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Utilisation of Artificial Neural Network in Predicting Crop Yield Based on Macronutrient (N, P and K) Uptake Rate from the Chilli (*Capsicum Annum* L.) Treated with Food Waste Compost

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ABSTRACT

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Food waste compost provides essential macronutrients (N, P, K) for chilli cultivation, but its inconsistent nutrient composition complicates precise application rate determination for optimal yield. To address this challenge, this study developed an artificial neural network (ANN) model predicting chilli yield based on plant N, P, and K uptake rates derived from compost applications. Chilli plants were grown under five food waste compost loading ratios (0%, 20%, 50%, 70%, 100% v/v). Leaf tissue were collected during the fruiting stage to quantify the macronutrient uptake rates, while chilli yield (total fruit weight per plant) were determined at day 84 and 112. A 3-10-1 topology ANN model, using N, P, and K uptake rates as inputs and yield as output, demonstrated high predictive accuracy (correlation coefficient = 0.922, RMSE = 11.2731). The 50% v/v compost treatment yielded the highest fruit production (29.58 g plant⁻¹), corresponding to uptake rates of 0.694 g N kg⁻¹, 0.312 g P kg⁻¹, and 0.767 g K kg⁻¹. This ANN model establishes a novel framework for determining site-specific food waste compost application rates based on target nutrient uptake, thereby optimizing chilli yield and enhancing resource efficiency in sustainable agriculture.

1. Introduction

Malaysia generates approximately 39,000 tonnes of municipal solid waste daily, with food waste constituting 30% [2]. The landfill capacity is expected to be exhausted by 2050 if current waste generation trends persist [2]. Composting offers a potential solution to reduce the organic fraction of municipal solid waste by 50-60% [17]. The end product, food waste compost, contains essential macronutrients (nitrogen, phosphorus, potassium - N, P, K), providing a cost-effective alternative to mineral fertilisers that supports resource recycling and circular economy principles.

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However, the inconsistent nutrient composition of the food waste compost complicates precise determination of application rates required for optimal crop yield. Critically, excessive food waste compost application poses substantial environmental and health risks: nutrient leaching can drive water eutrophication [23], disrupting water resource in semi-arid regions [24], and introduce salts (Na, Cl), trace elements (e.g., Ca, Mg, Pb), and organic pollutants that risk plant phytotoxicity and groundwater contamination [8]. Consequently, robust nutrient management models are required to estimate precise food waste compost quantities that maximize yield while minimizing environmental impacts.

Current models linking nutrient uptake to yield are limited. Logistic [14] and segmented [1] approaches typically analyze single nutrients, failing to capture the synergistic effects of combined N, P, and K uptake crucial for crop growth and yield [13]. While the Quantitative Evaluation of the Fertility of Tropical Soils (QUEFTS) model integrates multiple nutrients [20], it requires laborious, site-specific calibration of parameters like internal nutrient efficiency (IEX) and recovery efficiency (RE) for different plants, soils, and compost types [23]. Furthermore, QUEFTS is primarily designed for defined mineral fertilizer with fixed nutrient inputs and yield targets, rendering it poorly suited for the variable nutrient profiles inherent in food waste compost.

Machine learning, particularly Artificial Neural Networks (ANNs), presents a promising alternative for modeling complex, non-linear agricultural relationships. ANNs have been successfully applied to yield prediction [10], soil management, precision agriculture, plant phenology [26], and phenotyping [20]. However, a recent review by Javed and Murad [11] found that approximately 80% of machine learning based yield prediction studies rely on climatic and edaphic factors, with limited investigation into the specific effects of combined macronutrient (N, P, K) uptake rates on yield. Understanding these interactions is crucial for optimizing nutrient management with variable inputs like food waste compost.

To address this gap, this study aims to develop an ANN model to predict chili (*Capsicum annum*) yield based explicitly on combined N, P, and K uptake rates derived from varying food waste compost application rates. By establishing the relationship between N, P and K uptake rate and yield, this model identifies optimal nutrient uptake levels for maximum yield. This approach provides a framework to tailor food waste compost application based on its intrinsic nutrient content rather than fixed loading ratios alone, enabling precise nutrient delivery, maximizing yield potential, and mitigating the risks of over-fertilization and environmental pollution associated with inconsistent food waste compost composition.

2. Methodology

2.1 Preparation and Physicochemical Properties of Food Waste Compost

The food waste compost were collected from the Bio-Baja Zambri composting centre located at Layang-Layang, Johor, Malaysia. Table 1 shows the physicochemical properties of the generated food waste compost and leachate; pH, total organic carbon (TOC) and chemical oxygen demand (COD), macronutrient composition; nitrogen (N), potassium (P), phosphate (K) and micronutrient composition; calcium (Ca), magnesium (Mg), iron (Fe), sodium (Na), lead (Pb) and nickel (Ni) of the food waste compost and leachate collected from the site.

Table 1
 Physiochemical properties of the food waste compost and leachate

Properties	Parameter	Compost (g/kg)
Physical	pH	7.39
	TOC (%)	31.04
	COD	n/a
Macronutrient	N	6.64
	P	11.64
	K	6.80
Micronutrient	Ca	20
	Mg	5
	Na	6
	Fe	0.001
	Pb	0.099
	Cu	0.011
	Ni	0.004

2.2 Field Experiment

The planting preparation and experiment were conducted in a greenhouse located at the School of Biomedical Engineering and Health Science, Universiti Teknologi Malaysia (UTM). For four weeks, the chilli seeds were cultivated in a pot filled with peat moss (Serbajadi, YMWOO, Malaysia).

One cultivated seedling was transferred into the 4 – L polybag filled with a mixture of two types of planting medium; cocopeat (064/2018, BERNAS, Malaysia) and food waste compost (Biobaja Zambri, Layang-Layang, Johor, Malaysia). Table 2 shows the mixture composition of the two planting media expressed as v:v (%) ratio.

Table 2
 Planting medium composition for each treatment

Sample	Food waste compost (%)	Cocopeat (%)
C0	-	100
C20	20	80
C50	50	50
C70	70	30
C100	100	-

Each treatment has four replicate plants. All plants were irrigated with water at 750ml/min six times per day. The test duration was 112 days when the chilli plants reached maturity (plants with red and green fruits).

2.3 Chilli Growth and Yield

The sampling and measuring methods were based on Singh *et al.*, [18]. On day 21 and 112, the height of the plant was measured from the bottom of the stem to the tip of the plant using a thread and a 5 m measuring tape (D00006, Duratool, Malaysia). On day 21 and 112, three samples of leaves from each plant were collected from each chilli plant to determine the size of the leaves. On day 84 and day 112, all of the chillies were harvested to determine the chilli yield (total weight of chilli (g) plant⁻¹). The samples were weighed using the electronic measuring balance at the lab (EK-1200A, A&D, Japan).

2.4 Nutrient (N, P and K) Uptake in the Plant

The plant tissue samples were collected on days 56, 63, 70, and 105 from each polybag and washed with distilled water and oven dried at 70 °C for 72 h. The samples were grounded using a kitchen mixer (EBM-9179, Elba, Malaysia) and underwent an extraction treatment to obtain the liquid form samples for N, P and K analysis.

For the total N analysis, the plant samples were treated using a modified acid digestion method. The digested sample in liquid form was analysed with SpectroDirect nutrient analysis pack (535560, MERCK, Germany) and measured using a spectrophotometer (SpectroDirect[®] NOVA 60, MERCK, Germany).

For total P and K analysis, 0.5 g of plant samples were treated using a dry ashing digestion method (LaFleur 1975). The dissolved samples were analysed with SpectroDirect nutrient analysis pack (535560, MERCK, Germany) and measured using the spectrophotometer (SpectroDirect[®] NOVA 60, MERCK, Germany).

2.5 ANN Model Construction

The data collected during the experimental trial in sections 2.2 to 2.4 were used to construct the ANN model. An ANN model construction was conducted using the MATLAB version 7.14 (Mathworks Inc., Natick, USA) based on the methods used by Nayak *et al.*, [12]. A 3 x 10 x 1 ANN model with feed forward network and error back propagation was used in this study as refer to Figure 1.

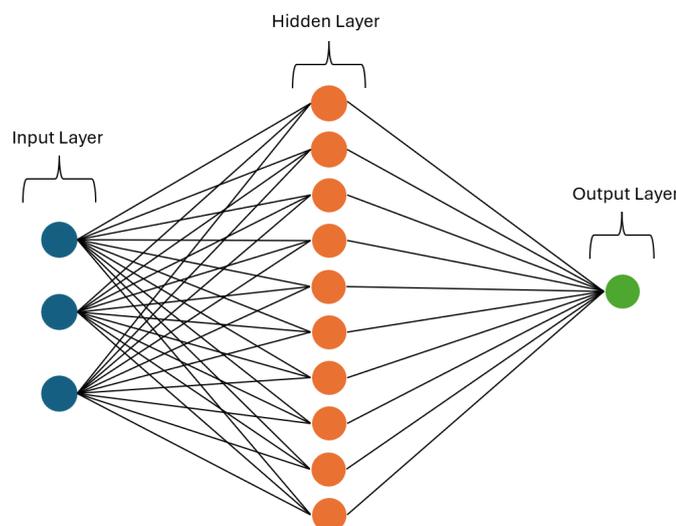


Fig. 1 The structure of ANN model used in predicting the chilli yield (output) based on the N, P and K uptake rate (input)

ANN architecture typically consists of an input layer, a hidden layer and an output layer. The neuronal connection between two layers is represented by biases and weights as shown in Equation (1).

$$Y_j = \sum(X_i W_{ij}) + b_j \tag{1}$$

Where W_{ij} denotes the weight connection from neuron i to neuron j , X_i is the input at neuron i , b_j is the bias of neuron j , then the activation at the j^{th} neuron. Using the data obtained from the experimental work, the network was trained by the Levenberg-Marquardt algorithm. This algorithm minimises the error between the training data and the network output by adjusting its weights and biases. The R^2 and mean squared error (RMSE) was used as performance index for ANN modelling was conducted using MATLAB version 7.14 (Mathworks Inc., Natick, USA). The model is considered a good fit if the $R^2 > 0.9$ and $RMSE < 25\%$ [16].

3. Results and Discussion

3.1 Growth Rate and Yield of Chili Plant

Chilli yield and growth rate is an important indicator that represents the performance of the food waste compost on the chilli plant. Figure 2 shows the cumulative chilli yield ($g\ plant^{-1}$) from all treatments from day 84 and day 112, as this represented the significant growing and fruiting stage of the chilli plants. Table 3 shows the plant height and diameter of leaves at day 21 and 112 for all plants treated with different compost loading ratios. Each sample was measured in five replicates for each batch of planting.

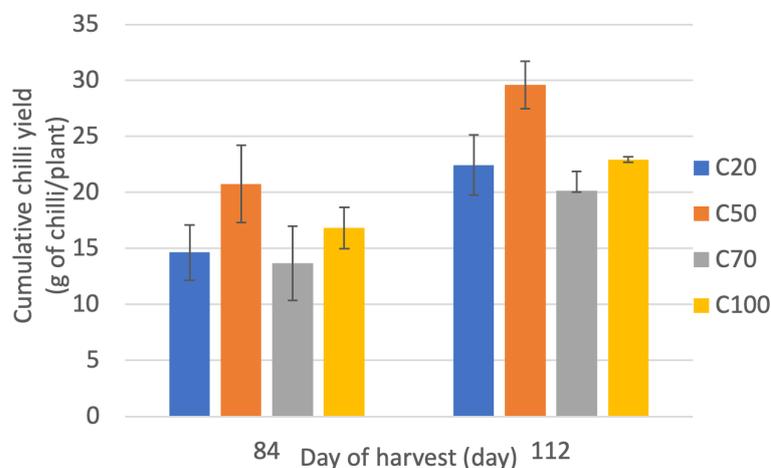


Fig. 2. Cumulative chilli yield at day 84 and 112 plants treated with different compost loading ratio

Table 3

Growth parameters for all chilli plants treated with different compost loading ratios with and without leachate at day 21 and 112

Treatment	Plant height (cm)		Diameter of leaves (cm)	
	day 21	day 112	day 21	day 112
C20	33.67 ± 3.68	43.33 ± 2.36	8.48 ± 0.87	8.83 ± 0.1
C50	27.33 ± 1.25	41.33 ± 1.25	7.64 ± 0.33	6.29 ± 0.54
C70	40.33 ± 2.62	58.67 ± 1.25	9.39 ± 0.78	6.43 ± 0.92
C100	31 ± 2.16	44.33 ± 0.94	9.10 ± 0.17	7.27 ± 0.07

The plant treated with 50 % compost reported the highest plant yield (29.58 g plant⁻¹) at day 112. Plants treated with 70 % and 100 % compost show a reduction in chilli yield by 14 – 30 % (5 - 7 g plant⁻¹). However, both the plant height and the diameter of leaves did not differ significantly ($p>0.05$) at different compost loading ratios. This finding is consistent with Vimala *et al.*, [22], which reported that chilli plants treated with different poultry manure compost loading ratios (20, 40, 60 tonne ha⁻¹) show no significant difference in plant height.

The results presented above highlight that as the compost loading ratio is greater than 70 %, it would result in poor chilli yield despite a higher macronutrient supply. Tzortzakis *et al.*, [21] who reported that the application of 20 % (v/v) compost resulted in a higher cumulative chilli yield (65 %) compared to plants treated with 40 % (v/v) compost. The application of FW compost at a high loading ratio could likely result in the accumulation of trace elements such as Ca, Mg, Na, Cu, Pb, Fe, and Ni, which could reduce the plants' growth performance [7].

To further explain the possible cause of lower chilli pepper yield at a higher compost loading ratio (> 70 %), the macronutrient and trace elements of the planting media after being treated with different compost loading ratios were analysed. The macronutrients (N, P, K) and trace elements in the initial planting media using different compost loading ratios (without leachate) were analysed and benchmarked against the maximum trace element threshold in the soil set by Malaysian [15] and United Nation's Food and Agriculture Organisation (FAO) standards [6], as shown in Table 4.

Table 4

Comparison of the macronutrient and trace element contents in the initial planting media using different compost loading ratios

Trace elements	Trace element composition in the food waste compost (g kg ⁻¹) at different compost loading ratio % (v/v)					
	20	50	70	100	Malaysia Standard	FAO Standard
Ca	3.17 ± 1.32	11.72 ± 3.22	15.78 ± 4.12	20 ± 4.28		10.02
Mg	0.94 ± 0.32	2.76 ± 0.73	3.82 ± 1.04	5 ± 1.87	ND	0.47
Na	1.13 ± 0.51	3.41 ± 1.05	4.71 ± 1.26	6 ± 2.10		1.30
Pb	ND	0.05 ± 0.01	0.07 ± 0.01	0.10 ± 0.01	0.030	ND

Referring to Table 4, applying compost at 70 – 100 % resulted in high trace element contents in the planting media (Ca, Mg, Na and Pb), which significantly exceeded the threshold limit set by the Malaysian [5] and the Food and Agriculture Organisation of the United Nations (Food And Agriculture Organization, 2010) standards. The excessive trace element in the planting media causes poor chilli yield and growth, as proven in Figure 2 and Table 3. On the contrary, applying compost at 20 % is not sufficient to meet the overall macronutrient requirement of the chilli plant. As a result, the 50 % compost loading ratio is the ideal loading ratio to balance the macronutrient requirement of the plant while avoiding excess trace element accumulation in the planting media.

3.2 Nutrient Uptake Rate by Chilli Plants

The individual N, P and K uptake rate (N_U , P_U , K_U) of the chilli plant treated at different compost loading ratios (20- 100 %). The N_U , P_U and K_U were measured based on the chilli plant's macronutrient content on days 56, 63, 70, and 105. Table 5 shows the N, P and K uptake rate of the chilli plants treated at different food waste compost loading ratios. Each sample was measured in five replicates for each batch of planting.

Table 5

N, P and K uptake rate of the chilli plants treated at different food waste compost loading ratio

Sample	Nutrient uptake rate (g kg ⁻¹ of plants day ⁻¹)		
	N _u	P _u	K _u
C0	0.126 ± 0.010	0.057 ± 0.011	0.077 ± 0.024
C20	0.438 ± 0.041	0.198 ± 0.016	0.357 ± 0.061
C50	0.694 ± 0.055	0.312 ± 0.010	0.767 ± 0.075
C70	0.737 ± 0.099	0.375 ± 0.010	1.023 ± 0.099
C100	0.780 ± 0.075	0.410 ± 0.008	1.057 ± 0.099

Referring to Table 5, the individual N, P or K uptake rate (N_u, P_u, K_u) at different loading ratios of compost (0-100 %) increase rapidly with the rising food waste compost loading ratio. The N_u, P_u and K_u were plateaued from 70 % (v/v) (C70) composting loading ratio, indicating that 70 % (v/v) compost is the macronutrient dosage for the plant to reach the maximum uptake rate.

Applying 100 % compost (C100) decreased the N_u, P_u and K_u, likely due to trace element accumulation such as Ca and Na. As discussed in Table 4, the Ca and Na content in 100 % (v/v) compost (C100 and XC100) is 20 g kg⁻¹ and 6 g kg⁻¹, which exceeded the recommended limit by 5 - 10 g kg⁻¹ (10.02 g kg⁻¹ for Ca and 1.3 g kg⁻¹ for Na), as set by United Nation’s Food and Agriculture Organisation (FAO) standards (Food And Agriculture Organization, 2010). Excess Na content in 100 % compost was likely led to extreme saline conditions, which could inhibit the N uptake rate (Gondek et al., 2020) and K uptake by the plant [19]. The reduced N_u, P_u and K_u are likely to cause poor chilli yield and growth for plants treated with 100 % compost, as reported in Figure 2. To evaluate the effects of the N_u, P_u and K_u on the chilli yield, an ANN model will be employed. The dataset used for the ANN model is listed in Supplementary File 1.

3.3 ANN Model Generation

In this study, a 3-10-1 topology was selected for the ANN. The ANN training was carried out until it reached the validation check point. Figure 3 shows the ANN training performance plot.

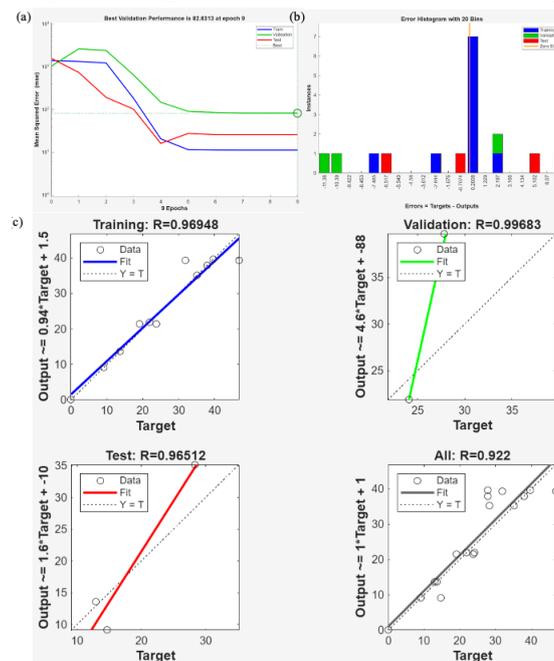


Fig. 3. ANN training performance plot (a), error histogram (b) and artificial neural network to regress the experimental value and the predicted value (c)

As shown in Figure 3, the ANN achieved the best performance during training with the R^2 value of 0.94695, 0.9668 and 0.9651 in the training, test, and validation phases and an overall RMSE value of 11.2731. This indicates that the established ANN model provided a more accurate simulation of chilli yield based on the N, P and K uptake rate by the chilli plant treated with food waste compost.

The ANN model were benchmarked with the segmented and logistic mathematical models commonly used to predict the crop yield based on a single macronutrient uptake rate [1,14]. The data from the experiment (N_u , P_u , K_u) in Supplementary Files 1 was introduced to the existing models, and the accuracy of the existing models (R^2 and RMSE) was determined and compared with the ANN model generated in this study. Table 6 compares the R^2 and RMSE of the logistic and segmented models from the literature with the ANN models generated from this study.

Table 6

Comparison of R^2 and RMSE of the existing models from the literature with the models generated from this study

Model	Independent variables	R^2	RMSE (%)
Logistic model Overmaan and Brock, [14]	N uptake rate only (N_u)	0.90	10.55
	P uptake rate only (P_u)	0.76	15.57
	K uptake rate only (K_u)	0.52	20.34
Segmented model Bakhshandeh <i>et al.</i> , [1]	N uptake rate only (N_u)	0.73	73.74
	P uptake rate only (P_u)	0.71	29.18
	K uptake rate only (K_u)	0.52	28.76
ANN model (this study)	N and K uptake rate (N_u , P_u , K_u)	0.922	11.273

Referring to Table 6, ANN were proved as the superior model in predicting the chilli yields ($R^2 > 0.9$; $RMSE < 25\%$). The logistic and segmented model, which considered only a single macronutrient input data, reported poor prediction in the yield, as evidenced by the R^2 lower than 0.9 and RMSE value above 25%. The results suggest that both the logistic and segmented models are unable to predict the chilli yield accurately when considering only a single macronutrient uptake rate. The finding in this section highlights the importance of considering multiple macronutrient uptake rates in creating an accurate chilli yield prediction model. It is known that the chilli yield is heavily dependent on the macronutrient (N, P and K) uptake rate by the plant [13]. An improved model based on an ANN framework using multiple macronutrient uptake rates is developed to accurately predict the chilli yield.

4. Conclusion

This study successfully develops an artificial neural network (ANN) model to optimise nutrient management in food waste compost systems, specifically targeting chilli cultivation. The model addresses a critical gap in sustainable agriculture: the inherent inconsistency and complexity of nutrient profiles in food waste-derived composts. Unlike conventional crop management models that rely on individual nutrient uptake rates (N, P, or K), the ANN framework leverages the synergistic interactions of combined NPK uptake to predict chilli yield with significantly enhanced precision.

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