generated by initial predictions. Unlike traditional algorithms, RC-ELM incorporates a residual learning mechanism that sequentially improves prediction accuracy by compensating for discrepancies in earlier outputs. This iterative refinement enhances the model's ability to capture complex, nonlinear patterns, especially in high-variability datasets typical of agricultural growth modeling. Additionally, RC-ELM's computational efficiency, ensures optimal performance with reduced overfitting risks, making it particularly suited for dynamic systems like KDML 105 rice cultivation.

4.5 Training and testing time of SVR MLP BNNs ELM and RC-ELM

The training and testing times are critical metrics in evaluating the computational efficiency of machine learning algorithms, as they directly impact the feasibility and scalability of models in practical applications. These metrics are crucial when comparing all algorithms across different kernel functions and organic fertilizers, as they provide insight into the trade-offs between model complexity and computational demand. We present the training and testing times in Table 8.

The analysis of training and testing times reveals notable differences in computational efficiency among the algorithms. ELM with a Linear Kernel is the fastest, with training times as low as 3.5123 seconds and testing at 0.4234 seconds, making it ideal for tasks with linear relationships. BNNs, however, require up to 23.1789 seconds for training due to their complex probabilistic models, making them less efficient. RC-ELM strikes a balances between speed and accuracy, especially with the RBF Kernel, making it suitable when both computational efficiency and predictive accuracy are essential.

Table 8: *Training time and testing time of SVR, MLP, BNNs, ELM and RC-ELM.*

Models	Organic Fertilizer	Training Time (s)	Testing Time (s)
SVR	Cow Manure	5.1234	0.6789
	Filter Cake	5.0678	0.6453
	Aerated Compost	5.1476	0.6821
	Control 27-12-6	5.1089	0.6724
MLP	Cow Manure	12.4567	1.1234
	Filter Cake	12.0345	1.0789
	Aerated Compost	12.6234	1.2123
	Control 27-12-6	12.3789	1.1567
BNNs	Cow Manure	22.5123	1.5678
	Filter Cake	21.8765	1.4678
	Aerated Compost	23.1789	1.6123
	Control 27-12-6	22.3456	1.5234
ELM (Linear Kernel)	Cow Manure	3.7234	0.4567
	Filter Cake	3.5123	0.4234
	Aerated Compost	3.7890	0.4789
	Control 27-12-6	3.6456	0.4456
ELM (Sigmoid Kernel)	Cow Manure	4.0345	0.5234
	Filter Cake	3.9456	0.4789
	Aerated Compost	4.1123	0.5345
	Control 27-12-6	4.0345	0.489
ELM (RBF Kernel)	Cow Manure	4.2123	0.5678
	Filter Cake	4.1456	0.5345
	Aerated Compost	4.3345	0.5789
	Control 27-12-6	4.2678	0.5234
RC-ELM (Linear Kernel)	Cow Manure	4.3789	0.5234
	Filter Cake	4.0567	0.4789
	Aerated Compost	4.5123	0.5345
	Control 27-12-6	4.2890	0.489
RC-ELM (Sigmoid Kernel)	Cow Manure	4.6234	0.6789
	Filter Cake	4.4567	0.589
	Aerated Compost	4.7890	0.6345
	Control 27-12-6	4.5345	0.589
RC-ELM (RBF Kernel)	Cow Manure	4.7890	0.7345
	Filter Cake	4.6456	0.6789
	Aerated Compost	5.0456	0.7345
	Control 27-12-6	4.8234	0.689

4.6 Model Performance Evaluation Obtained Linear Kernel Function within both ELM and RC-ELM

The evaluation of the Linear Kernel Function within both ELM and RC-ELM algorithms reveals significant differences in model performance, as evidenced by the MAE, MSE, and RMSE metrics. The Linear Kernel in ELM performs adequately across various organic fertilizers, with MAE values ranging from 0.1510 to 0.1743, MSE values between 0.0347 and 0.0496, and RMSE values from 0.1863 to 0.2227. These results indicate that while ELM with a Linear Kernel is capable of can capture linear growth patterns, its predictive accuracy and error metrics suggest room for improvement, particularly when dealing with complex growth data such as that seen with Cow Manure, Shown in Table 9.

The RC-ELM with Linear Kernel demonstrates superior performance across key metrics compared to standard ELM. RC-ELM achieves lower MAE values (0.1243–0.1382), indicating reduced prediction error, and MSE values (0.0234–0.0293), leading to lower RMSE (0.1529–0.1712). These improvements highlight the strength of the residual compensation mechanism in RC-ELM, allowing for more accurate predictions and better handling of residual errors. The superior accuracy and reliability demonstrated by RC-ELM make it the preferred choice for modeling the linear growth of KDML105, outperforming ELM.

Table 9: *Comparison of Model Performance Evaluation Linear Kernel Function within ELM and RC-ELM.*

Models	Organic Fertilizer	MSE	MAE	RMSE
ELM (Linear Kernel)	Cow Manure	0.1743	0.0496	0.2227
	Filter Cake	0.1567	0.0378	0.1944
	Aerated Compost	0.1541	0.0365	0.1911
	Control 27-12-6	0.1510	0.0347	0.1863
RC-ELM (Linear Kernel)	Cow Manure	0.1325	0.0271	0.1645
	Filter Cake	0.1382	0.0293	0.1712
	Aerated Compost	0.1274	0.0256	0.1600
	Control 27-12-6	0.1243	0.0234	0.1529

4.7 Assessment of KDML 105 Tillers, Panicles, and Grain Yield Per Clump: Insights from RC-ELM and ELM with SROFs

A comparative analysis of tillers per clump using RC-ELM and ELM across different fertilizers shows that the RC-ELM model's control group (no fertilizer) achieved the highest number of tillers at 119, outperforming the ELM model's 90 tillers. Among fertilizers, Aerated Compost consistently produced the most tillers across both models, outperforming Filter Cake and Cow Manure. Overall, RC-ELM generated more tillers than ELM, demonstrating its superior ability in optimize rice growth predictions. These findings highlight RC-ELM's effectiveness, especially when paired with proper fertilizers in Fig. 5.

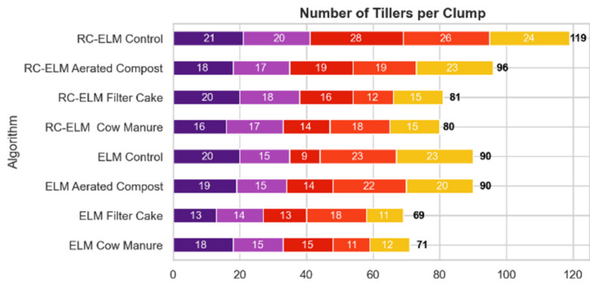

Fig.5: *Number of Tillers per Clump.*

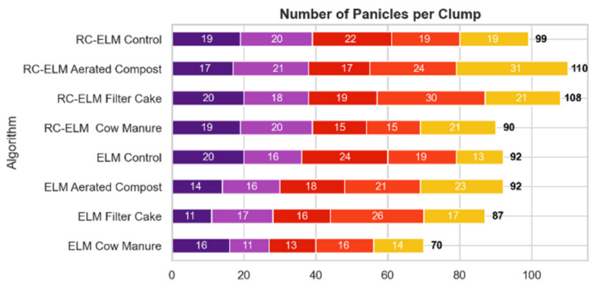

Fig.6: *Number of Panicles per Clump.*

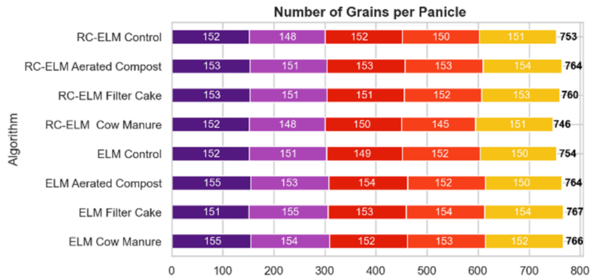

Fig. 7: *Number of Grains per Panicle.*

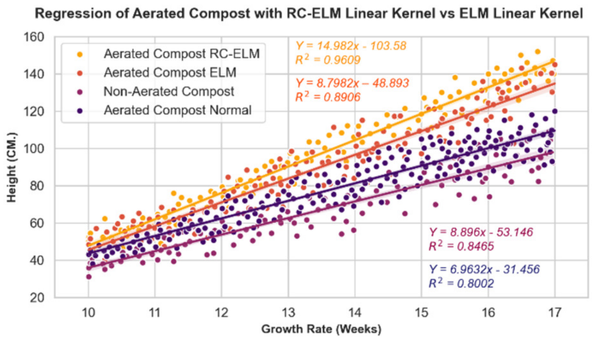

Fig. 8: *Linear Regression of Aerated Compost RC-ELM Linear Kernel vs. ELM Linear Kernel*

Fig. 6 shows the number of panicles per clump in Jasmine 105 rice under different slow-release fertilizers using RC-ELM and ELM models. The RC-ELM model with Aerated Compost achieves the highest panicle count at 110, followed by RC-ELM with Filter Cake at 108. The ELM Control model also performs well with 99 panicles. However, RC-ELM and ELM models with Cow Manure produce the lowest counts, at 90 and 72, respectively. These findings emphasize the significant influence of fertilizer type on rice productivity, with advanced models like RC-ELM enhancing panicle production when combined with optimized fertilizers, demonstrating the potential for improved agricultural outcomes.

Fig. 7 illustrates the number of grains per panicle across different experiments using RC-ELM and ELM combined with slow-release organic fertilizers. Results indicate that RC-ELM with Aerated Compost resulted in the highest grain count per panicle at 764 grains, while RC-ELM with Filter Cake and Cow Manure showed 760 and 746 grains, respectively. Conversely, the ELM experiments demonstrated that Aerated Compost and Filter Cake produced 767 and 766 grains per panicle, respectively, outperforming RC-ELM in these cases.

The regression analysis using the Aerated Compost RC-ELM Linear Kernel model ($Y = 14.982x103.58$, R^2=0.9609) in Fig. 8 demonstrates the highest predictive accuracy for plant growth with compost, as the R^2 value close to 1 indicates the model explains nearly all data variance. Comparatively, the Aerated Compost ELM Linear Kernel model (R^2=0.8906,$Y = 8.782x + 48.893$) demonstrates marginally lower predictive accuracy. Non-Compost and Compost Normal models further decrease accuracy, with R^2 values of 0.8465 and 0.6002, respectively. The analysis of post-harvest production for KDML 105 rice using the Aerated Compost RC-ELM Linear Kernel model shows promising profitability. Assuming an average yield of 500 kg per rai (1,600 m^2) and market prices between 10–15 THB per kilogram, the expected revenue per rai ranges from 5,000 to 7,500 THB. After deducting fertilizer costs, which are estimated at 4,000–6,000 THB per rai, the net profit per rai varies between 1,000 and 3,500 THB. This profitability highlights the efficiency of the Aerated Compost RC-ELM model in optimizing growth and resource allocation, reinforcing its potential for sustainable agricultural practices.

4.8 Application Rates of Slow-Release Organic Fertilizers, Costs, and Economic Viability

In the experiment, fertilizers applied to 9 plots (36 m^2 total, 2 × 2 m per plot) included 11.25 kg each of Cow Manure, Filter Cake, Aerated Compost, and Control 27-12-6. Costs ranged from 56.25–112.50 THB for Cow Manure, 33.75–56.25 THB for Filter Cake, 90.00–135.00 THB for Aerated Compost, and 168.75–225.00 THB for Control 27-12-6, highlighting the higher cost of chemical fertilizer. Show in Table 10.

Table 10: *Cost Comparison of SROFs for Experimental 9 Plots (36 m^2) and 1 Rai (1,600 m^2).*

Organic Fertilizer	Cost THB per kg	Cost for nine plots 11.25 kg (36 m²)	Cost per rai 500 kg (1,600 m²)
Cow Manure	5-10 THB	56.25 - 112.50 THB	2,500 - 5,000 THB
Filter Cake	3-5 THB	33.75 - 56.25 THB	1,500 - 2,500 THB
Aerated Compost	8-12 THB	90.00 - 135.00 THB	4,000 - 6,000 THB
Control (27-12-6)	15-20 THB	168.75 - 225.00 THB	7,500 - 10,000 THB

The evaluation of four fertilizers for rice cultivation on a one-rai area shows varying investment costs and quantities. Cow Manure, Filter Cake, and Aerated Compost each require 500 kg or 20 sacks per rai, costing 2,500–5,000 THB, 1,500–2,500 THB, and 4,000–6,000 THB, respectively. Chemical fertilizer (27-12-6) also requires 500 kg, which is equivalent to 10 sacks, with a higher cost ranging from 7,500 to 10,000 THB per rai. While organic fertilizers like Aerated Compost can be more expensive, they improve long-term soil health by reducing degradation and enhancing fertility. The increasing use of sustainable, natural inputs aligns with global standards such as Organic Thailand and IFOAM [15, 35], which emphasize environmentally friendly practices. Despite higher costs, consumer demand for organic products is rising due to increased awareness of food safety and environmental benefits [35].

5. DISCUSSION

The RC-ELM model's accuracy in predicting growth performance was critical in determining the most suitable SROF for sustainable rice cultivation. Among the SROFs tested, Compost provided the best results, achieving an R^2=0.9609, indicating a strong correlation between predicted and actual growth outcomes. The regression equation for Compost ($Y = 14.982x - 103.58$) demonstrates its positive impact on rice growth, as evidenced by its low MAE (0.1274), MSE (0.0256), and RMSE (0.1600). In comparison, Cow Manure and Filter Cake yielded lower R^2 values of 0.9265 and 0.9121, respectively, and higher error metrics, indicating less predictive accuracy. Compost's superior performance suggests that it provides more consistent nutrient release and better soil health, key to sustainable rice production.

One of the key findings from this research is that Compost, while having a higher initial cost per kilogram (THB 8-12), offers the best growth performance among the SROFs tested. These findings highlight the importance of balancing cost and performance, as the ability of compost to promote robust growth may outweigh its higher price over the long term. The cost comparison for nine plots (11.25 kg) shows that Compost costs between THB 90 and 135, while Cow Manure and Filter Cake are cheaper (THB 56.25-112.50 and THB 33.75-56.25, respectively). However, the superior growth outcomes associated with Compost suggest that it may offer better value when scaled to larger areas, such as 1 rai (1,600 m^2). The implications of this research are multifaceted. First, using RC-ELM Linear Kernel as a predictive tool in agricultural applications demonstrates its value in optimizing fertilizer selection for rice cultivation. The findings also support the broader adoption of Compost as a sustainable and effective organic fertilizer for KDML105, which aligns with global trends toward reducing chemical fertilizer use.

Future research could expand on this study by exploring the use of other predictive models or kernel functions within the RC-ELM framework to capture non-linear growth patterns under varying environmental conditions. Additionally, a more extensive examination of different organic fertilizer formulations and their long-term impacts on soil health and rice productivity would provide valuable insights. Research could also focus on integrating real-time environmental monitoring data with RC-ELM to optimize fertilizer applications dynamically, further enhancing the accuracy of predictions and sustainability in rice cultivation.

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AUTHOR CONTRIBUTIONS

Conceptualization, Worachai Srimuang. and Karun Phungbunhan.; methodology, Worachai Srimuang; software, Worachai Srimuang.; validation, Worachai Srimuang., Napaporn Toomthongkum., Somkid Ritnathikul. and Karun Phungbunhan.; formal analysis, Worachai Srimuang; investigation, Worachai Srimuang; data curation, Worachai Srimuang.; writing—original draft preparation, Worachai Srimuang.; writing—review and editing, Worachai Srimuang., Napaporn Toomthongkum., Somkid Ritnathikul. and Karun Phungbunhan.; visualization, Worachai Srimuang.; supervision, Worachai Srimuang.; funding acquisition, Worachai Srimuang. and Karun Phungbunhan. All authors have read and agreed to the published version of the manuscript.

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