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Application of Artificial Neural Networks for Classifying Earthworms (*Eudrilus eugeniae*) Moisture Content During the Drying Process

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ABSTRACT

Earthworms (*Eudrilus eugeniae*) have many benefits for the health and animal feed industries. The drying process of earthworms is necessary to extend their shelf life, yet conventional gravimetric moisture tests are slow and destructive. The purpose of this study was to classify the moisture content of earthworms using machine vision and artificial neural networks (ANN) during the drying process, with classified worms into wet (> 40% wb), semi-dry (40%–12%), and dry (< 12%) states. RGB images (n = 450) were acquired every 15 min during cabinet drying at 60 °C; reference moisture was obtained gravimetrically. Nine color and texture features were extracted and ranked in WEKA; then, the top eight features were retained. An external feed-forward ANN implemented in MATLAB with 8-40-3 architecture, TrainLM optimiser, logsig–logsig–purelin transfer functions yielded MSE = 0.0733 (training) and 0.086058 (validation) and R = 0.95309 (training) and 0.92962 (validation). The modest MSE gap reflects class imbalance rather than overfitting, as classification metrics on the unseen test set match the validation results.

Keywords: Artificial neural networks, drying process, earthworms, machine vision

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INTRODUCTION

Earthworms (*Eudrilus eugeniae*) are a great source of protein for animal feed with a protein content of 65.4%, 19% nitrogen, 11% fat, and 6% ash, and also contain 9 essential amino acids and 4 non-essential amino acids (Deepika et al., 2018). The nutritional content makes earthworms widely used in the livestock, cosmetic, and pharmaceutical industries (Azmi et al.,

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2014; Sun, 2015). The addition of earthworms to animal feed as the main or additive feed has been proven to increase the productivity of eggs and meat, and the livestock becomes more resistant to bacteria, viruses, and fungi (Mohanta et al., 2016; Musyoka et al., 2019). Several types of earthworms that can be used for animal feed are *Lumbricus rubellus*, *Eudrilus eugeniae*, and *Eisenia fetida* (Antonova et al., 2021). Earthworms are processed into dried earthworms for the shipping process because living earthworms are sensitive to environmental changes such as soil moisture, soil pH, and temperature (Wu et al., 2019). Earthworms that have been dried have a longer shelf life as well as nutritional content that is still maintained (Fortu Jr et al., 2019).

Conventional production relies on cabinet ovens heated by gas stoves, where temperature control is coarse, and drying must continue for ≥12 h; this often produces overly dark material with uncertain moisture content (Letner & Kajtar, 2018). Moisture content can be used as the main parameter in determining the quality of dried earthworm products (Kröncke et al., 2019). Moisture content is an important parameter in dry matter because it greatly affects the activity of microorganisms that can cause spoilage (Zambrano et al., 2019). Decay bacteria can grow well at a moisture content of 46%–16% (Uyeh et al., 2021). Dried earthworms must have a moisture content below the point of growth of these spoilage bacteria to maintain their quality during shipping and storage. The moisture content test is commonly analyzed with a gravimetric test. The standard gravimetric test is time-consuming and destructive: a sample is weighed repeatedly until mass stabilizes at 60 °C, then re-dried at 105 °C for 3 h to obtain the residual water mass (Carneiro et al., 2018). This two-stage protocol can take half a day and may denature heat-labile proteins, making it impractical for in-process control. This analysis is inefficient because it must be carried out in every production process, and the protein content is likely to be damaged above 100 °C (Suryana et al., 2022).

Accordingly, a rapid and non-destructive alternative is required. Machine-vision techniques offer real-time moisture estimation because the color and surface texture of biomaterials changes predictably with water loss (Prilianti et al., 2021). Sandra et al. (2021) demonstrated that color-texture features coupled with image analysis describe moisture dynamics in cassava chips during drying. Artificial neural networks (ANNs) further enhance predictive performance when suitably optimized (Damayanti et al., 2021; Hendrawan et al., 2019, 2023; Rohmatulloh et al., 2022). Prior work using ANN and feature selection achieved an $R^2 \approx 0.9$ for cassava-chip moisture prediction (Hendrawan et al., 2018) and markedly improved coffee bean quality estimation (Hendrawan, Widyaningtyas et al., 2019).

Building on these findings, the present study develops a machine-vision system that combines color and grey-level co-occurrence-matrix (GLCM) texture descriptors, ranks them using the Waikato Environment for Knowledge Analysis (WEKA) feature-selection toolkit (Hall et al., 2009), and feeds the optimal subset into an ANN to classify *E. eugeniae* into wet (>40%), semi-dry (40%–12%), and dry (<12%) states. The purpose of this study was to classify the moisture content of earthworms using machine vision and ANN during the drying process. This study developed digital image analysis, which included color and texture with ANN models to predict the moisture content of dried earthworms.

MATERIAL AND METHODS

Samples of fresh earthworms were obtained from Malang City, East Java, Indonesia. The oven process and image data collection were carried out at the Laboratory of Biosystem Mechatronics, Faculty of Agricultural Technology, Universitas Brawijaya, Indonesia. The tools used in this research were as follows: a modified 400-watt Kirin oven with the addition of a Pt100 thermocouple temperature sensor with an Autonic TCN4S controller; a computer with Intel Core i3-4150 CPU @3.50GHz (4 CPUs) 10 GB RAM to run ANN programs; Canon DSLR 700D camera (EF 110 mm macro lens for capturing image data, effective pixel of 18 MP, CMOS sensor, sensor size of 22.3 × 14.9 mm); 4 LED spotlights 50W, 110-220V coated with PL Filter CPL 72 mm with an average light intensity of 1394 lux and lens distance to object 280 mm; a standard color card containing 24 colors (85 × 55 mm) used for color correction and white balance reference; and a digital scale (0.001 g) for gravimetric measurements. Prior to drying, worms were harvested, rinsed under running water, blanched for 10 s at 90 °C to stabilize tissue (Gunya et al., 2016), cooled, and cut to a length of 40 mm of earthworms from the head (Sivasubramaniam, 2021). Image acquisition inside the tray dryer is illustrated in Figure 1.

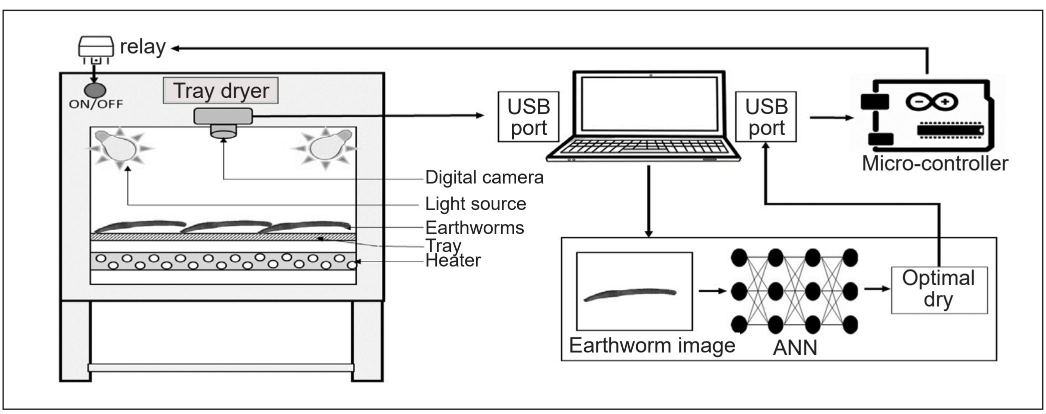

Figure 1. Earthworm drying machine model with moisture content monitoring system

Experimental Design

This study uses 450 earthworm images, which are divided into three classifications: i.e., dry (moisture content > 40%) of 150 images, semi-dry (moisture content between 40%–12%) of 150 images, and wet (< 12%) of 150 images as shown in Figure 2. The semi-dry class was an optimal moisture content condition for animal feed products; however, the storage

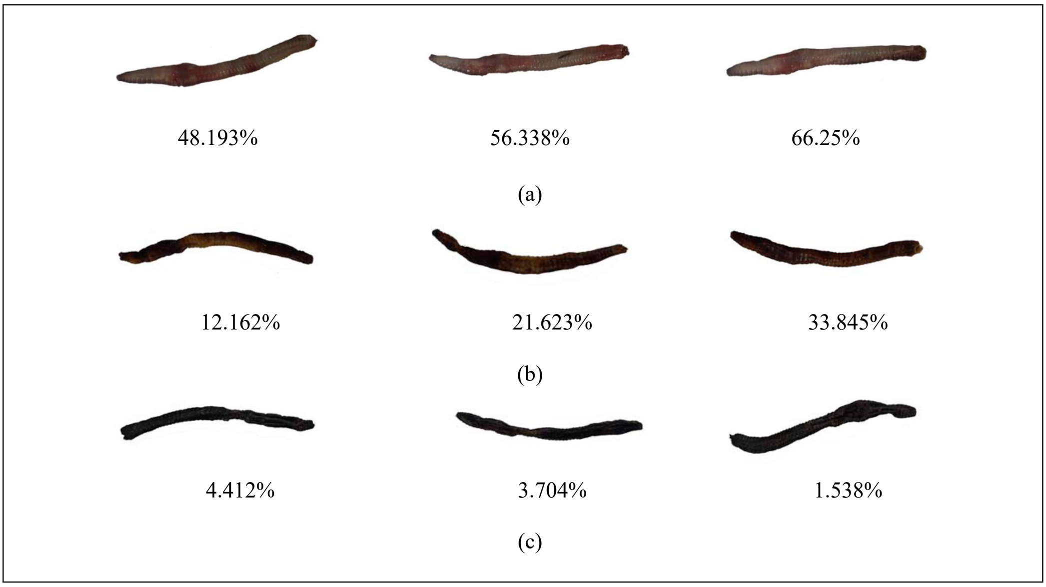

Figure 2. The appearance of dried earthworms in three types of moisture content categories: (a) Wet (moisture content >40%); (b) Semi-dry (moisture content 40%–12%); (c) Dry (moisture content <12%)

time was short, and the products could not be processed into flour. In the dry class, dried earthworms can be stored for a long time and can be processed into flour (Hamdan et al., 2021). The calculation of moisture content in this study used a wet basis (Antia et al., 2021; Chukwunonye et al., 2016).

Three independent drying runs were performed. Each run used 50 worm pieces placed on a perforated tray, with a total of 9 drying repetitions, resulting in 450 images being obtained. Images and masses were recorded simultaneously every 15 min for 2–3 hours at a temperature of 60 ºC. Immediately after each image capture, the tray was removed, weighed to obtain wet-basis mass, and returned to the dryer; thus, the gravimetric reference corresponds one-to-one with each image. Drying continued until equilibrium mass (< 12 % wb) was reached, followed by a 4 h post-dry at 105 °C to determine residual moisture for calibration.

Feature Selection

The image dimensions were changed to 451 × 300 pixels in BMP format. The extracted features were texture features and color features. Texture features are extracted using gray-level co-occurrence matrices (GLCM), with texture parameters such as contrast, correlation, and energy. This research also used color parameters, which were red-green-blue (RGB) and hue-saturation-value (HSV). The next process was feature selection, which functioned to reduce irrelevant data so that the identification process would be effective and efficient, resulting in higher accuracy. The Waikato Environment for Knowledge Analysis (WEKA) toolkit (version 3.9.6; Hall et al., 2009) was employed. Four evaluators (Correlation, Gain Ratio, Relief F, and One-R) were combined with the Ranker search method to score and order features; the top-ranked subsets were forwarded to the classifiers. Image data generated by feature selection was then used as ANN input. In the learning process using an ANN, digital images were divided into two groups: 60% of the data were used in the training process (270 images), and 40% of the data were used in the validation process (180 images). ANN learning used back-propagation (Matlab, 2021a) with a goal MSE of 0.01, a learning rate of 0.1, a momentum of 0.5, and an epoch cap of 1000. This study used several variations of learning functions (traincgb, traincgf, traincgp, traingda, traingdm, traingdx, trainoss, trainr, trainrp, and trainscg) and activation functions (logsig, tansig, and purelin). The output variable was the moisture content of earthworms, consisting of three classes (wet, semi-dry, and dry). Sensitivity analysis was performed by varying the number of nodes (30 or 40), hidden layer (1 or 2), learning function variation, and activation function.

RESULTS AND DISCUSSIONS

Dried earthworms need about 2–3 hours at a temperature of 60 ºC to reach a moisture content below 12%. The average initial moisture content of dried earthworms was 79%. Then, in the first 15 minutes, it increased to 60.2% and continued to decrease by 21.1% at the 45th minute. At the 60th minute, the moisture content reached 13.6%. At 75 minutes, the average moisture content was 11.0%; at 90th minutes, the moisture content became 9.5%; and finally, at 105th and 120th minutes, the moisture content became 7.8% and 7.5%, respectively. The product experienced a reduction in moisture content to the equilibrium point, whereas in this study, at 120th minutes, there was no significant change in moisture content. Figure 2 shows the appearance of dried earthworms in three moisture content categories: dry, semi-dry, and wet. Earthworms with moisture content above 40% had brown skin color characteristics where the clitellum and segments of the earthworm can be seen, and the vessels inside the earthworm's body were also clearly visible. An example of an earthworm image at a moisture content above 40%, which was classified in the soak class, is shown in Figure 2a. Then, an example of a dried earthworm image from the first 15 minutes of drying is shown in Figure 2b. The dried earthworm in Figure 2b can be classified in the semi-dry class with a moisture content of 12%–40%. It had a dark brown color with a slightly faint clitellum, but the skin segments were still visible. The veins in the middle of the earthworm's body were still visible even though they were slightly blackened, approaching a brick-red color. An example of dried earthworms at 45th minutes of drying can be seen in Figure 2c. The dried earthworm in Figure 2c can be classified in the dry class. Dried earthworms in the dry class had a moisture content below 12% and had a characteristic dark brown color close to black. There were no reddish or brick-red marks. The part of the clitellum that was slightly wider becomes narrower. The black color of the earthworm's body was uneven, and there were still brown parts. The line of the earthworm's veins was faint. The line of earthworm vessels was visible only in the brown part, while the black part at the head and bottom ends of the earthworm was not clearly visible.

Based on the drying data in Figure 3, the longer the drying time, the smaller the moisture content. The moisture content decreased significantly from 15 minutes to 120 minutes of drying, and the value equilibrated at 105 to 120 minutes of drying with a moisture content range of 2.5%–10%.

The results of feature selection are shown in Table 1. Feature selection uses WEKA software with several attributes, namely one ratio attribute, correlation attribute, relief F, and gain ratio attribute, with a ranker scoring method. Based on feature selection, image features were sorted starting from the largest weight. ANN modeling was performed based on the ranking of feature selection, as shown in Table 2 so that the mean squared error (MSE) training and validation MSE values were obtained. The lowest validation MSE value, based on the ANN modeling, was achieved for features ranked 1-8 when using the gain ratio attribute, with a training MSE value of 0.0683 and a validation MSE value of 0.087045. Therefore, the color and textural features used as input to the ANN modeling in this study were 8 image features: saturation, value, green, blue, hue, red, correlation, energy, and contrast.

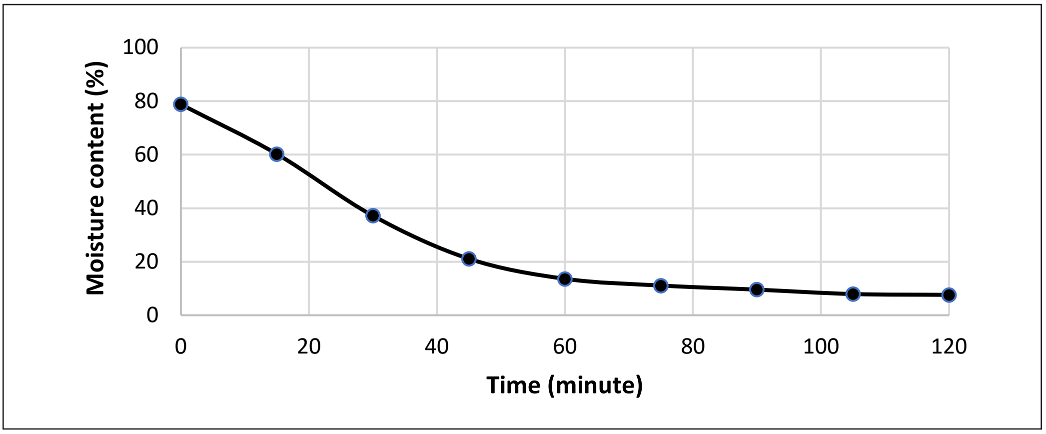

Figure 3. Relationship graph of moisture content to drying time

Table 1
Feature selection using WEKA

No	Attribute Evaluator	Search Method	Feature	Weight	Rank
1	Gain Ratio Attribute Evaluator	Ranker	Saturation	0.996	1
			Value	0.996	2
			Green	0.996	3
			Blue	0.996	4
			hue	0.996	5

Table 1 *(continue)*

No	Attribute Evaluator	Search Method	Feature	Weight	Rank
			Red	0.996	6
			Correlation	0.996	7
			Energy	0.996	8
			Contrast	0.994	9
2	One R Attribute Evaluator	Ranker	Energy	0.667	1
			Hue	0.667	2
			Green	0.667	3
			Blue	0.667	4
			Saturation	0.667	5
			Correlation	0.667	6
			Value	0.667	7
			Contrast	0.667	8
			Red	0.667	9
3	Correlation Attribute Evaluator	Ranker	Contrast	0.00465	1
			Energy	0.00461	2
			Red	0.0046	3
			Correlation	0.0046	4
			Hue	0.0046	5
			Value	0.00459	6
			Blue	0.00459	7
			Green	0.00459	8
			Saturation	0.00459	9
4	Relief F Attribute Evaluator	Ranker	Saturation	0.94	1
			Blue	0.94	2
			Value	0.94	3
			Green	0.94	4
			Correlation	0.94	5
			Hue	0.94	6
			Red	0.94	7
			Energy	0.94	8
			Contrast	0.94	9

Table 2
ANN modeling results with input from feature selection

No	Attribute Evaluator	Search Method	ANN Input	Training MSE	Validation MSE
1	Gain Ratio Attribute Evaluator	Ranker	feature rank 1–2	0.1900	0.20647
			feature rank 1–3	0.1233	0.1718
			feature rank 1–4	0.0700	0.11165
			feature rank 1–5	0.0850	0.13269
			feature rank 1–6	0.0933	0.099578
			feature rank 1–7	0.0733	0.13527

Table 2 *(continue)*

No	Attribute Evaluator	Search Method	ANN Input	Training MSE	Validation MSE
			feature rank 1–8	**0.0683**	**0.087045**
			feature rank 1–9	0.0950	0.14473
2	One R Attribute Evaluator	Ranker	feature rank 1–2	0.3100	0.41313
			feature rank 1–3	0.2000	0.3358
			feature rank 1–4	0.1050	0.13558
			feature rank 1–5	0.0767	0.13222
			feature rank 1–6	0.0950	0.10087
			feature rank 1–7	0.0633	0.11232
			feature rank 1–8	0.1033	0.10517
			feature rank 1–9	0.0783	0.14958
3	Correlation Attribute Evaluator	Ranker	feature rank 1–2	0.3367	0.38067
			feature rank 1–3	0.3150	0.43197
			feature rank 1–4	0.3117	0.37057
			feature rank 1–5	0.2317	0.36141
			feature rank 1–6	0.2600	0.28416
			feature rank 1–7	0.1083	0.14317
			feature rank 1–8	0.0800	0.098798
			feature rank 1–9	0.0700	0.15072
4	Relief F Attribute Evaluator	Ranker	feature rank 1–2	0.1767	0.16878
			feature rank 1–3	0.1500	0.21119
			feature rank 1–4	0.0817	0.10963
			feature rank 1–5	0.0883	0.13556
			feature rank 1–6	0.0883	0.11003
			feature rank 1–7	0.0917	0.13928
			feature rank 1–8	0.0583	0.08956
			feature rank 1–9	0.0950	0.13446

In industrial practice, the three moisture bands are intentionally broad; a worm batch needs only to fall below 12% wb to be safely milled into flour, while 40%–12% represents a still-pliable product used directly as feed. Thus, a precise percentage prediction is unnecessary; rapid band classification suffices to trigger dryer shut-off or progression to the next process stage, saving energy and preserving color. The small overlap observed in single-feature distributions (Figure 4) reflects natural color variability among individual worms but is readily resolved by the multivariate ANN. Based on the results, the standard deviation value in the dry classification was 0.080619, semi-dry 0.112439, and wet 0.074115. The average saturation value in the dry classification was 0.26, semi-dry 0.19, and wet 0.24, indicating that the saturation value in the dry classification was greater when compared to the semi-dry and wet classifications. Value is part of the HSV color that describes the proportion of color brightness levels.

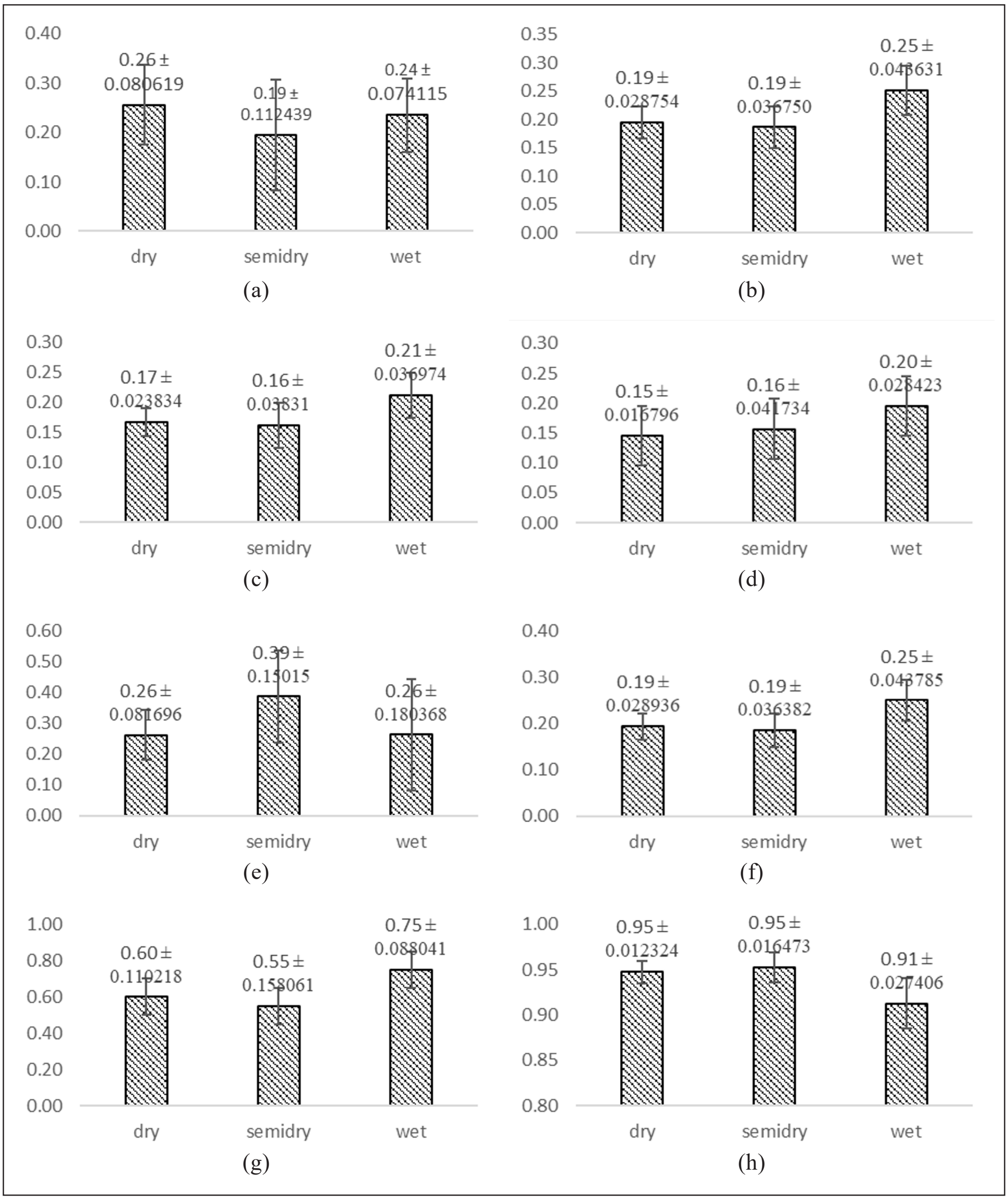

Figure 4. Relationship between moisture content and image features: (a) normalized saturation; (b) normalized value; (c) normalized green; (d) normalized blue; (e) normalized hue; (f) normalized red; (g) normalized correlation; and (h) normalized energy

The standard deviation value in the dry classification was 0.028754, semi-dry 0.036750, and wet 0.043631. The average value in the dry classification was 0.19, semi-dry 0.19, and wet 0.25, indicating that the value in the dry and semi-dry classifications was smaller when compared to the wet classification. Green is part of the RGB color space, which shows the greenness of the object. The standard deviation value in the dry classification was 0.023834, semi-dry 0.03831, and wet 0.036974. The average green value in the dry classification was 0.17, semi-dry 0.16, and wet 0.21, indicating that the green value in the dry and semi-dry classifications was smaller when compared to the wet classification. Blue is part of the RGB color space, which shows the blueness of the object. The standard deviation value in the dry classification was 0.016796, semi-dry 0.041734, and wet 0.028432.

The average value of blue in the dry classification was 0.15, semi-dry 0.16, and wet 0.20, indicating that the blue value in the dry and semi-dry classifications was smaller when compared to the wet classification. Hue is part of HSV, which is defined as the color reflected or transmitted by the object. The standard deviation value in the dry classification was 0.081696, semi-dry 0.15015, and wet 0.180368. The average hue value in the dry classification was 0.26, semi-dry 0.39, and wet 0.26, indicating that the hue value in the dry and semi-dry classifications was close to 1 because in this classification, visually, the color of dry worms was dark brown, close to black. Red is part of the RGB color space, which shows the level of redness of the object.

Based on the research results, the standard deviation value in the dry classification was 0.028936, semi-dry 0.036382, and wet 0.043785. The average red value in the dry classification was 0.19, semi-dry 0.19, and wet 0.25, indicating that the red value in the dry and semi-dry classifications was smaller when compared to the wet classification. Correlation is part of textural analysis to measure how correlated pixels are with other pixels in the whole image. The standard deviation value in the dry classification was 0.110218, semi-dry 0.158061, and wet 0.088041. The average correlation value in the dry classification was 0.60, semi-dry 0.55, and wet 0.75. The energy feature is part of the textural analysis to measure the level of texture uniformity or repetition of pixel pairs. The standard deviation value in the dry classification was 0.012324, semi-dry 0.016473, and wet 0.027406. The average energy value in the dry classification was 0.95, semi-dry 0.95, and wet 0.91. However, from the eight graphs, single individual features cannot be used for classifying dry earthworm moisture content because, based on the standard deviation data, there is still an overlap between one class and another. So, the use of ANN models involving multiple variables is needed for moisture content classification. The use of multiple variables as input to the ANN model can improve classification performance.

Sensitivity analysis in ANN was used to select the right hyperparameter so that the ANN model could be optimized with high accuracy. Table 3 shows the results of trial and error on the learning function. The learning functions used were traincgb, traincgf, traincgp, traind, trainda, traingdm, traingdx, trainlm, trainnoss, trainrp, and trainscg. This study uses variations of hidden layers 30 and 40 at a learning rate parameter of 0.1, momentum of 0.5, maximum epoch of 1000, and error tolerance of 0.01. Based on the results, the lowest validation MSE value was trainlm of 0.087045 with a training MSE value of 0.0683, R training of 0.95023, and R validation of 0.92417. Table 4 shows the activation functions used in this study, i.e., tansig, logsig, and purelin. The lowest validation MSE result was obtained when using the logsig activation function in the hidden layer and purelin in the output layer. MSE validation was 0.087045, MSE training was 0.0683, R validation was 0.92417, and R training was 0.95023.

Table 5 shows the trial and error on ANN structure using a learning rate of 0.1 and momentum of 0.5. Trials and errors were conducted to find the optimal hidden neuron

Table 3
Trial and error on learning function

No	Learning function	R Training	R Validation	MSE Training	MSE Validation
1	Traincgb *(Conjugate Gradient BP with Powell – Beale Restart)*	0.91743	0.90795	0.1017	0.10472
2	Traincgf *(Conjugate BP with Fletcher Reeves Update)*	0.8564	0.83575	0.1950	0.18009
3	Traincgp *(Conjugate Gradient BP with Polak Ribiere Update)*	0.90475	0.8984	0.1233	0.11395
4	Traingd (*Gradient Descent BP*)	0.17559	0.26246	1.2483	1.6844
5	Traingda (*Gradient Descent with Adaptive Learning Rate BP*)	0.70683	0.72575	0.3250	0.28115
6	Traingdm (*Gradient Descent with momentum Adaptive Learning*)	0.88174	0.86137	0.1633	0.15542
7	Traingdx (*Gradient Descent with momentum Adaptive Learning*)	0.74743	0.74934	0.2983	0.26591
8	Trainlm **(***Lavenberg Marquadt BP***)**	**0.95023**	**0.92417**	**0.0683**	**0.087045**
9	Trainoss (*One Step Secant BP*)	0.87884	0.85749	0.1717	0.15822
10	Trainrp (*Resilient BP*)	0.93682	0.91723	0.0817	0.093759
11	Trainscg Scaled (*Conjugate Gradient BP*)	0.84967	0.82758	0.2133	0.18772

Table 4
Trial and error on the activation function

Learning function	Activation function			R Training	R Validation	MSE Training	MSE Validation
	Hidden layer 1	Hidden layer 2	Hidden layer 3				
Trainlm	Tansig	Tansig	Purelin	0.94796	0.91402	0.0667	0.097982
	Tansig	Tansig	Tansig	0.95957	0.91153	0.0683	0.10217
	Tansig	Tansig	Logsig	0.83925	0.78914	0.2933	0.31569
	Logsig	**Logsig**	**Purelin**	**0.95023**	**0.92417**	**0.0683**	**0.087045**
	Logsig	Logsig	Tansig	0.95392	0.9244	0.0750	0.088424
	Logsig	Logsig	Logsig	0.83641	0.8202	0.3017	0.30992

Table 5
Trial and error on ANN structure

ANN Structure	R Training	R Validation	MSE Training	MSE Validation
8-30-1	0.9549	0.92766	0.0733	0.097926
8-40-1	0.94893	0.92355	0.0733	0.091087
8-30-30-1	0.95081	0.91226	0.0833	0.11343
8-30-40-1	0.94522	0.8721	0.0800	0.14774
8-40-40-1	0.95294	0.90299	0.0700	0.12699
8-30-2	0.94985	0.92423	0.0683	0.096321
8-40-2	0.95438	0.90485	0.0767	0.11266
8-30-30-2	0.93096	0.90348	0.1017	0.12542
8-30-40-2	0.95933	0.87961	0.0683	0.1414
8-40-40-2	0.91691	0.91563	0.1117	0.11479
8-30-3	0.9432	0.89883	0.0833	0.11639
8-40-3	**0.95309**	**0.92962**	**0.0733**	**0.086058**
8-30-30-3	0.93983	0.9223	0.0750	0.10842
8-30-40-3	0.95205	0.92244	0.0717	0.099762
8-40-40-3	0.95512	0.9121	0.0617	0.11349

and hidden neuron parameters. The smallest validation MSE value was 0.086058, the training MSE was 0.0733, the training R-value was 0.95309, and the validation R was 0.92962. The gap between training (0.073) and validation (0.086) MSE is modest (≈ 0.013). This difference stems mainly from a slight class imbalance in the validation set, not from over-fitting. The learning performance graph for ANN modeling is shown in Figure 5. Based on the graph, the error value decreases as the epoch value increases. Epoch stops at 19 with a validation MSE of 0.086058. The training correlation coefficient value was 0.95309, and the validation correlation coefficient value was 0.92962, as shown in Figure 6. The best ANN architecture model recommended in this study is one with 8 inputs, 40 nodes in the hidden layer, and 3 outputs (8-40-3), as shown in Figure 7. The input layer consists of 8 features: saturation, value, green, blue, hue, red, correlation, and energy. The 3 outputs were levels of dry earthworm moisture content, namely dry, semi-dry, and wet.

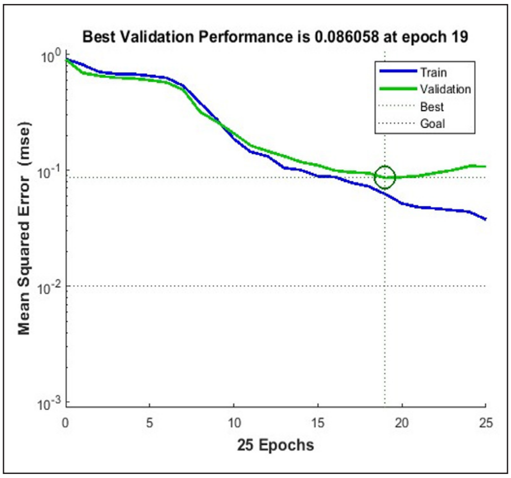

Figure 5. Best training and validation performance of the ANN model

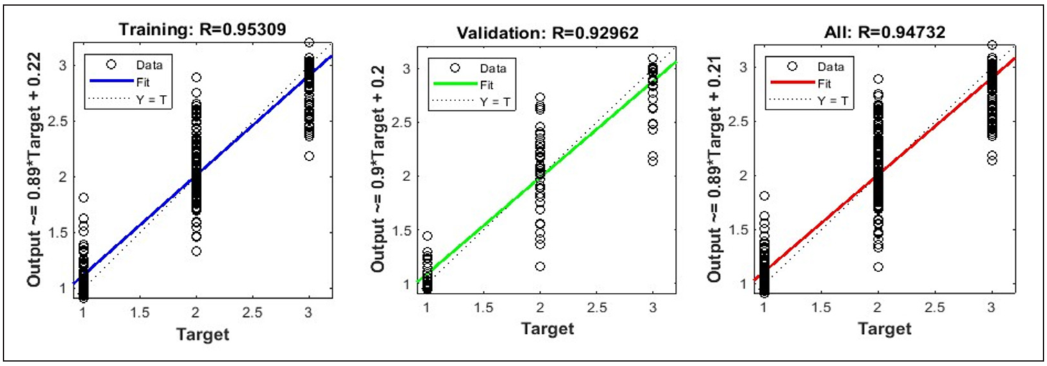

Figure 6. The correlation coefficient between the target and predicted data

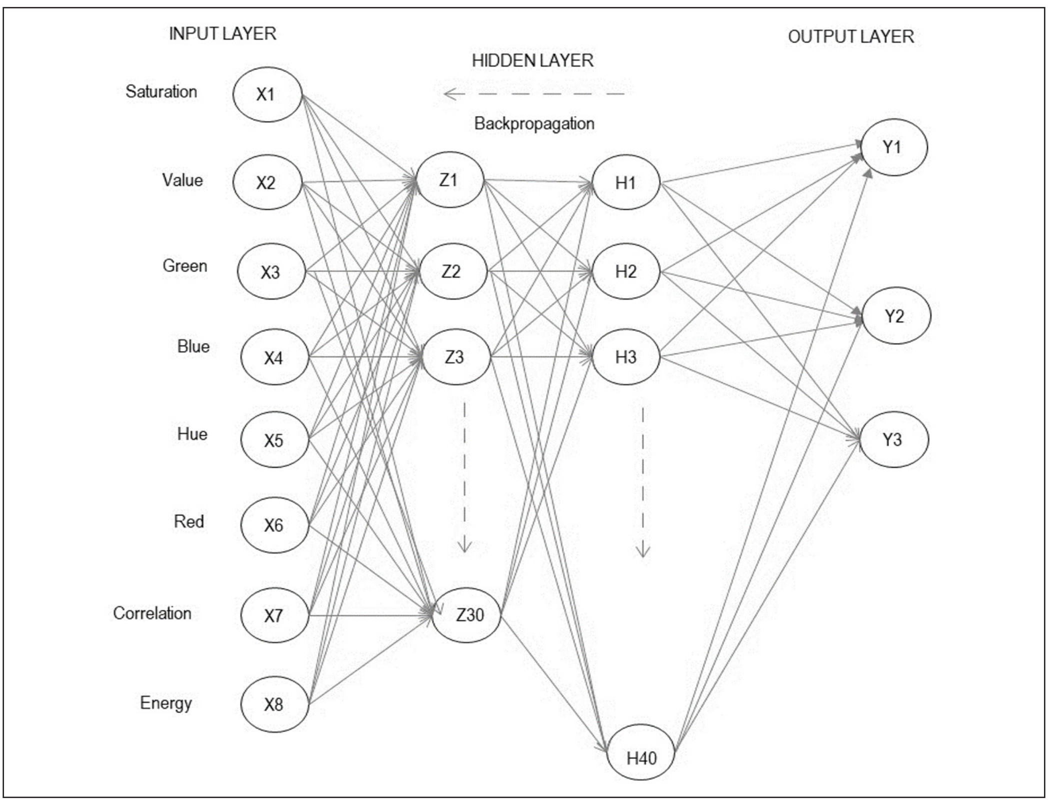

Figure 7. ANN structure for dry earthworm classification

The vision-ANN system can be embedded in line with low-cost cameras and a microcontroller running the 8-40-3 network (≈ 2 kB weight matrix), enabling real-time moisture feedback without destructive sampling. Future studies should extend the approach to other edible insect species and explore hyperspectral imaging to tighten the semi-dry band for premium products.

CONCLUSION

This study demonstrates that a compact machine-vision platform, coupled with supervised learning, can provide rapid, non-destructive moisture control during *Eudrilus eugeniae* drying. After WEKA-based feature ranking, eight color/texture descriptors (S, V, G, B, H, R, correlation, energy) were retained and fed to an 8-40-3 feed-forward ANN, with MSE training of 0.0733 and MSE validation of 0.086058 (R = 0.95309 and 0.92962, respectively). The three moisture bands used (>40%, 40%–12%, <12% wb) match industrial decision points, allowing the classifier to trigger dryer shut-off or downstream processing in real time. This avoids the 3-h gravimetric assay and minimizes energy use and color darkening. Because the final network contains only ~2 kB of weight, it can be embedded in low-cost edge hardware. Future work should extend the model to other edible insect species, explore hyperspectral or NIR imaging to refine the semi-dry band for premium feed products and integrate the vision sensor with closed-loop heater control to create a fully automated, quality-driven drying line.

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