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Modelling of energy demand prediction system in potato farming using deep learning method

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Abstract: Agriculture and energy are intricately connected, with agriculture being a significant energy consumer and supplier. In this comprehensive study, SPSS and Jupyter Notebook were used to model and predict the energy requirements of potato plants during cultivation. A system using deep learning methods, specifically the Convolutional Neural Network (CNN), was also developed to accurately predict the classification of potato plant growth phases using image data. The CNN model, developed with 100 epochs and 5 layers, used 1 125 image data of potato plants, categorising them into two classes: the vegetative phase, with an energy requirement of 4 195.80 MJ·ha^{-1}, and the generative phase, with an energy requirement of 746.45 MJ·ha^{-1}. The model's accuracy in reflecting the actual data, with a mean absolute error of 0.11, mean square error of 0.01, and root mean square of 0.13, indicates no significant issues. The test predicted categorization with 99% precision, underscoring the thoroughness and validity of this study and reassuring the audience about the accuracy of the results. The study findings not only validate the use of deep learning in agriculture but also inspire the development of applications to predict the energy demand for each growth phase using plant image data.

Keywords: convolutional neural network; machine learning; maxpooling; tuber; yield

The agricultural sector, a vital part of the Indonesian economy, is facing a pressing issue of rising energy demand due to mechanised crop production practices, growing populations, and limited arable land area. The need to optimise instruments and technology to meet the expanding population's dietary requirements is urgent. Forecasting energy needs can lead to immediate action in production process optimisation and reduce wastage like potato crops. In annuals and short-lived dicotyledons, potato plants have four growth phases: vegetative, initiation, expansion, and maturation.

Agriculture and energy have a close relationship, with the agricultural sector being one of the most significant consumers and suppliers of bioenergy. With mechanised crop production practises, increasing populations, increasing high-yielding varieties, and limited arable land area, but rising

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requirements and living standards, the agricultural sector's energy demand is rising rapidly (Gómez et al. 2019). It is expected that the agricultural sector will advance rapidly to complete work more efficiently, quickly, and effectively with the advancement of technology in the modern era, such as the development of software that can mimic human intelligence and mechanisation technology that can make work more concise.

Deep learning techniques have been used to forecast crop output and growth, and artificial neural networks have been employed to estimate potato yield based on energy inputs. The use of artificial intelligence and mathematical models has been explored in the field of agriculture to anticipate energy consumption (Pishgar-Komleh et al. 2012; Muazu et al. 2014; Bogner et al. 2019; Gómez et al. 2019; Mosavi and Bahmani, 2019; Bolandnazar et al. 2020; Mehta et al. 2023; Sigalingging et al. 2023). Several deep-learning studies have predicted potato output and identified diseases. PLDPNet, a hybrid deep learning network, can automatically segment and classify potato leaf diseases (Arshad et al. 2023). Energy inputs have been utilised to estimate potato output in Saudi Arabia using artificial neural networks (Al-Hamed and Wahby 2016). Another research suggests deep learning for field-based potato blight diagnosis (Johnson et al. 2021; Al-Adhaileh et al. 2023). PotatoPestNet uses a neural network to identify potato pests automatically (Talukder et al. 2023). Nevertheless, the existing literature on using deep learning techniques for about modelling potato energy demand forecast in the context of potatoes is limited.

For fruit analysis, Convolutional neural networks (CNNs) and advanced detection models like R-CNN and YOLO have been tested for precision, recall, and F1 scores (Espinoza et al. 2024). This field has data shortages, labelling issues, and fruit variety (Espinoza et al., 2024; Khalid 2024). However, optimizing deep-learning approaches has significantly improved fruit categorisation accuracy, marking significant progress in the field (Gill et al. 2023). Fruit recognition and localisation using semantic segmentation and deep learning seem promising (Maheswari et al. 2021).

Mechanisation and artificial intelligence software are two examples of technological progress improving agriculture productivity and efficiency. Artificial intelligence (AI) may be used throughout the agricultural process, from fertilisation through harvesting and beyond. Deep learning is a branch of AI that employs the concept of deep artificial neural networks to improve data precision. CNNs are frequently employed for image learning (Albelwi and Mahmood 2017).

Achieving a balance between model training performance and efficiency is crucial in the field of neural network training. This balance is influenced by the dataset size, which varies depending on task difficulty and model design. For instance, Modified National Institute of Standards and Technology (MNIST) digit identification can use 1 489 photos (2.5% of the dataset) (Aki et al. 2017), while complex tasks usually demand larger datasets. Thian et al. (2022) found that medical picture classification performance improved with dataset sizes of 20 000–291 000 images. The pioneering ImageNet classification model by Krizhevsky et al. (2012) used 1.2 million photos. The link between dataset size and model performance frequently follows a learning curve with declining returns (Szyc 2020; Thian et al. 2022). CNNs and hybrid models combining CNNs with artificial neural networks, have been employed to achieve high accuracy in classifying potato diseases with dataset sizes range from 1 574 to 34 657 images (Biswas and Barma 2021; Hasan et al. 2021).

The output of individual convolutional layers may help explain how a picture transforms as it traverses a deep CNN. The feature or activation maps may be graphically connected to the input picture. Each convolutional layer filters the picture using a set of functions. The feature helps relate the learned filter to model performance and increase performance (Kuo 2016). Lee et al. (2017) found that the hierarchical change of characteristics from lower-level to higher-level abstraction for species classes is better represented by plants' distinct orders of venation than the leaf outline shape. Forecasting, which estimates future values using past data, can be used to interpret predictions. The objective of this study is to develop a modelling system that utilises deep learning techniques to forecast the energy requirements of potato plants based on growth phase.

MATERIAL AND METHODS

Data collection and processing. Data was collected on a significant scale, by recording all the necessary data requirements according to the vari-

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ables determined from planting to harvest in Food Estate Hutajulu, Humbang Hasundutan, North Sumatra, Indonesia. This comprehensive approach provides a deep understanding of the subject. Next, the collected data was converted into energy units (MJ·ha^{-1}) using the energy coefficient as shown in Table 1. In addition to acquiring energy demand data, image data was also collected on potato plants. There were 1 125 images of potato plants in the obtained image data.

Modelling design. The design of energy demand modelling was made by Cobb-Douglas modelling in (1) to produce energy productivity values. From Equation (1), the simplified expression in Equation (3) can be used to predict the value of energy productivity. The process of designing this equation is assisted by IMD SPSS (Pishgar-Komleh et al. 2012; Arshad et al. 2023). The Cobb-Douglas function model is:

$$Y = \mathrm{f}(x)\ \exp(u) \tag{1}$$

where: u – an unidentified parameter that requires estimation from data as a latent variable that modifies the model's predictions.

The equation model is transformed into a linear equation using the natural logarithm (ln) (Beigi et al. 2016):

$$\ln Y_i = \alpha_0 + \sum_{(j=1)}^{n} \alpha_j \ln(X_{ij}) + e_i; i = 1, 2, 3\ldots, n \tag{2}$$

The variable Y_i represents the yield of the ith potato, X_{ij} represents the vector of inputs utilised in the production process, α_0 is a constant, α_j represents coefficients of inputs, and e_i is the error term. Equation (2) can be reformulated for potato production with the eight inputs, assuming that yield depends on energy inputs as shown in Equation (3)

$$\ln Y_i = \alpha_0 + \alpha_1 \ln X_1 + \alpha_2 \ln X_2 + \alpha_3 \ln X_3 + \\ + \alpha_4 \ln X_4 \alpha_5 \ln X_5 + e_i \tag{3}$$

where: X_1, X_2, X_3, X_4, and X_5 – fertilisation, pesticide, irrigation, electrical, and human energy, respectively.

The modeling design for energy demand, carried out using Python and Jupiter Notebook, determined the intercept value and coefficient value of each variable. This equation, in the form of multiple linear regressions, is crucial part of our work. ANOVA, a reliable independent statistical method for input-output significance, checks for significant output differences using the *F* ratio or *P* value (Amor et al. 2022), instilling confidence in our statistical analysis.

CNN design for image classification according to growth phases. This design was carried out with the Convolutional Neural Network (CNN) method using Python through Jupyter Notebook (Figures 1 and 2), with the following stages:

Dataset collection. At this stage, image data collection was carried out, which is used for research every day by taking pictures of potato plants with the help of cameras in each growth phase: vegetative and generative phases. From the dataset collection, 1 125 images were generated for the entire image data. Image data began to be taken on potato

Table 1. The energy coefficient of labour, machinery, fuel, fertiliser, pesticide, irrigation, and potato seed

Particulars		Energy coefficient (MJ·unit^{-1})	Unit	References
Input				
Labour	women	1.57	person	Yaldız et al. (1993)
	man	1.96	person	
Diesel		56.31	L	Khoshnevisan et al. (2013)
Machinary		64.8		
Fertiliser	nitrogen (N)	66.14	kg	Bolandnazar et al. (2014)
	potasium (K_2O)	11.15	kg	
	phospat	12.44	kg	
Manuer		0.3	kg	Muazu et al. (2014)
Pesticiede		120	kg	Mohammadi et al. (2008)
Seeds		3.6	kg	Ozkan et al. (2004)
Irrigation		1.02	m^3	Bolandnazar et al. (2014)
Output				
Potato tuber		3.6	kg	Esengun et al. (2007)

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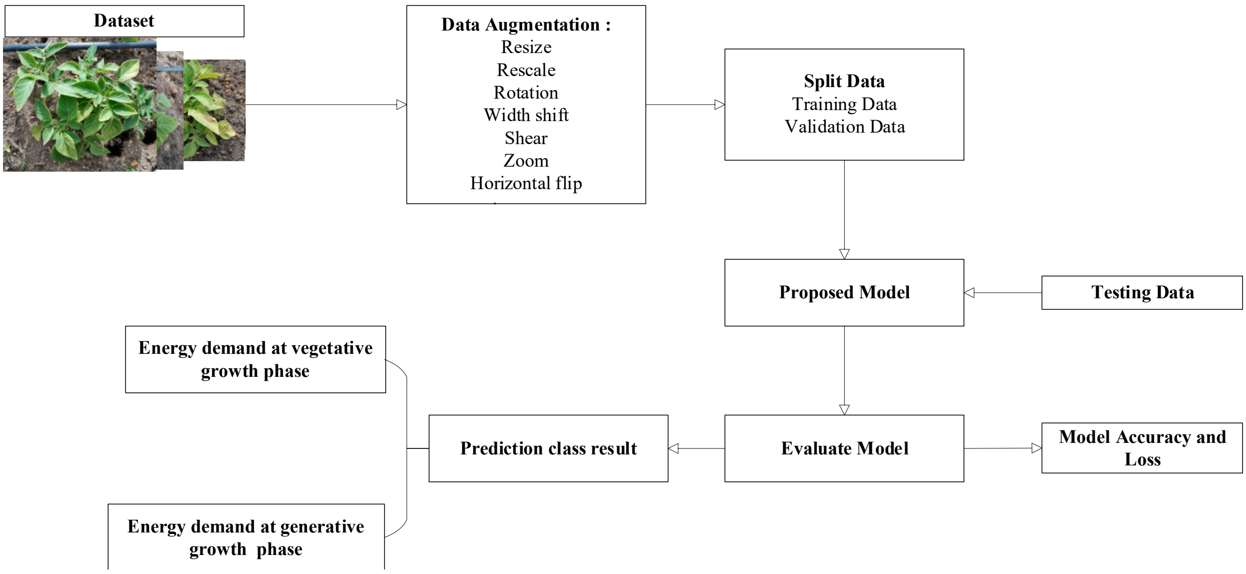

Figure 1. Flowchart of the potato energy demand on classification growth phase

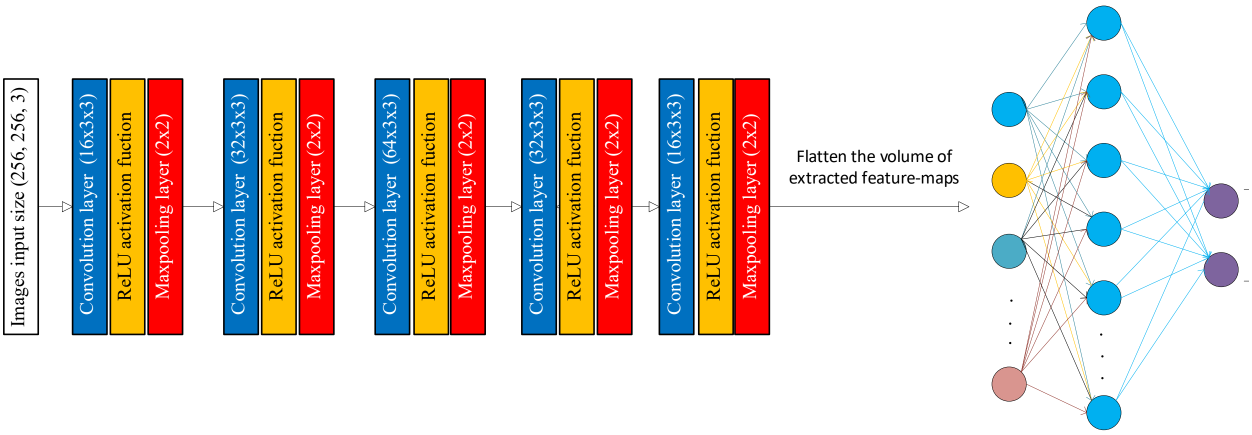

Figure 2. The architectural design of the proposed model

plants aged 20 days after planting (DAP), so potato plant image data was taken for 70 days after 20 DAP.

Dataset preprocessing. At this stage, the image data that had been collected were resized to the same size. After resizing the image size, the next stage is to convert the image into an array. The next stage is to divide the image data into several parts, namely testing data, training data and validation data. This preprocessing stage is vital because the data to be processed must be in a format that can be accepted by Convolutional Neural Network (CNN).

Classification. Image classification was carried out with the CNN method, with the CNN Convolutional layer helping the neural network on CNN to recognise images based on their attributes so that later, it can predict the phase of the potato plant based on the image. In classification, there are several stages, namely convolution, pooling and fully connected layer (Figure 2).

Evaluation. The evaluation stage involves calculating the predictions' mean absolute error (MAE) to determine the CNN model's accuracy value.

RESULTS AND DISCUSSION

Mathematical modelling with SPSS. In this study, the mathematical model was developed based on the Cobb-Douglas model. This Cobb-Douglas modelling can estimate the relationship between input energy (MJ·ha^{-1}) and crop yield (kg·ha^{-1}), and then energy productivity (kg·MJ^{-1}) can be determined using Equation 4 during potato cultivation (Hatirli

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et al. 2006; Ghoshal and Goswami 2017; Sigalingging et al. 2023). The value of energy productivity is calculated by dividing the yield by the total energy input (Mohammadi et al. 2008; McAndrew 2016).

$$\text{Energy productivity} = \frac{\text{Yield}}{\text{Input energy total}} \tag{4}$$

$$\text{Yield} = \frac{\text{Production}}{\text{Areas}} \tag{5}$$

The data reveals that a potato plant area of 0.13 ha resulted in a harvest output of 323 kg. The data indicates that the yield value, calculated using Equation (5) was 2 484.62 kg·ha^{-1}. The total input energy value is derived from the cumulative energy need numbers obtained in Table 2. In order to determine the coefficient values for each variable of model, the subsequent procedure involves transforming the secondary data presented in Table 3 into natural logarithms (ln) (Table 4). This conversion is necessary to turn the data into multiple linear forms, which can be incorporated into the modelling process.

In this study, there were two variables used, namely the dependent variable (Y) and the inde-

Table 2. Energy productivity and total input energy during potato plant growth

Growth phase	Period (week)	Energy productivity (kg·MJ^{-1})	Total input energy (MJ·ha^{-1})
Vegetative	1	2.171	1 144.601
	2	8.705	285.418
	3	8.705	285.418
	4	2.343	1 060.614
	5	1.750	1 419.747
Generative	6	1.266	1 962.699
	7	0.256	9 705.967
	8	0.256	9 714.868
	9	0.317	7 831.926
	10	1.519	1 635.973
	11	1.490	1 667.865
	12	2.113	1 175.704
	13	1.434	1 733.018
	14	7.803	318.430

Table 3. Potato plant growth energy dataset

Growth phase	Period (week)	Fertiliser energy (MJ·ha^{-1})	Pesticide energy (MJ·ha^{-1})	Irrigation energy (MJ·ha^{-1})	Electrical energy (MJ·ha^{-1})	Labour energy (MJ·ha^{-1})
Vegetative	1	201.90	708.92	203.87	4.26	25.65
	2	0.00	0.00	285.42	0.00	0.00
	3	0.00	0.00	285.42	0.00	0.00
	4	72.51	679.38	285.42	8.32	14.98
	5	157.11	945.23	285.42	12.04	19.95
Generative	6	19.34	1 627.38	285.42	10.61	19.95
	7	40.37	9 341.54	285.42	14.33	24.30
	8	75.41	9 307.38	285.42	16.63	30.02
	9	58.01	7441.85	285.42	16.63	30.02
	10	20.30	1 299.69	285.42	10.61	19.95
	11	43.51	1 299.69	285.42	14.33	24.91
	12	31.14	827.08	285.42	12.04	20.03
	13	13.74	1 403.08	285.42	10.61	20.18
	14	0.00	304.62	0.00	4.26	9.56

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Table 4. Energy needed during potato plant growth using Equation 6 in natural logarithm

Growth phase	Period (week)	ln$Y$ (MJ·ha^{-1})	lnX_1 (MJ·ha^{-1})	lnX_2 (MJ·ha^{-1})	lnX_3 (MJ·ha^{-1})	lnX_4 (MJ·ha^{-1})	lnX_5 (MJ·ha^{-1})
Vegetative	1	7.043	2.510	1.254	2.500	6.369	4.573
	2	5.654	0.000	0.000	2.164	0.000	0.000
	3	5.654	0.000	0.000	2.164	0.000	0.000
	4	6.967	3.534	1.297	2.164	5.700	5.111
	5	7.258	2.761	0.966	2.164	5.330	4.825
Generative	6	7.582	4.856	0.423	2.164	5.456	4.825
	7	9.180	4.120	–1.324	2.164	5.155	4.627
	8	9.181	3.495	–1.321	2.164	5.007	4.416
	9	8.966	3.757	–1.097	2.164	5.007	4.416
	10	7.400	4.807	0.648	2.164	5.456	4.825
	11	7.419	4.045	0.648	2.164	5.155	4.603
	12	7.070	4.379	1.100	2.164	5.330	4.821
	13	7.458	5.198	0.571	2.164	5.456	4.813
	14	5.763	0.000	2.099	0.000	6.369	5.561

ln$Y$ – total input energy; lnX_1 – fertiliser energy; lnX_2 – pesticide energy; lnX_3 – irrigation energy; lnX_4 – electrical energy; lnX_5 – labour energy

pendent variable (X). The dependent variable is total energy demand (Y), while the independent variables are energy from fertilisation (X_1), pesticides (X_2), irrigation (X_3), electricity (X_4), and labour (X_5) as displayed in Equations (6 and 7). Table 4 provides information on the labelling of various energy components. Total energy demand is denoted as Y, while fertiliser, pesticide, irrigation, electrical, and human (labour) energy are denoted as X_1, X_2, X_3, X_4, and X_5, respectively. Then, it proceeds with analysis of variance (ANOVA) regression testing using the SPSS software (version 25) . The outcomes of the tests that were conducted are presented in Table 5.

The ANOVA regression test produces a constant value of 3.907 and the following coefficient values for each variable: 0.055 for X_1, 1.081 for X_2, 0.293 for X_3, –0.448 for X_4 and –1.625 for X_5. The intercept (constant) value of 3.907 is statistically significant as the P-value < 0.001. The coefficient for X_1 (fertilisation energy) and X_4 (electricity energy) is not statistically significant (P-value > 0.05). On the other hand, the coefficient for X_2 (pesticide energy), X_3 (irrigation energy) and X_5 (labour energy) are statistically significant (P-value < 0.05). The R-value of 0.98 indicates a strong association between predictors and dependent variables. The R^2 value of 0.96 means the model has 96 % of the variation in the dependent variable, which is reassuring. A high match is confirmed by the Adjusted R^2 score of 0.94, which accounts for the number of predictors in the model.

Table 5. The coefficient of X variables for Equation 6 using the ANOVA

Particulars	Coefficients		SE	P-value
Intercept	α_0	3.907	0.536	0.000
lnX_1	α_1	0.055	0.128	0.678
lnX_2	α_2	1.081	0.156	0.000
lnX_3	α_3	0.295	0.092	0.013
lnX_4	α_4	–0.448	0.353	0.239
lnX_5	α_5	–1.625	0.440	0.006
R	0.98			
R^2	0.96			
Adjusted R^2	0.94			
SE	0.30			

SE – standard error; R – correlation coefficient; R^2 – coefficient of determination; lnX_1 – fertiliser energy; lnX_2 – pesticide energy; lnX_3 – irrigation energy; lnX_4 – electrical energy; lnX_5 – labour energy

An equation model was created using each of these values to forecast the value of total energy demand during potato plant growth (Equation 6). Equation 6 reveals that the Y value represents total energy demand, and the constant coefficient value is 3.907. This equation serves as a predictive model for total energy demand, which is presented in Figure 3. These results indicate that there are still limitations

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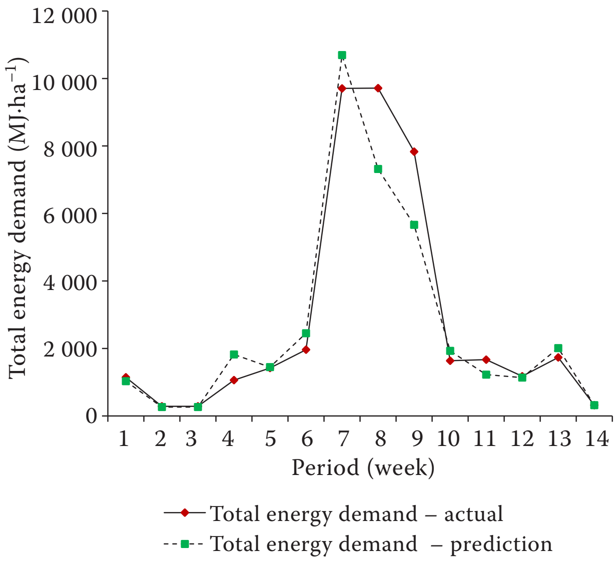

Figure 3. Comparison of actual data and predicted results

as it lacks an error value, resulting in variations in the obtained values. The disparity in results is evident from the graph depicted in Figure 3. To produce a more accurate prediction value, it is necessary to find the error value (called X_{error} or X_{er}).

$$\ln Y_i = 3.907 + 0.555 \ln X_1 + 1.081 \ln X_2 + 0.293 X_3 + 0.448 \ln X_4 + 1.625 \ln X_5 \quad (6)$$

The error value, the difference between the actual value and the prediction value, was determined by adding an error variable to Equation 6. This was followed by a comprehensive ANOVA and regression testing using SPSS to determine the coefficients X variables for Equation 7, as shown in Table 6. Table 6 shows that all coefficients X variables are not just statistically significant, but also crucial in predicting the total energy demand, underscoring the importance of all findings.

$$\ln Y_i = 3.910 - 0.556 \ln X_1 - 1.0821 \ln X_2 - 0.295 X_3 + 0.450 \ln X_4 + 1.627 \ln X_5 - 1.644 X_{er} \quad (7)$$

The resulting error data refers to additional independent variable data that can influence the value of the dependent variable or total energy demand value (Y). The error data obtained, a result of thorough observation, can be observed in Table 7. Upon applying the data error. the independent variables are transformed into six X variables, specifically X_1, X_2, X_3, X_4, X_5, and X_{er}. These variables represent the overall fertilisation energy, pesticide energy, irrigation power, electric energy, labour energy, and error value.

Designing mathematical modelling in Python. The Cobb-Douglas equation was tested by modelling in Python using a Jupyter Notebook. The equation, a linear one, was applied to a dataset consistent with prior data, specifically in natural ln. The dataset uses the ln transformation for variables: total energy demand (ln$Y$), fertilisation energy (lnX_1), pesticide energy (lnX_2), irrigation energy (lnX_3), electrical energy (lnX_4), and labour energy (lnX_5). The study, which aims to understand the

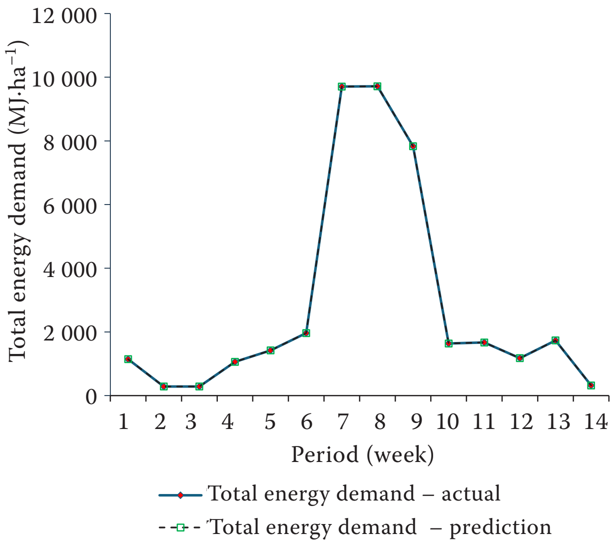

Figure 4. The comparison of actual data and predicted results with error data

Table 6. The coefficient of X variables for Equation 7 using ANOVA

Particulars	Coefficients		SE	*P*-value
Intercept	α_0	3.910	0.000	0.000
lnX_1	α_1	−0.056	0.000	0.000
lnX_2	α_2	−1.082	0.000	0.000
lnX_3	α_3	−0.295	0.000	0.000
lnX_4	α_4	0.450	0.000	0.000
lnX_5	α_5	1.627	0.000	0.000
X_{err}	e_0	−1.644	0.000	0.000
R	1			
R^2	1			
Adjusted R^2	1			
SE	$7.8 \cdot 10^{-16}$			

SE – standard error; R – correlation coefficient; R^2 – coefficient of determination; lnX_1 – fertiliser energy; lnX_2 – pesticide energy; lnX_3 – irrigation energy; lnX_4 – electrical energy; lnX_5 – labour energy

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Table 7. Potato growth phase energy demand in logarithm natural for Equation 7

Growth phase	Period (week)	ln$Y$ (MJ·ha^{-1})	lnX_1 (MJ·ha^{-1})	lnX_2 (MJ·ha^{-1})	lnX_3 (MJ·ha^{-1})	lnX_4 (MJ·ha^{-1})	lnX_5 (MJ·ha^{-1})	X_{er} (MJ·ha^{-1})
Vegetative	1	7.043	2.510	1.254	2.500	6.369	4.573	–0.753
	2	5.654	0.000	0.000	2.164	0.000	0.000	–2.075
	3	5.654	0.000	0.000	2.164	0.000	0.000	–0.275
	4	6.967	3.534	1.297	2.164	5.700	5.111	–4.053
	5	7.258	2.761	0.966	2.164	5.330	4.825	–4.090
Generative	6	7.582	4.856	0.423	2.164	5.456	4.825	–4.090
	7	9.180	4.120	–1.324	2.164	5.155	4.627	–6.477
	8	9.181	3.495	–1.321	2.164	5.007	4.416	–6.247
	9	8.966	3.757	–1.097	2.164	5.007	4.416	–5.959
	10	7.400	4.807	0.648	2.164	5.456	4.825	–4.350
	11	7.419	4.045	0.648	2.164	5.155	4.603	–4.086
	12	7.070	4.379	1.100	2.164	5.330	4.821	–3.828
	13	7.458	5.198	0.571	2.164	5.456	4.813	–4.411
	14	5.763	0.000	2.099	0.000	6.369	5.561	–2.261

ln$Y$ – total input energy; lnX_1 – fertiliser energy; lnX_2 – pesticide energy; lnX_3 – irrigation energy; lnX_4 – electrical energy; lnX_5 – labour energy; X_{er} – error value

energy demand in agriculture, considers the logarithm value of total energy demand (Y) as the dependent variable and includes fertiliser energy (X_1), pesticide energy (X_2), irrigation energy (X_3), electrical energy (X_4), and labour energy (X_5) as independent factors. An intercept value of 3.907 was derived from the output, along with the following coefficients: X_1 (0.055), X_2 (1.081), X_3 (0.293), X_4 (–0.448), and X_5 (–1.625) as shown in Table 5. Equation 6 was derived from these data. However, the equation yields an R^2 value of 0.96, indicating that the accuracy was not 100%.

It is essential to incorporate error numbers from earlier processes by including the ln_Xer variable with annotated error data to improve the accuracy of results. The ANOVA results show that the intercept value of 3.91, the coefficient of lnX_1 is –0.056, the coefficient of lnX_2 is –1.082, the coefficient of lnX_3 is –0.295, the coefficient of lnX_4 is 0.450, coefficient of lnX_5 as 1.627, and coefficient of X_{er} as –1.644 (Table 6). After the value of each variable has been determined, a linear equation with a regression function is constructed, as shown in Equation (7). From the modelling produces an R^2 value of 1, indicating an accuracy of 100%. This high level of accuracy should reassure you of the reliability of our findings. Comparison between actual data and prediction results through SPSS and Python, as shown in Table 8.

The modelling findings with SPSS and Python in Table 8 fit the actual data. The equation reveals that the MAE is 0.11, the MSE is 0.01, and the Root Mean Square (RMS) is 0.13. These values, while not ranking number one individually, collectively demonstrate the high accuracy of the model. This accuracy is further reinforced by the model's close approximation to the actual value.

Image classification design with CNN by phase growth. The design of image classification with CNN based on the growth phase is done through Jupyter Notebooks with Python programming language. In this design, data in the form of images that have been collected previously during the cultivation process of planting potatoes was used and then was classified based on two phases of growth, namely vegetative and generative phases, as many as 1 125 images (McAndrew 2016; Sigalingging et al. 2023).

TensorFlow and the operating system were utilised to construct a CNN. TensorFlow can train and execute neural networks for image and object classification and recognition. The Imghdr library was utilised to test and identify the image format in the data. The cv2 library was utilised to display images in Windows, while the matplotlib module was employed to visualise data. A CNN is constructed with multiple hidden layers using a Sequential model, where each layer is connected to the preceding

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Table 8. Comparison data actual and prediction (MJ·ha^{-1})

Growth phase	Period (week)	Total energy demand	Total energy demand prediction by SPSS	Total energy demand prediction by Python
Vegetative	1	1 144.601	1 144.601	1 144.601
	2	285.418	285.418	285.418
	3	285.418	285.418	285.418
	4	1 060.614	1 060.614	1 060.614
	5	1 419.747	1 419.747	1 419.747
Generative	6	1 962.699	1 962.699	1 962.699
	7	9 705.967	9 705.967	9 705.967
	8	9 714.868	9 714.868	9 714.868
	9	7 831.926	7 831.926	7 831.926
	10	1 635.973	1 635.973	1 635.973
	11	1 667.865	1 667.865	1 667.865
	12	1 175.704	1 175.704	1 175.704
	13	1 733.018	1 733.018	1 733.018

layer (Figure 2). The Conv2D function is utilised for convolution. It incorporates the ReLu and Sigmoid activation functions. At the pooling stage, the Max-Pooling2D function uses the same filter size as Convo2D. The Flatten function was then utilised to transform the data from a 2D format into a vector. The subsequent phase is the fully connected layer stage, the ultimate stage for processing data for classification (Figure 2).

The training process consisted of 100 epochs, meaning that learning occurred 100 times. Epochs are beneficial for the model's learning process using the given data. Higher epoch values lead to higher accuracy values. The investigation yielded an accuracy of 99%, precision of 92%, and sensitivity (recall) of 100%. Accuracy measures a model's ability to classify an image correctly. Precision is used to indicate the level of precision in the categorization findings based on the data used. Recall or sensitivity measures how well the model retrieves information. A data test is conducted to verify the accuracy of the processed data. Test data is used to assess the performance of the image categorisation prediction model.

From the results of the data test conducted, the image data used is image data in the generative phase. The CNN modelling system also reads the image data as an image in the generative phase where the energy requirement in the generative phase is 35 746.45 MJ·ha^{-1} and in the vegetative phase is 4 195.80 MJ·ha^{-1} means the test data is accurate.

Using the Cobb-Douglas equation to predict total energy demand yielded 100 % accuracy, according to (Sigalingging et al. 2023). In addition, the Cobb-Douglas equation was transformed into a linear regression form. Cobb-Douglas was utilised as an exponential production function in (Hastuti et al. 2022) to determine the impact of production factors on the quantity of production generated.

In (Arshad et al. 2023), images of leaf diseases in potato, apple and tomato plants were used. The accuracy value of leaf disease prediction in potatoes is 97.63% with 3 classes and has 2 152 images; in apples. it is 96.42% with 4 classes and has 3 171 images; and in tomatoes, it is 94.25% with 10 classes and has 18 160 images. This proves that the fewer classes to be classified, the greater the accuracy of the system in predicting. In addition, (Al-Adhaileh et al. 2023) reported that using Fine-Tuned CNN Architecture can achieve 99% accuracy with 839 203 trainable parameters in 183 s of training time. Fin-Tuned CNN Architecture can enhance accuracy while reducing computation time, information loss, and the number of trainable parameters.

CONCLUSION

The ANOVA regression test of the model has a constant value of 3.910, with coefficients of inputs (X_1, X_2, X_3, X_4, X_5 and X_{er} for fertilisation, pesticide, irrigation, electrical, human energy and error) values of –0.056, –1.082, –0.295, 0.450, 1.627, and –1.644 , respectively. The CNN modelling was

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designed on a Jupyter notebook with an epoch of 100 and 5 layers using 1 125 images of potato plants. The image data used was in the generative and vegetative phases, with an energy requirement of 35 746.45 MJ·ha^{-1} in the generative phase and 4 195.80 MJ·ha^{-1} in the vegetative phase. The investigation has an accuracy of 99%, precision of 92%, and sensitivity (recall) of 100%. The model's mean absolute error of 0.11, mean square error of 0.01, and root mean square of 0.13 show no severe concerns. The study validates deep learning in agriculture and inspires applications to anticipate energy requirements for each growth phase using plant image data, opening up exciting possibilities for the future of agriculture.

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