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A novel deep learning model to predict the soil nutrient levels (N, P, and K) in cabbage cultivation

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ABSTRACT

Cabbage (*Brassica oleracea*) is a green cruciferous vegetable. Major nutrients (nitrogen, phosphorus, and potassium) are frequently applied to the soil due to low fertility levels. However, optimizing required fertilizer levels are extremely important to avoid any overuse and underuse. Therefore, it is important to develop a comprehensive methodology for evaluating the major nutrients in the soil. In this research, a deep learning model was introduced to predict the nitrogen, phosphorus, and potassium content of the soil by analyzing the growing characteristics of the plants, such as plant height, the number of leaves, and the average leaf area of the plant. To achieve this, the growing characteristics of the cabbage plants were recorded weekly along with the respective soil nitrogen, phosphorus, and potassium content of the nearby soil. After the data was trained using the Levenberg–Marquardt algorithm and tested with different transfer functions such as logarithmic sigmoid, pure linear, and tangent sigmoid, better predictions were obtained through the model. According to the Pearson correlation values, pure linear and tangent sigmoid showed higher values, ranging from 0.99 for training, testing, validation, and all data points from the model, indicating a strong relationship between the actual and predicted values. According to the Mean Square Error values, the tangent sigmoid transfer function outperformed the others, giving a value of 1.0813, indicating better predictions of the soil nitrogen, phosphorus, and potassium content from the model.

1. Introduction

Cabbage (*Brassica oleracea*) is a green cruciferous vegetable belonging to the Brassicaceae family and is characterized by its spherical or oblong shape, with a dense cluster of leaves forming what is commonly referred to as the `cabbage head' in the center [1,2]. Renowned for its versatility, cabbage finds application in a diverse range of culinary preparations worldwide. It boasts a notable nutritional profile, featuring substantial levels of vitamins C and K, dietary fiber, and antioxidants, while maintaining a low-calorie content, rendering it a favored choice for individuals seeking to augment their diet with healthier food options. Four common cabbage varieties, namely Napa, Savoy, Green, and Red, are cultivated worldwide [3]. According to literature sources, the optimum temperature for the head formation phenophase ranges from 16 to 20 °C [4], 17.2 to 19.9 °C [5], 17 °C to 22 °C [6], and 17.5–19.1 °C [7]. Growing cabbage in greenhouses during the spring and autumn necessitates maintaining average daily temperatures at 15–25 °C and 10–30 °C, respectively [8]. Its widespread cultivation and consumption span the globe, facilitated by its ability to thrive in various climates and cultivation conditions.

Fertilization holds immense significance, particularly in the successful cultivation of cabbage [9]. Cabbage plants, like all other crops, have specific nutrient requirements, with nitrogen (N), phosphorus (P), and potassium (K) being the primary macronutrients mainly required for their growth and development [9,10]. To meet these nutritional needs effectively, chemical fertilizers such as urea, Triple Superphosphate, and Muriate of Potash are commonly employed when growing cabbage [11]. In organic cabbage cultivation, growers rely on natural sources such as grass, cow dung, wood ash, rice bran, and poultry manure to fulfill these nutrient requirements of the crop [12]. It is crucial to provide farmers with insights into the soil conditions, particularly regarding major nutrients, and to enhance soil nutrition through the application of innovative prediction models.

Artificial intelligence techniques find applicability in a wide range of

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prediction tasks, serving as fundamental elements within the framework of global precision agriculture. These models and tools leverage various methodologies, including linear regression techniques, non-linear simulations, expert systems, pattern recognition, data analysis, decision making, automation, and Artificial Neural Networks to predict various agricultural components [13–15]. Neural networks, inspired by the nonlinear parallel structure of the human brain system, represent a large-scale, parallel distributed information processing system. They were originally derived from the biological central nervous system [16, 17]. Deep neural networks (DNNs) belong to a class of machine learning algorithms related to artificial neural networks, with the objective of emulating the information processing mechanisms of the human brain [18]. DNNs, often simply referred to as deep learning, constitute a subset of artificial neural networks characterized by their multiple layers of interconnected nodes, or artificial neurons [19]. These networks have gained remarkable prominence in recent years due to their extraordinary ability to tackle complex tasks, especially in the domains of machine vision, natural language processing, and reinforcement learning [19,20]. DNNs are inspired by, albeit in a simplified and mathematical form. They excel at feature extraction and abstraction, automatically learning hierarchical representations of data from raw inputs. This ability makes them adept at recognizing patterns and making high-level decisions [21,22]. The depth of these networks allows them to capture intricate, abstract, and nuanced features within data, enabling their exceptional performance on tasks such as image classification, speech recognition, and autonomous navigation [20,23]. DNNs have become a cornerstone technology in modern artificial intelligence and have enabled groundbreaking advances in areas like crop yield prediction [24], precision agriculture in fertilizer and pesticide applications [25, 26], weed detection and removal [27,28], soil health monitoring [29], and livestock health and behavior management in the agriculture sector [30].

In the context of Sri Lanka, the annual cabbage production reached 116,662.2 MT in 2022 [31]. Cabbage cultivation is most effective in cool climatic conditions found in upcountry areas. Varieties with heat tolerance characteristics are suitable for cultivation in the dry zone [32, 33]. The Department of Agriculture in Sri Lanka recommends several cabbage cultivars for specific regions. Varieties like Exotic and Hercules are recommended for the up-country wet zone, while Exotic, AS Cross, and KY Cross are suggested for the mid-country areas. Additionally, hybrid varieties with attributes such as higher heads, early head formation, and uniform-size compact heads have been developed and are available in the market. These hybrid varieties include Royal Sluis, Green 123, Green Coronet, Golden Cross, GS Cabbage, and Tropicana [34]. When cultivating cabbage in Sri Lanka, the Horticultural Crop Research and Development Institute recommends various conditions, including maintaining the soil pH within the range of 6 to 6.5, applying 200 to 250 g of seeds per hectare, adhering to a planting spacing of 40 × 50 cm, applying appropriate fertilizers, ensuring an adequate water supply, implementing effective weed control, managing pests, addressing diseases, and employing proper harvesting techniques [35].

This study delves into the dynamic relationship between major soil nutrients and the evolving characteristics, such as plant height, leaf count, and average leaf area, observed in cabbage plants' growth over time in the central province of Sri Lanka, utilizing advanced deep learning techniques. The authors' objective is to provide valuable insights to local farmers and growers, with a particular focus on soil health monitoring and optimal fertilizer applications in Sri Lanka. By harnessing the capabilities of advanced deep learning methods, this research can uncover nuanced patterns and trends that may escape detection by traditional approaches. This empowers agricultural practitioners to make well-informed decisions regarding soil management. In essence, this research marks a crucial stride in advancing precision agriculture, safeguarding soil health, and enhancing the long-term productivity of agricultural ecosystems.

2. Materials and methods

2.1. Deep neural networks and their training algorithms and transfer functions

DNNs, commonly known as deep learning, constitute a significant component of the expansive field of Artificial Intelligence [36]. Consequently, DNNs have become a prominent tool in the realm of machine learning and artificial intelligence. Their layered architecture and ability to process complex features make them particularly effective for addressing real-world challenges that exhibit non-linear traits. By capturing intricate patterns and relationships within data, DNNs offer solutions that are more nuanced and comprehensive than traditional linear models, especially when the problems involve intricate complexities and non-linear dynamics. These networks can be conceptualized as a succession of layers, wherein each layer executes a linear transformation followed by an elementwise nonlinearity. The amalgamation of multiple layers imbues the model with substantial predictive capabilities [37]. Eq. (1) represents the mathematical formulation of the nonlinear relationship modeled in this study.

$$\mathrm{N_{content}} + \mathrm{P_{content}} + \mathrm{K_{content}} = \phi\left(\begin{array}{c} \textit{Plant Height},\ \textit{Number of Leaves}, \\ \textit{Average Leaf Area},\ \textit{Number of Days} \end{array}\right) \tag{1}$$

In this equation, ϕ denotes the nonlinear function that captures the association between the N, P and K content and plant growth characteristics. To achieve our study objectives, the significant capabilities of deep neural networks were leveraged within the MATLAB (version 9.6-R2019a) numerical computing environment. This computational framework formed the robust foundation for the execution of our research endeavors. Our neural network architecture, meticulously designed for this task, emphasizes a total of four hidden layers, each crafted to contain ten nodes (Fig. 1). These hidden layers, situated between the input and output layers, were instrumental in enabling the network to capture intricate patterns and relationships within our data.

The input layer was structured to encompass four nodes, each dedicated to accommodating vital input factors. These factors included the number of days on a weekly basis, the height of the cabbage on a weekly basis, the number of cabbage leaves on a weekly basis, and the average area of cabbage leaves on a weekly basis. This selection of input variables ensured that our model could ingest critical information to drive its predictions. The output layer was structured with equal precision, featuring three nodes. These nodes were associated with essential output factors, namely $\mathrm{N_{content}}$, $\mathrm{P_{content}}$, and $\mathrm{K_{content}}$, which are pivotal in characterizing the soil under consideration.

During the rigorous analytical phase, a trio of distinct transfer functions, namely logarithmic sigmoid (LogSig), pure linear (PureLin), and tangent sigmoid (TanSig), were employed separately. These functions played a pivotal role in shaping the behavior of designed neural network, allowing it to adapt, process information, and provide accurate predictions effectively. Furthermore, in the steadfast quest for enhancing model performance, the choice was made to utilize the Levenberg–Marquardt (LM) Algorithm as the training algorithm for the DNN model. This selection stems from the widespread recognition that the LM Algorithm has demonstrated superior performance in training neural network models, resulting in heightened model performance compared to alternative training algorithms [20,38]. As a result, the application of this algorithm guaranteed the attainment of the highest level of predictive capability by the models, ultimately propelling the progress of research endeavors.

2.1.1. Levenberg–Marquardt algorithm

The LM algorithm combines elements of Gradient Descent and the Gauss–Newton methodologies, enhancing its effectiveness in converging toward optimal solutions, particularly in the context of neural network

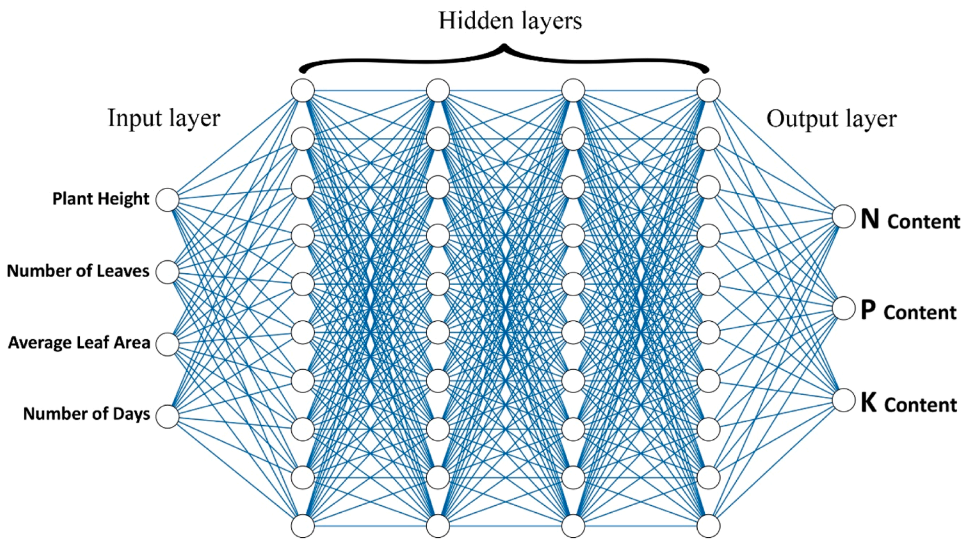

Fig. 1. Architecture of the DNN model.

backpropagation [39]. A pivotal element in the LM algorithm is the approximation of the Hessian matrix (H) and the computation of the gradient (g). This approximation of the Hessian is derived from the product of the Jacobian matrix (J) and its Jacobian transposed matrix (J^T) [38,40], as delineated in Eq. (2).

$$H = J^T J \tag{2}$$

Conversely, the gradient (g) is computed through the matrix multiplication of the transposed Jacobian (J^T) with the network error vector (e), as expressed in Eq. (3).

$$g = J^T e \tag{3}$$

The LM algorithm, in its behavior, resembles the classical optimization technique known as Newton's method. This method, captured in the updated Eq. (4), underscores the iterative nature of the LM algorithm. By iteratively refining parameter estimates, the LM algorithm strives to optimize and fine-tune models, making it a valuable tool in various scientific and computational applications [38,41].

$$x_{(k+1)} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e \tag{4}$$

In the given equation, $x_{(k+1)}$ represents the updated weight obtained through the gradient function, while x_k denotes the current weight derived from the Newton algorithm, and $J^T J$ results from the transposed Jacobian matrix multiplied by the original Jacobian matrix. Concurrently, the term J^T e is derived from the matrix multiplication of the Jacobian's transpose and the network error vector [20]. The constant μ and the identity matrix (I) are integral components of this equation and play a pivotal role in determining the algorithm's path to convergence [39,42].

2.1.2. Logistic sigmoid transfer function

The LogSig transfer function is a sigmoid-shaped mathematical function frequently employed as an transfer function within artificial neural networks [43]. This function is highly suitable for applications demanding probabilistic behavior, characterized by its sigmoidal curve that effectively transforms input values into a bounded range spanning from 0 to 1 (Fig. 2) [44]. By introducing non-linearity into neural network computations, the LogSig transfer function makes it possible to simulate intricate, non-linear connections in data. It is a desirable option in a variety of neural network topologies, particularly in traditional contexts like multilayered perceptron networks [45], because of its smooth and differentiable nature, which aids gradient-based optimization during training.

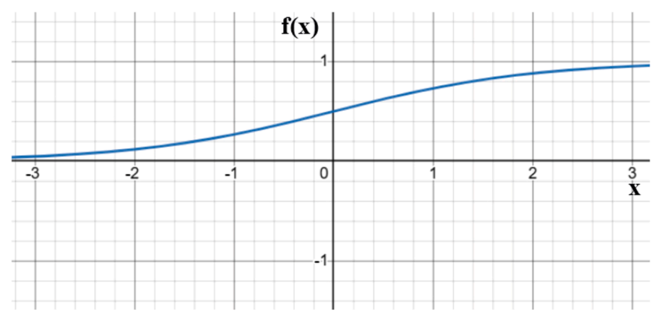

Fig. 2. Graph of the standard LogSig transfer function.

The LogSig transfer function can be defined as shown in Eq. (5) [44,46].

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

$f(x)$ represents the output of the LogSig function for a given input x, where x is the input to the function. e is the base of the natural logarithm, approximately equal to 2.71828.

2.1.3. Pure linear transfer function

The PureLin transfer function constitutes a foundational element in neural network theory and application. PureLin is characterized by its straightforward linearity (Fig. 3), hence directly maps input values to corresponding output values without introducing any non-linear transformations [47]. This simplicity grants it particular utility in regression tasks and situations where a linear mapping is explicitly required, such as in linear neural network models. Despite its apparent simplicity, PureLin maintains its significance within neural network architectures due to its efficiency in gradient propagation during training [48]. The PureLin transfer function can be defined as shown in Eq. (6) [46].

$$f(x) = x \tag{6}$$

$f(x)$ represents the output of the PureLin function for a given input x, where x is the input to the function.

2.1.4. Tangent sigmoid transfer function

TanSig is another mathematical function commonly used in artificial neural networks [49], particularly in the context of neural network

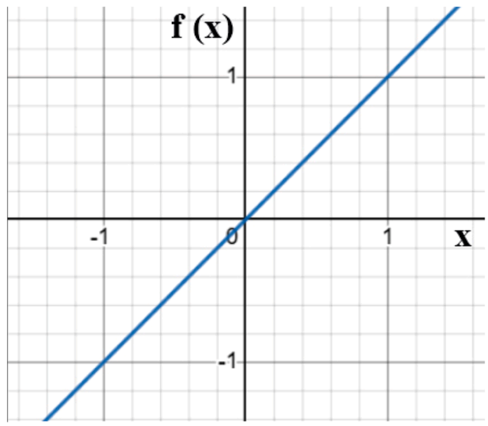

Fig. 3. Graph of the standard PureLin transfer function.

activation functions. It is characterized by its sigmoid-shaped curve, reminiscent of the sigmoid function. The TanSig function maps input values to an output range between −1 and 1 (Fig. 4), making it well-suited for tasks such as binary classification, complex non-linear and regression [50]. Its non-linear nature enables neural networks to capture complex relationships in data, facilitating the training and convergence of models. The TanSig transfer function can be defined as shown in Eq. (7) [46].

$$f(x) = \frac{2}{1 + e^{-2x}} - 1 \tag{7}$$

f(x) represents the output of the TanSig function for a given input x, where x is the input to the function. e is the base of the natural logarithm, approximately equal to 2.71828.

2.2. Study area and data

In this study, greenhouses located in Marassana, Welimada, and Nuwara Eliya within the central hills in Sri Lanka were carefully selected as the research sites (Fig. 5). These greenhouses were meticulously maintained, with each one strictly adhering to standardized conditions and agricultural protocols designed for cabbage cultivation homogeneously. These protocols encompassed precise control of various variables, including temperature, humidity, lighting, ventilation, irrigation management, soil pH, as well as the comprehensive implementation of pest and disease control measures [13].

For the experimental setup, germinated seeds of Green Coronet cabbage were simultaneously planted in soil pots within each of the three selected greenhouses. At the end of every 7-day interval, the concentrations of essential nutrients, namely N, P, and K, in the plant near the soil were measured using an NPK conductivity sensor (JXBS-3001-DLJ, Shandong, China). This monitoring continued for a total duration of 85 days. The nutrient concentrations were recorded in units of milligrams per kilogram (mg/kg). In addition, plant measurements, such as plant height, the number of leaves, and average leaf area, were recorded at 7-day intervals throughout the entire 85-day duration. Plant height and average leaf area were determined for each selected plant using a flexible tape graduated in millimeters and a portable leaf area meter (LI-3000C, Lincoln, USA) [51,52]. The cabbage plant height was determined by measuring the vertical distance from the soil surface to the apex of the cabbage plant throughout its growth stages. Cabbage leaf area was quantified using a scanning head equipped with diodes and paired detectors, allowing for the measurement of leaf area as the cabbage leaf passes through the scanning mechanism.

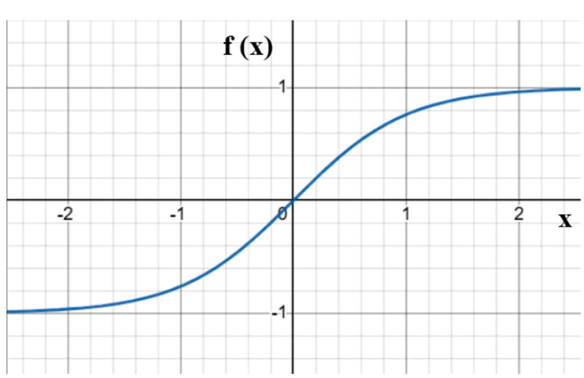

Fig. 4. Graph of the standard TanSig transfer function.

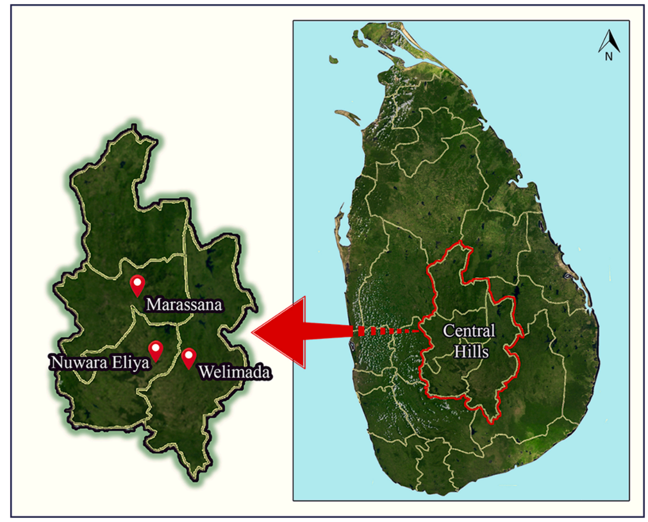

Fig. 5. Selected locations for cabbage cultivation in central hills, Sri Lanka.

2.3. Overall methodology

This research measures the concentrations of N, P, and K in the soil alongside plant growth characteristics over 7-day intervals. When plants grow without the application of fertilizer, they tend to deplete the soil nutrients, such as N, P, and K [53]. The measured data of the plant characteristics were subjected to training using the LM training algorithm for utilization in the DNN under various transfer functions, including LogSig, TanSig, and PureLin transfer functions, as illustrated in Fig. 6.

The MATLAB numerical computing environment (version 9.6-R2019a) was used to develop DNN architectures for predicting soil N, P, and K conditions. From the initial data set, 80 % was allocated for training the DNN model, while the remaining 20 % of the data set was reserved for evaluating the predictive performance of the model. Prediction was conducted based on the evaluation of *r* (Coefficient of Correlation) and MSE (Mean Squared Error) values to identify the most suitable activation functions.

2.4. Model accuracy evaluation

The primary aim was to minimize the MSE and maximize the *r* when predicting the N, P, and K content of the soil. The reduction in MSE signified an improved level of prediction accuracy. An elevation in the *r* value denoted a more pronounced linear relationship between the input and output variables, suggesting a closer alignment in a linear manner [54]. Eqs. (8) and (9) delineate the mathematical formulas employed for computing *r* and MSE, respectively. Higher *r* values demonstrated a stronger correlation with the observed values, while a higher MSE value suggested a greater difference between predicted and observed values,

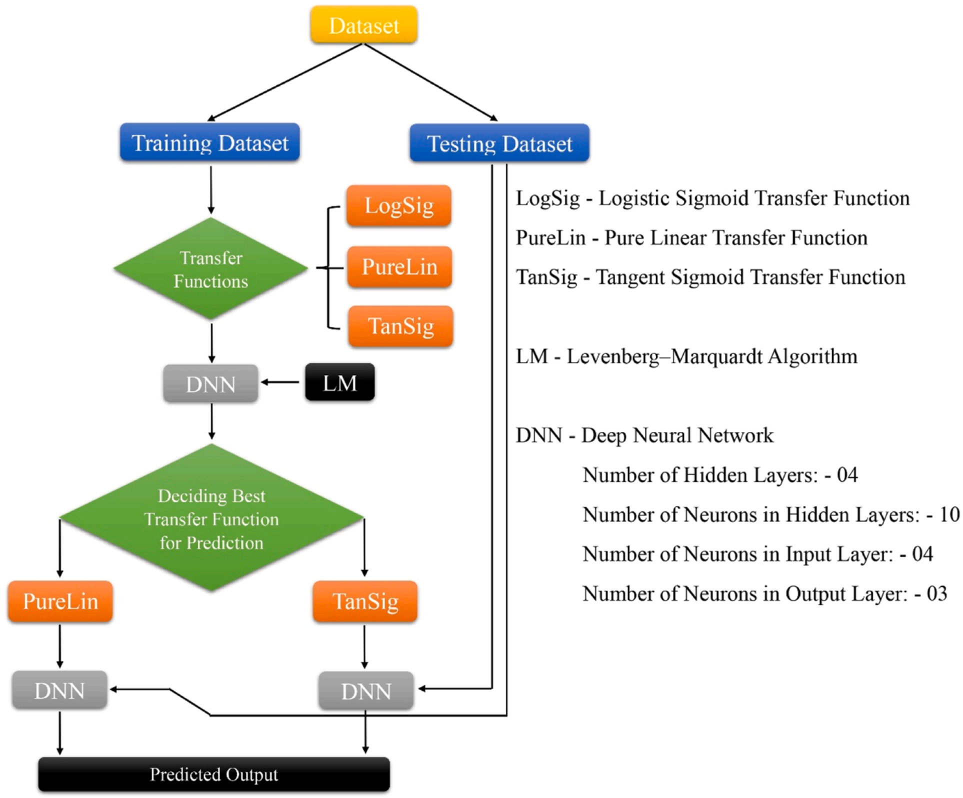

Fig. 6. Overall methodology for employing the dataset.

pointing towards a reduction in the model's accuracy in capturing data variability [55]. Consider p as representing the observed values and q as denoting the predicted maximum value for a given observation, ranging from i to n. Both p and q correspond to the actual and predicted values, respectively, while $\bar{p}$ and $\bar{q}$ represent the mean values of the actual and predicted values, respectively. The parameter N indicates the total number of observations [56].

$$r = \frac{\sum_{i=1}^{N}(q-\bar{q})(p_i-\bar{p})}{\sqrt{\sum_{i=1}^{N}(q_i-\bar{q})^2 . \sum (p_i-\bar{p})^2}} \quad (8)$$

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N}[p_i-q_i]}{N} \quad (9)$$

3. Results and discussion

This study aimed to establish the relationship between cabbage plant growth characteristics and the changing levels of soil N, P, and K content over time. Additionally, based on the plant's growth characteristics, predictions were made regarding soil N, P, and K content. As time progressed, the absorption of nutrients by the plant led to a decrease in soil nutrient content. After the DNN model was developed to identify the complex relationship between soil N, P, and K content and plant growth characteristics with time. This section describes the experimental procedure and presents the outcomes obtained from the experiment. It outlines the results achieved through the model's performance using various transfer functions and evaluates the predictive performance

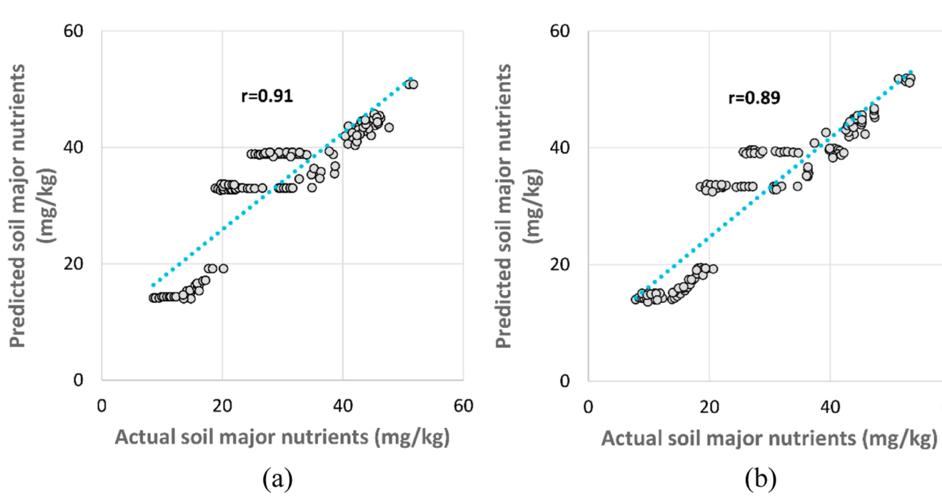

Fig. 7. Actual vs. predicted soil major nutrient content under LogSig transfer function. (a) for test (b) for validation.

when employing improved transfer functions in the model.

3.1. Results obtained under logistic sigmoid transfer function

Fig. 7 illustrates the values of *r* for predicting soil major nutrient content using the LogSig transfer function for test and validation. The results obtained using the LogSig transfer function yielded *r* values of 0.91, 0.89, 0.91, and 0.91 for Training, Validation, Testing, and All Data Points, respectively. These *r* values, approaching 1, signify an improved goodness-of-fit and a strong correlation between the predicted and actual values of soil nutrient content [20,57]. However, the model exhibited a higher MSE value of 60.6966 from 16 epochs, indicating lower prediction accuracy. Consequently, the LogSig transfer function was not deemed suitable for predicting soil major nutrient content. To enhance model accuracy, it is crucial to establish a robust relationship between input and output factors while minimizing the MSE value [20,

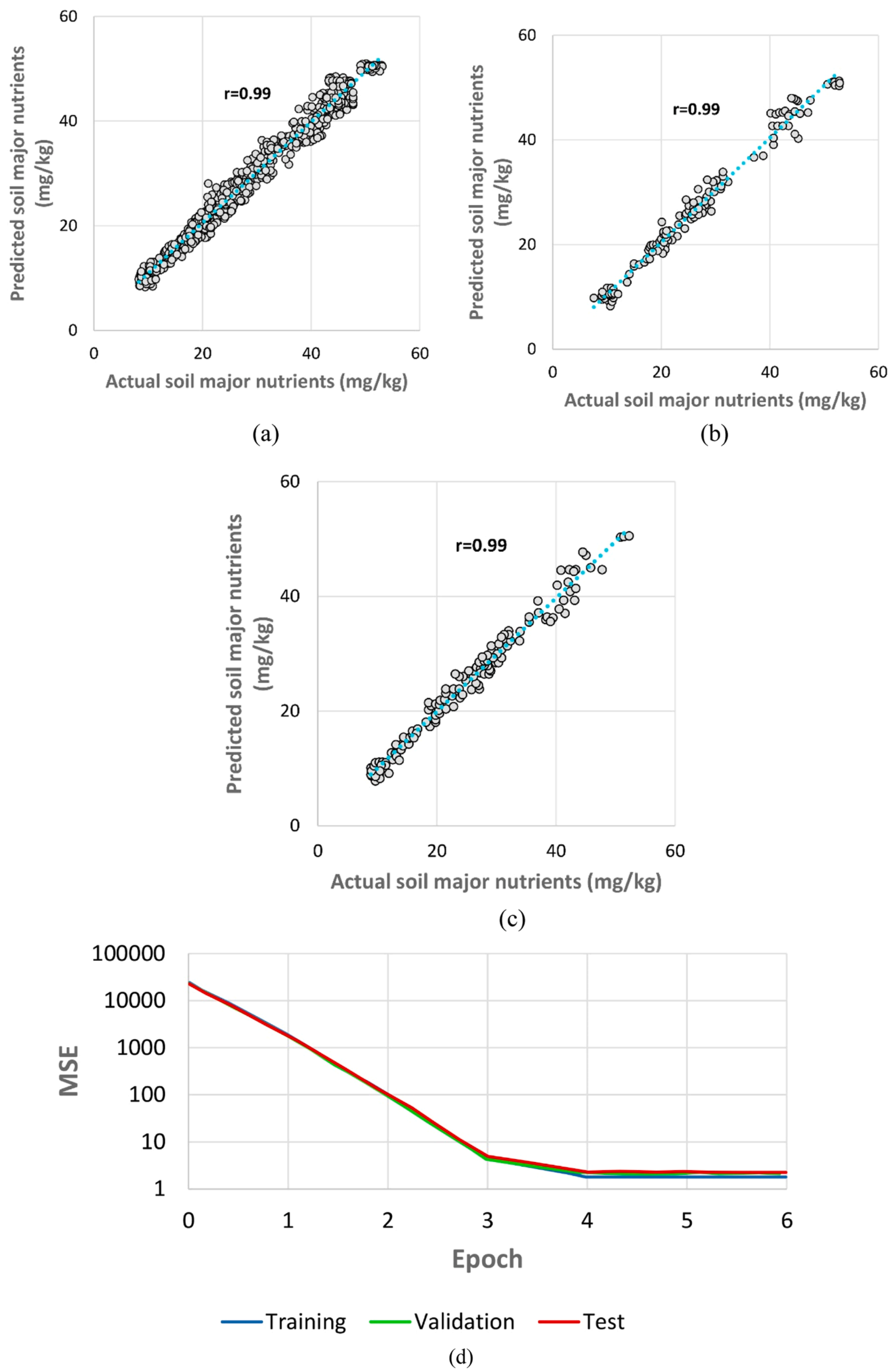

Fig. 8. Actual vs. predicted soil major nutrient content under PureLin transfer function. (a) for training (b) for testing (c) for validation (d) validation performance for the model under PureLin transfer function.

58–60]. The obtained r values from this analysis were satisfactory; however, the MSE value was higher. Therefore, a decision was made to explore another transfer function. Consequently, the PureLin transfer function was selected for further analysis [61].

3.2. Results obtained under PureLin transfer function

Fig. 8 illustrates the values of r and MSE for predicting soil major nutrient content using the PureLin transfer function. In contrast, the PureLin transfer function resulted in identical r values of 0.99 for Training, Validation, Testing, and All Data Points. The r values closely approached 1, suggesting an improved goodness-of-fit and a stronger correlation between predicted and actual values of soil nutrient content compared to the LogSig transfer function. Importantly, the MSE value decreased to 2.1499 (Fig. 8(d)) from 5 epochs under the PureLin transfer function, a notable improvement than the LogSig transfer function. Due

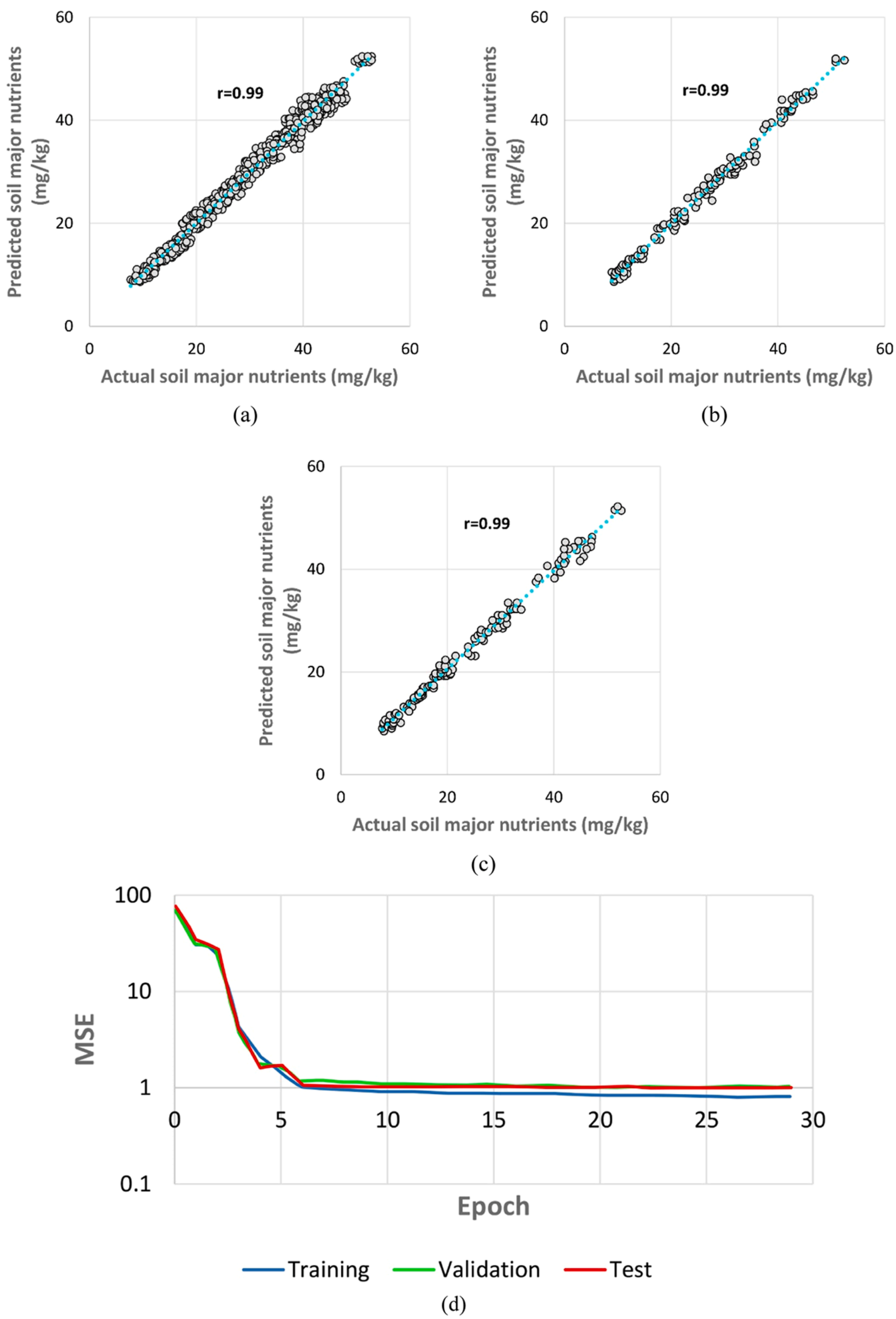

Fig. 9. Actual vs. predicted soil major nutrient content under TanSig transfer function. (a) for training (b) for testing (c) for validation (d) validation performance for the model under TanSig transfer function.

to the higher *r* value and lower MSE value, the PureLin transfer function was chosen as a more accurate predictor of soil major nutrients.

The *r* and MSE values obtained from this analysis were satisfactory. However, in an effort to further reduce the MSE value, a decision was made to explore another transfer function. Consequently, the TanSig Transfer Function was selected for further analysis.

3.3. Results obtained under TanSig transfer function

Fig. 9 illustrates the values of *r* and MSE for predicting soil major nutrient content using the TanSig transfer function. Similarly, the TanSig transfer function also yielded *r* values of 0.99 for Training, Validation, Testing, and All Data Points, respectively. Although the *r* values remained unchanged, the MSE value decreased to 1.0813 (Fig. 9(d)) from 23 epochs under the TanSig transfer function compared to the PureLin transfer function. Considering the MSE value, the TanSig transfer function emerged as the most suitable function for predicting soil N, P, and K content. Table 1 provides a summary of the *r* and MSE values for each transfer function. The *r* and MSE values obtained from this analysis were satisfactory.

The analysis involved the independent consideration of three transfer functions. A summary of the results is presented in Table 1, highlighting the selection of the most effective transfer functions for predicting soil conditions.

3.4. Prediction from DNN model under PureLin and TanSig transfer functions

Following the selection of transfer functions based on the outcomes presented in Table 1, an assessment of the prediction results was conducted, as depicted in Table 2. For enhanced clarity and visualization, Fig. 10 graphically illustrates the comparison between actual and predicted soil nutrient values. Further confirmation of the predictive capabilities of the DNN model under the TanSig function was obtained from Table 2, which presents prediction values. The model under the TanSig transfer function exhibited prediction values with the minimum difference from the actual N, P, and K values. To gain a clearer understanding of these prediction accuracy, a randomly selected plant growth characteristics was employed under both the PureLin and TanSig transfer functions, as illustrated in Fig. 10. In this section, a detailed evaluation of the various transfer functions and their influence on the predictive accuracy of the DNN model has been presented, with a focus on highlighting the superiority of the TanSig transfer function in predicting soil nutrient content.

4. Conclusions

Throughout this extensive research endeavor, an in-depth exploration of cabbage cultivation and the intricate interplay between these cruciferous plants, soil nutrient content, and their growth characteristics was embarked upon. Significance was attributed to nutrient management, with particular emphasis on the pivotal roles played by N, P, and K in the successful cultivation of cabbage. To augment capabilities in monitoring soil health and predicting nutrient dynamics, the innovative application of DNNs was introduced. Cutting-edge technology was utilized to revolutionize the way precision agriculture is approached, offering invaluable insights into soil nutrient levels. To harness the potential of DNNs, the LM algorithm was employed for data training, and the model was fine-tuned to achieve optimal results. The core of experimentation, however, was in the selection and deployment of diverse transfer functions within the DNN model.

Findings yielded compelling revelations about the varying performance of these transfer functions. Notably, relatively lower *r*-values were exhibited by the LogSig transfer function while concurrently displaying higher MSE values. These results pointed towards suboptimal accuracy in soil nutrient predictions, highlighting the limitations of this function within the model. Conversely, commendable *r*-values of 0.99 across all stages of analysis were showcased by both PureLin and TanSig transfer functions, indicative of an enhanced goodness-of-fit and stronger correlations between predicted and actual soil nutrient content. The ultimate distinction between these two successful transfer functions emerged through a comparison of MSE values. TanSig triumphed with the lowest MSE value of 1.0813, signifying its superiority in predicting soil N, P, and K content within the DNN model. This outcome underscored the tangible potential of TanSig transfer functions, elevating them as the preferred choice for precise soil nutrient predictions.

In summary, this comprehensive research undertaking has contributed invaluable insights to the realm of cabbage cultivation. Significance has been attributed to nutrient management and judicious fertilizer application, in sync with plant growth characteristics. Furthermore, the innovative integration of DNNs, alongside the strategic timing of fertilizer applications in response to plant growth dynamics, offers substantial benefits to the agriculture sector. The notable success of TanSig

Table 1
The *r* and MSE values of considered transfer functions.

Transfer function	R				MSE	Num of epochs
	Training	Validation	Testing	All data points		
LogSig	0.91	0.89	0.91	0.91	60.6966	16
PureLin	0.99	0.99	0.99	0.99	2.1499	5
TanSig	0.99	0.99	0.99	0.99	1.0813	23

Table 2
Actual and predicted nutrient contents under PureLin and TanSig transfer functions.

Num of days	Considered soil nutrients	Actual content (mg/kg)	Predicted content from PureLin function (mg/kg)	Predicted content from TanSig function (mg/kg)
	N	42.33	44.85	43.99
7	P	18.57	18.87	19.51
	K	50.69	50.45	51.71
	N	39.58	42.37	41.82
14	P	16.82	17.21	17.38
	K	44.2	47.51	45.67
	N	43.28	38.75	40.42
21	P	15.59	15.27	15.59
	K	46.42	43.35	44.62
	N	34.81	36.15	35.45
28	P	14.85	14.57	14.17
	K	43.32	41.08	42.61
	N	31.86	33.04	33.19
35	P	13.21	13.10	13.53
	K	39.89	37.80	40.32
	N	30.82	29.79	31.35
42	P	11.5	12.09	11.28
	K	32.33	34.63	32.07
	N	23.16	26.01	25.05
49	P	10.07	10.80	10.02
	K	29.4	31.00	30.20
	N	25.19	23.19	24.20
56	P	10.2	9.78	10.32
	K	29.5	28.10	28.72
	N	21.93	20.70	21.04
63	P	9.24	9.25	10.21
	K	26.6	26.32	27.28
	N	19.22	22.24	21.19
70	P	11.33	9.83	10.51
	K	28.17	27.98	27.43
	N	20.98	21.18	20.16
77	P	10.3	9.87	9.94
	K	27.1	27.37	26.58
	N	20.07	19.91	19.80
84	P	8.92	10.07	9.45
	K	26.18	26.69	26.11

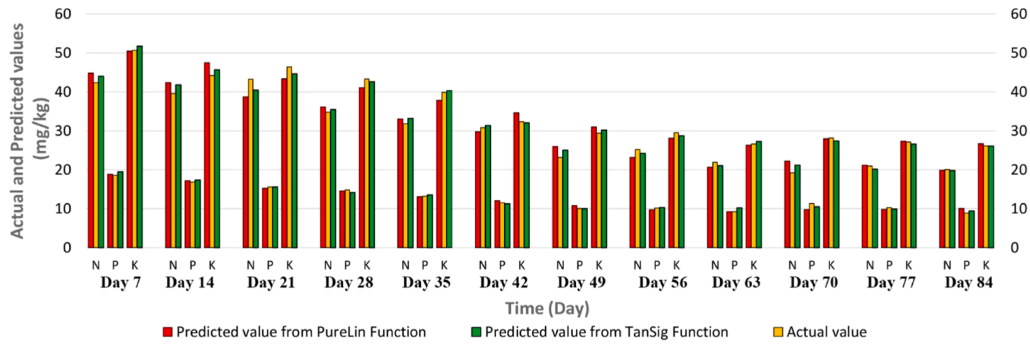

Fig. 10. Actual vs predicted soil nutrient values under PureLin and TanSig transfer Functions.

transfer functions in predicting soil nutrient content stands as a testament to the potential of this technology in the realm of precision agriculture and soil health monitoring, not only for cabbage but also for broader applications in sustainable agriculture. In essence, this research serves as both a knowledge advancement and a practical guide for elevating agricultural practices and fostering sustainability in crop cultivation.

CRediT authorship contribution statement

Hirushan Sajindra: Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Writing – original draft. **Thilina Abekoon:** Data curation, Formal analysis, Investigation, Methodology, Writing – original draft. **J.A.D.C.A. Jayakody:** Methodology, Supervision, Validation. **Upaka Rathnayake:** Conceptualization, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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