Accredited SINTA 2 Ranking
Decree of the Director General of Higher Education, Research, and Technology, No. 158/E/KPT/2021
Validity period from Volume 5 Number 2 of 2021 to Volume 10 Number 1 of 2026

Published online at: **http://jurnal.iaii.or.id**

JURNAL RESTI
(Rekayasa Sistem dan Teknologi Informasi)
Vol. 8 No. 5 (2024) 674 - 680 e-ISSN: 2580-0760

Prototype of Swiftlet Nest Moisture Content Measurement Using Resistance Sensor and Machine Learning

Ratu Anggriani Tangke Parung[1], Hanna Arini Parhusip[2]*, Suryasatriya Trihandaru[3]
[1,2,3]Master of Data Science, Faculty of Science and Mathematics, Satya Wacana Christian University, Salatiga, Indonesia
[1]632023005@student.uksw.edu
[2*]hanna.parhusip@uksw.edu, [3]suryasatriya@uksw.edu

Abstract

Swiftlet nests are highly valued for their health and cosmetic benefits, with moisture content crucial in determining their quality. Traditional moisture measurement methods are often slow and can potentially damage the samples. This study introduces PRORESKA, an innovative system utilizing resistance sensors and Machine Learning (ML) for non-destructive, and real-time moisture measurement. The system incorporates a voltage divider circuit to establish a correlation between resistance data and moisture content. Three mathematical models (linear, exponential, and modulated exponential) and a neural network were employed to predict moisture content. Validation tests conducted on paper and swiftlet nests indicated that the neural network model, enhanced through transfer learning, achieved superior accuracy. The results demonstrated a strong correlation between predicted and actual moisture content (R^2 = 0.9759), with the neural network model attaining a mean squared error (MSE) of 0.01. This method holds significant potential to improve the efficiency and cost-effectiveness of moisture measurement for swiftlet nests and similar applications.

Keywords: *swiftlet nest; moisture content; IoT; Machine Learning; Neural Network; PRORESKA*

How to Cite: R. A. T. Parung, H. A. Parhusip, and S. Trihandaru, “Prototype of Swiftlet Nest Moisture Content Measurement Using Resistance Sensor and Machine Learning”, *J. RESTI (Rekayasa Sist. Teknol. Inf.)* , vol. 8, no. 5, pp. 674 - 680, Oct. 2024.
DOI: https://doi.org/10.29207/resti.v8i5.5923

1. Introduction

Highly prized for their use in health and cosmetic products, Swiftlet nests have substantial economic value in Indonesia and globally. These nests contain proteins, amino acids, and bioactive compounds that contribute to their health benefits, including anti-aging and antioxidant properties [1]. The quality of swiftlet nests critically depends on their moisture content [2], with optimal levels typically ranging between 13% and 15% [3]. Accurate measurement of moisture content is thus essential for maintaining the quality and economic value of these nests.

Traditional methods for measuring moisture content, such as gravimetry and light refractive index techniques, have been widely used [4]. Gravimetry involves drying the sample and measuring the weight difference, which can be time-consuming and may damage delicate swiftlet nests [5]. Similarly, light refractive index methods, while non-destructive, often need more precision for real-time monitoring [6]. Research by Dafico *et al.* [7] emphasized the limitations of these methods, noting that they are often unsuitable for continuous, on-site measurements, thus revealing a significant gap in the need for more efficient and real-time measurement techniques.

Recent advancements have introduced more efficient approaches to moisture measurement. The utilization of resistance sensors, particularly within Internet of Things (IoT) systems, has emerged as a promising alternative. Resistance sensors measure changes in electrical resistance caused by variations in moisture content, providing a non-destructive and real-time measurement method [8]. Resistance sensors measure changes in electrical resistance in response to moisture content, offering an efficient and durable solution for continuous monitoring [9]. In a review of several studies, Majhi *et al.* [10] showed that resistance sensors are effective in various agricultural applications,

Received: 13-07-2024 | Accepted: 26-10-2024 | Published Online: 28-10-2024

especially for continuous monitoring of moisture content. They highlight the advantages of accuracy and speed over traditional methods. However, translating resistance measurements into accurate moisture content predictions requires sophisticated data analysis techniques.

Machine Learning (ML) and Neural Network (NN) models are powerful tools for improving moisture content prediction by processing complex data patterns [11]. Techniques such as Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) have proven highly effective in various measurement applications, including moisture detection. However, challenges remain in adapting these models to diverse materials and ensuring robustness under different environmental conditions [12]. Recent advancements focus on leveraging ML with IoT sensor data to develop intelligent, real-time monitoring systems.

A 2024 study developed a real-time moisture detection system for agricultural drying processes using multi-sensor fusion and CNN. By integrating data from sensors measuring load, air velocity, temperature, and tray position, the CNN model outperformed traditional models such as Partial Least Squares Regression (PLSR) and Support Vector Machine (SVM), achieving an accuracy of $R^2 = 0.9989$. System validation further confirmed the model's reliability with $R^2 = 0.9901$ demonstrating its effectiveness for online moisture detection [13, 14].

This study aims to address these challenges by developing and evaluating a novel prototype, PRORESKA, which combines resistance sensors with machine learning techniques. PRORESKA is designed to measure moisture content in swiftlet nests and substitute materials, such as paper, with improved accuracy and efficiency. The study focuses on validating the PRORESKA sensor in non-conductive materials, examining the relationship between resistance and voltage through a voltage divider circuit, and employing mathematical functions and neural networks to predict moisture content based on voltage data.

The urgency of this research is underscored by the economic importance of swiftlet nests and the need for efficient measurement methods. By enhancing the accuracy and reducing the cost of moisture measurement, this study has the potential to benefit the industry significantly. Additionally, integrating transfer learning in neural network models aims to improve prediction accuracy for both swiftlet nests and their substitutes, facilitating better industrial applications.

2. Research Methods

This study took an innovative approach as shown in Figure 1, using swiftlet nest samples and substitutes to develop the PRORESKA prototype for moisture content measurement. The initial stage involved determining the optimal resistance and voltage through simulations with substitute materials, which were then applied to swiftlet nests using PRORESKA. Machine learning and simple neural networks were employed with Python for tool development, inspiring new ways of thinking in the field.

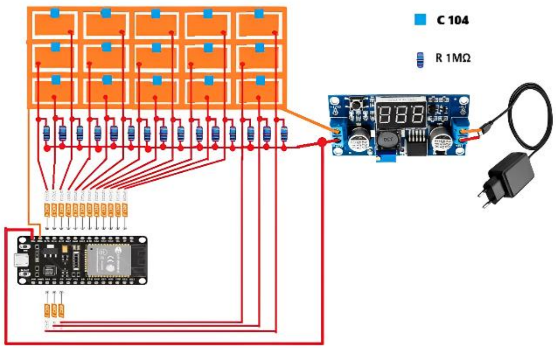

Figure 1. Preliminary Design of PRORESKA

2.1 Measurement of Moisture Content

The moisture content of a material can be defined as Equation 1.

$$h = \frac{w_1 - w_2}{w_2} \tag{1}$$

h is the moisture content, w_1 is the weight of the material in the wet state by water, w_2 is the weight of the material in the dry state, usually the material is heated to evaporate all the water. In definition (1), the wet weight is equal to the dry weight w_2 plus the water weight w_a, so definition (1) becomes:

$$h = \frac{w_a}{w_2} \tag{2}$$

Equation 2 makes it easy to calibrate a resistor-based moisture content sensor by using a dry material and adding a certain weight of water, eliminating the need for a drying process. Another alternative for measuring moisture content is:

$$h = \frac{w_1 - w_2}{w_1} = \frac{w_a}{w_a + w_2} \tag{3}$$

In Equation 1, 100% moisture content is achieved when the weight of water equals the weight of dry matter, while in Equation 3 the value is 100% if the material consists entirely of water. In this research, both equations can be used with h_2 for Equation 1 and h_1 for Equation 3.

2.2 Voltage Divider Circuit Method

An electric voltage V_0 is applied across a series circuit composed of a reference resistor R_1 and the material with resistance R_2. The voltage across the material is given by Equation 4.

$$V_b = V_0 \frac{R_2}{R_1 + R_2} \tag{4}$$

2.3. Mathematical Modeling Equation

The moisture content in the material changes the resistance consistently or monotonically decreases [15]. The following models in Equations 5, 6 and 7 were used:

Linear model: $y = ax + b$ (5)

Exponential model: $y = a\exp(-bx) + c$ (6)

Modulated-exponential model:

$$y = a(1 - exp(bx)) + c \quad (7)$$

y is the moisture content and x is the resistance value.

2.4 Neural Network Regression Model

The relationship between voltage V_b and moisture content is modeled using a neural network in Equation 8.

$$y = \psi(X, W_1, b_1, W_2, b_2, \dots) \quad (8)$$

W_1, b_1, W_2, b_2 are the weight and bias matrices (or parameters) in the neural network, the non-linear form will be obtained by the composition of linear functions with activation functions in multiple neural network layers. Two layers in the neural network are required to achieve complex non-linear representation as in Equation 9.

$$y = W_2 \cdot (f_a(W_1 \cdot X + b_1) + b_2 \quad (9)$$

f_a is the activation function, if a layer is added with an activation function f_b then the neural network model is as shown in Equation 10.

$$y = W_3 \cdot (f_b(W_2 \cdot f_a(W_1 \cdot X + b_1) + b_2) + b_3 \quad (10)$$

In obtaining the optimal parameters, a function of the sum of the squares of the difference between the data and the model is required, which is called a loss-function with Equation 11.

$$L = \frac{1}{2}\Sigma_i(y_i - \psi_i)^2 \quad (11)$$

The optimal parameters are obtained through Equation 12.

$$W_1, b_1, W_2, b_2 = \arg\min \frac{1}{2}\Sigma_i(y_i - \psi_i(W_1, b_1, W_2, b_2,))^2 \quad (12)$$

Optimal parameters with a gradient-descent-based method that performs iterative calculations until converging results are achieved through Equation 13.:

$$\theta_{t+1} = \theta_t - \lambda\frac{\partial L(\theta_t)}{\partial\theta} \quad (13)$$

In Equation 13, θ represents each parameter W_1, b_1, W_2, b_2 dan λ as the learning rate [16].

3. Results and Discussions

3.1 Moisture Content Measurement Using PRORESKA

In this study, the method of measuring moisture content using electric current was applied to materials that do not conduct electricity, such as paper and swiftlet's nest. The assumption is that electric current is consistently related to the moisture content of a material. However, for materials that conduct electricity when dry, such as sand and iron, this method is not effective due to their changing conductivity. In non-conductive materials, the electric current is transported by ions in the water contained within.

Therefore, moisture sensors for each material need to be specially designed and calibrated according to the characteristics of the material, such as soil moisture sensors and wood moisture sensors. PRORESKA is specifically designed to measure the moisture content of a swiftlet's nest and its substitutes, such as paper. It uses an ESP32 microcontroller equipped with 15 sensors integrated on one board and resistors selected based on simulation analysis results to optimize moisture content measurement. The calculation method used has been adapted to the characteristics of water content measurement to ensure measurement accuracy and reliability.

3.2 Voltage Divider Circuit

The relationship between the value of resistor R_2 and the voltage V_b is generated by varying resistor R_1. The ESP32 microcontroller adjusted the initial voltage V_0 value to 3.3V. Resistor R_1 is set at 0.5, 1, 1.5, 2 and resistor R_2 is varied from 0 to 5, with a total of 50 simulation data points.

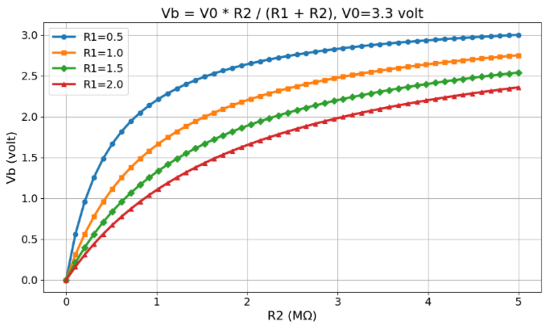

Figure 2. Graph of The Effect of R_1 Selection on V_b Voltage

The graph in Figure 2 shows that the higher the value of resistor R_1, the voltage V_b tends to decrease in the same range of resistor R_2 values. Then, simulations were conducted to determine the relationship between resistor R_2 and voltage V_b by setting two different initial voltages, namely 3.3V and 5V. Resistor R_1 remains constant at 1 MΩ, while resistor R_2 is varied from 0 to 5 MΩ with 50 data points.

The results in Figure 3 show graphs of the relationship of voltage V_b with resistor R_2 for two different initial voltage values (V_0), namely 3.3V and 5V, with resistor R_1 fixed at 1 MΩ. The resulting curves show that as the value of resistor R_2 increases, the voltage V_b tends to increase proportionally for both values of V_0. The curve with V_0 = 5V shows a more significant voltage increase compared to V_0 = 3.3V over the same range of R_2 resistor values.

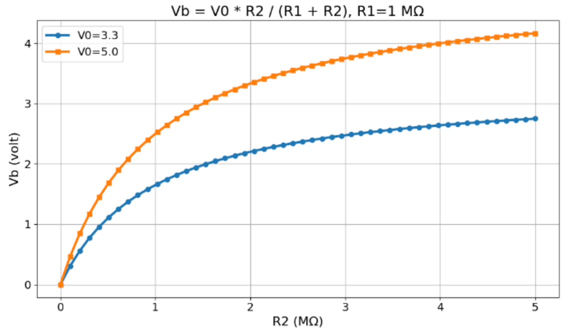

Figure 3. Graph of the Effect of Initial Voltage (V_0) on Output Voltage (V_b) at Fixed Resistor (R_1)

The variation of the voltage curve V_b is highly dependent on the values of V_0 and R_1. The resistance R_2 as an experimental variable, is chosen according to the characteristics of the material being tested, such as paper which has an R_2 value between 0.3 to 5 MΩ. The selection of V_0 is important in ensuring that the voltage V_b does not exceed the maximum limit of the ESP32 microcontroller, which is typically 3.3 volts at the maximum value of R_2.

The value of R_1 is chosen to ensure the voltage curve V_b remains gentle. For example, R_1 = 0.5 MΩ produces a sharp voltage rise at low R_2, while R_1 = 2 MΩ produces a gentler curve without reaching 3.3 volts. The combination of R_1 = 2 MΩ and V_0 = 5 volts, as shown in (Figure 3), produces a curve with a gentle decline and a maximum voltage of approximately 3.5 volts.

In the initial research phase, measurements with PRORESKA were taken to determine the resistance domain (R_2) of the swiftlet's nest substitute material, paper. Based on the previous discussion, a resistor range of 0.5 - 2.0 MΩ produces a gentle curve without exceeding a voltage of 3.3 volts. Therefore, for measurements on paper, a 1 MΩ resistor was used with a focus on one of the sensors, ADCSEN9.

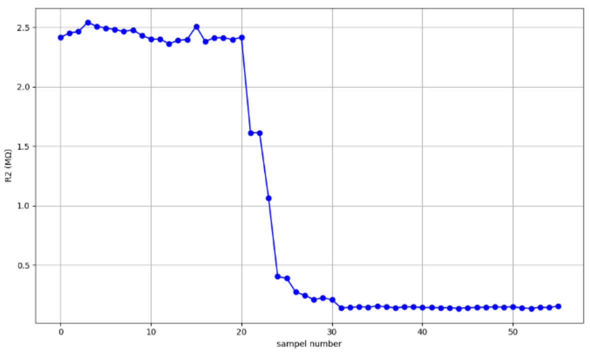

Figure 4. Resistance Value (R_2) of Paper on ADCSEN9 PRORESKA

The graph in (Figure 4) shows that the resistance domain (R_2) on water-soaked paper and dry paper is 0.13 - 2.54 MΩ.

3.3 Modeling Using Three Mathematical Functions.

The relationship between moisture content and resistance R_2 was explored using three distinct mathematical models: a standard exponential function, a linear function, and a more complex one with additional modulation. Each model aims to capture how moisture content varies with resistance, which is crucial for accurate predictions in various applications such as agriculture, material science, and environmental monitoring.

To investigate these models, resistance data were used as input to generate corresponding moisture content values. The output from each model was then plotted, allowing for a visual comparison of how well each function represents the moisture-resistance relationship. The exponential function typically effectively captures non-linear trends, while the linear model provides a simpler, though less precise, approximation. The exponential model with additional modulation is designed to account for more nuanced variations in the data, potentially offering the best fit.

The plots were carefully crafted with detailed labels, distinct markers for each data point, and grids to aid visual analysis. These elements enhance the readability of the graphs and make it easier to discern the differences between the models. By examining these plots, it becomes evident that the relationship between moisture content and resistance is inherently non-linear, as the linear model needs to account for the complexities observed in the data as shown in Figures 5 and 6.

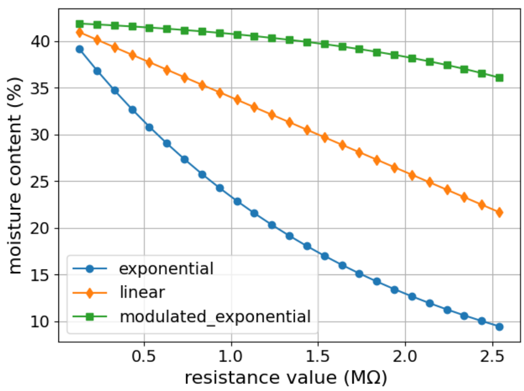

Figure 5. Prediction Graph of Moisture Content Based on Resistance R_2 Using Three Mathematical Models.

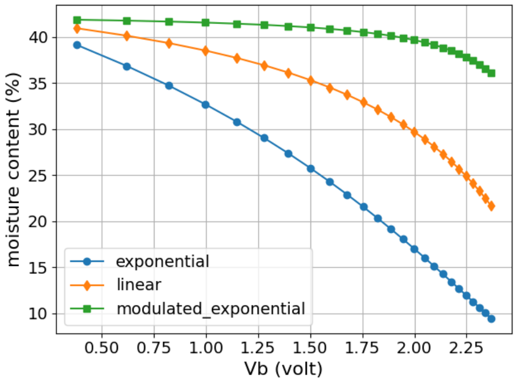

Figure 6. Graph of the Relationship Between Voltage (V_b) and Predicted Moisture Content Using Three Mathematical Models.

3.4 Modeling Using Simple Neural Networks

This study uses a simple Neural Network model to predict moisture content based on voltage data. Three Neural Network models with the same architecture were applied in predicting three different types of data: exponential, linear, and modulated exponential. The data in this study was normalized to facilitate model training. Voltage was divided by a constant k = 5 and moisture content was divided by a constant g = 100. Normalization is done in equalizing the scale of the data, so that the model training is more stable and converges quickly.

Three neural network models with the same architecture were created using Keras. Each model consists of three layers: an input layer with 32 neurons and ReLU activation, a hidden layer with 16 neurons and ReLU activation, and an output layer with one neuron for moisture content prediction. The three models were then trained using normalized data for 300 epochs with Adam's optimizer and the loss function mean squared error (MSE) [13, 14].

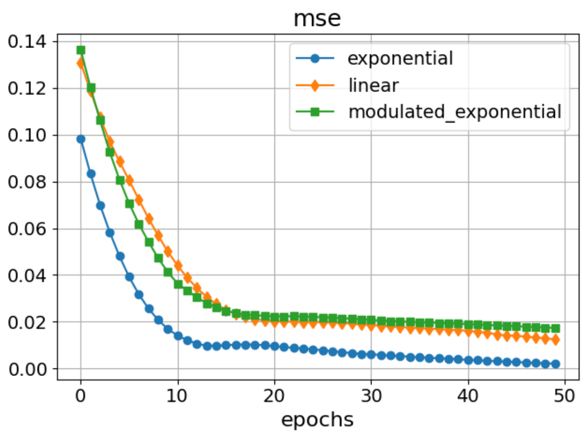

Figure 8. MSE Graph for Evaluating the Performance of Three Mathematical Models

An evaluation of model performance follows the training process by comparing the MSE value of each model for the first 50 epochs. The MSE graph in Figure 8 shows a decrease in error as the number of epochs increases [19]. The graph shows whether or not the model adapts and learns from the given data.

The chart shows the performance of three different learning rate schedules: exponential, linear, and modulated exponential. The exponential learning rate scheduler results in an MSE of ~0.01, while the linear and modulated exponential learning rate schedulers result in MSEs of ~0.02. This shows that the exponential learning rate scheduler is the best performer in this situation, likely because it decays at a faster rate early in training, allowing the model to find the optimal parameter values more quickly.

The prediction results are compared with the normalized original data and visualized as a scatter graph after training. Based on the graph shown in (Figure 9), how accurately the model prediction compares exponential, linear, and modulated exponential data can be evaluated.

A transfer learning approach can be used to reduce the expensive costs of measuring moisture content in Swiftlet's nest samples and to develop models for substitute materials such as paper [20].

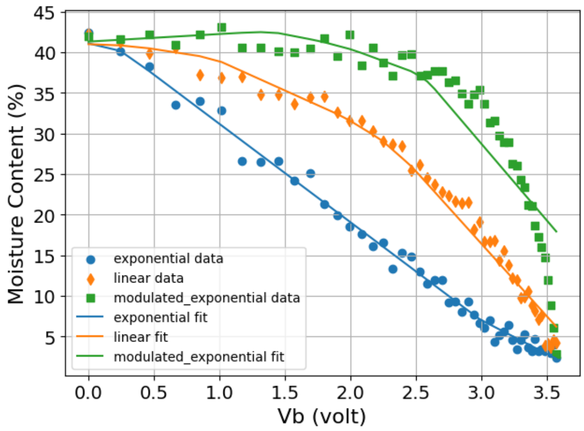

Figure 9. Graph of Noise Addition on Water Content Prediction Based on R2 Resistance Using Three Mathematical Models

The neural network model uses transfer learning to predict the moisture content of the swiftlet with data from the wet and dry weighing process and input from the sensor voltage from PRORESKA. The NN architecture of Model1, which was pre-trained for the swiftlet surrogate material paper, was adapted for the swiftlet model by performing similar duplication on the weights and optimized using Adam's optimizer and the loss function MSE. The previous layers of the swiftlet model were not changed during optimization, focusing on adjusting the final parameters specific to the swiftlet's moisture content characteristics and retaining knowledge from the previous model as shown in Figure 10.

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_11 (Dense)            (None, 32)                64

 dense_12 (Dense)            (None, 16)                528

 dense_13 (Dense)            (None, 1)                 17

=================================================================
Total params: 609
Trainable params: 17
Non-trainable params: 592
_________________________________________________________________
```

Figure 10. Neural Network Model Architecture for Predicting Swiftlet's Nest Moisture Content.

The training process is performed by dividing the normalized PRORESKA sensor voltage data by a constant k and the swiftlet moisture content data by a constant g for 1000 epochs. After training, the prediction results of the swiftlet model of voltage are visualized along with the original data and the prediction of the previous model.

The graph in Figure 11 compares empirically observed moisture content data with predictions from both models, providing a direct evaluation of the accuracy of the models in generalizing the moisture content characteristics of swiftlet nests.

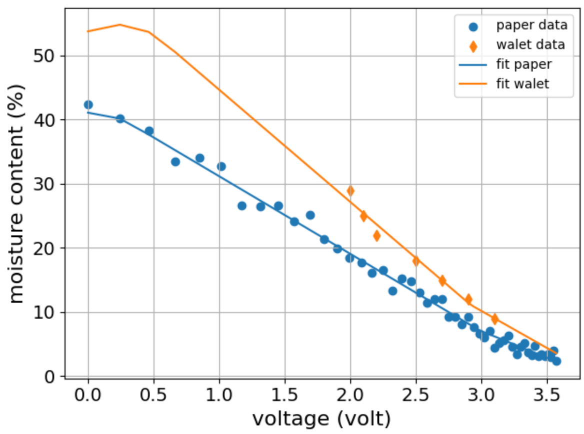

Figure 11. Prediction Graph of Swiftlet Water Content Using PRORESKA Sensor Voltage Using Transfer Learning.

In this study, the developed neural network model demonstrated excellent performance in predicting moisture content based on resistance measurements, as indicated by an R^2 value of 0.9759 obtained during the validation phase. This R^2 value, close to 1, suggests that the model successfully explained 97.59% of the variability in the validation data, indicating a robust correlation between the model's predictions and the actual values. These results highlight the model's high capability in capturing the complex relationship between resistance and moisture content, serving as a critical indicator of the accuracy and effectiveness of this predictive system in real-world applications. This success underscores the model's potential for precise moisture measurement, which is crucial for applications such as those required by the PRORESKA system.

4. Conclusions

Using a moisture content measurement method utilizing the PRORESKA sensor voltage effectively measures moisture content in non-conductive materials such as paper and swiftlet's nest. This research shows that PRORESKA, using an ESP32 microcontroller and integrated sensors, can provide accurate and reliable measurement results. In addition, the modeling approach using three mathematical functions and transfer learning to predict moisture content shows potential for reducing expensive measurement costs and increasing efficiency in model development for swiftlet's nest replacement materials.

Acknowledgements

The author expresses gratitude for supporting the research grant from the Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia through the PTM grant No : 001/LL6/PB/AL.04/2024, 047/SPK-PTM/RIK/6/2024. This support has played a crucial role in facilitating this research without any conflicts of interest with the institution involved.

References

[1] H. M. Kim, Y. M. Lee, E. H. Kim, S. W. Eun, H. K. Sung, H. Ko, S. J. Youn, Y. Choi, W. Yamada, and S. M. Shin., "Anti-Wrinkle Efficacy of Edible Bird's Nest Extract: A Randomized, Double-Blind, Placebo-Controlled, Comparative Study," *Front. Pharmacol.*, vol. 13, no. March, hal. 1–10, 2022, doi: 10.3389/fphar.2022.843469..

[2] A. Septiarini, F. Maulana, H. Hamdani, R. Saputra, T. Wahyuningrum, and Indra, "Classifying the Swallow Nest Quality Using Support Vector Machine Based on Computer Vision," *Proc. - 2022 IEEE Int. Conf. Cybern. Comput. Intell. Cybern. 2022*, pp. 474–478, 2022, doi: 10.1109/CyberneticsCom55287.2022.9865498.

[3] L. Castillo, N. Ramírez, E. Baltodano, R. Vargas, and G. Hanley, "Design of Experiments Assessment for the Determination of Moisture Content in Five Herbal Raw Materials Contained in Tea Products," *Borneo J. Pharm.*, vol. 3, no. 1, pp. 22–35, 2020, doi: DOI: https://doi.org/10.33084/bjop.v3i1.1236.

[4] T. F. Prasetyo, A. F. Isdiana, and H. Sujadi, "Measure Device of Water Content On Food Materials Based On Internet of Things," *Int. J. Inf. Syst. Technol. Akreditasi*, vol. 3, no. 36, pp. 234–245, 2020.

[5] M. W. Rasheed, J. Tang, A. Sarwar, S. Shah, N. Saddique, M. U. Khan, M. I. Khan, S. Nawasz, R. R. Shamshiri, M. Aziz, and M. Sultan., "Soil Moisture Measuring Techniques and Factors Affecting the Moisture Dynamics : A Comprehensive Review," *Sustainability*, vol. 14, no. 11538, 2022, doi: https://doi.org/10.3390/su141811538.

[6] A. Daud, S. Suriati, and N. Nuzulyanti, "Kajian Penerapan Faktor yang Mempengaruhi Akurasi Penentuan Kadar Air Metode Thermogravimetri," *Lutjanus*, vol. 24, no. 2, pp. 11–16, 2020, doi: 10.51978/jlpp.v24i2.79.

[7] L. C. M. Dafico, E. Barreira, R. M. S. F. Almeida, and H. Carasek, "Comparison of Infrared Thermography and Other Traditional Techniques to Assess Moisture Content of Wall Specimens," *Sensors*, vol. 22, no. 9, 2022, doi: 10.3390/s22093182.

[8] B. M. Olivo and A. Pan, "Internet of Things: State-of-the-art, Computing Paradigms and Reference Architectures," *IEEE Lat. Am. Trans.*, vol. 20, no. 1, pp. 49–63, 2022, doi: 10.1109/TLA.2022.9662173.

[9] M. Hussain, S. Hasnain, N. A. Khan, S. Bano, F. Zuhra, M. Ali, M. Khan, N. Abbas, and A. Ali., "Design And Fabrication Of A Fast Response Resistive-Type Humidity Sensor Using Polypyrrole (Ppy) Polymer Thin Film Structures," *Polymers (Basel).*, vol. 13, no. 18, hal. 1–17, 2021, doi: 10.3390/polym13183019.

[10] S. M. Majhi, A. Mirzaei, H. W. Kim, S. S. Kim, and T. W. Kim, "Recent Advances in Energy-Saving Chemiresistive Gas Sensors: A review," *Nano Energy*, vol. 79, no. July 2020, p. 105369, 2021, doi: 10.1016/j.nanoen.2020.105369.

[11] D. Kim, T. Kim, J. Jeon, and Y. Son, "Convolutional Neural Network-Based Soil Water Content and Density Prediction Model for Agricultural Land Using Soil Surface Images," *Appl. Sci.*, vol. 13, no. 5, 2023, doi: 10.3390/app13052936.

[12] Y. Ren, C. Huang, Y. Jiang, and Z. Wu, "Neural Network Prediction Model for Sinter Mixture Water Content Based on KPCA-GA Optimization," *Metals (Basel).*, vol. 12, no. 8, pp. 1–14, 2022, doi: 10.3390/met12081287.

[13] M. Darwis, H. A. Al Banna, S. R. Aji, D. Khoirunnisa, and N. Natassa, "IoT Based Early Flood Detection System with Arduino and Ultrasonic Sensors in Flood-Prone Areas," *J. Tek. Inform.*, vol. 16, no. 2, pp. 133–140, 2023, doi: 10.15408/jti.v16i2.32161.

[14] T. Yang, X. Zheng, H. Xiao, C. Shan, and J. Zhang, "Moisture content online detection system based on multi-sensor fusion and convolutional neural network," *Front. Plant Sci.*, vol. 15, no. March, pp. 1–12, 2024, doi: 10.3389/fpls.2024.1289783.

[15] J. Zhang, A. Heath, H. M. T. Abdalgadir, R. J. Ball, and K. Paine, "Electrical Impedance Behaviour of cCarbon Fibre Reinforced Cement-based Sensors at Different Moisture Contents," *Constr. Build. Mater.*, vol. 353, no. September, p. 129049, 2022, doi: 10.1016/j.conbuildmat.2022.129049.

[16] A. Mollalo, K. M. Rivera, and B. Vahedi, "Artificial neural network modeling of novel coronavirus (COVID-19) incidence rates across the continental United States," *Int. J. Environ. Res. Public Health*, vol. 17, no. 12, pp. 1–13, 2020, doi: 10.3390/ijerph17124204.

[17] B. Asadi and Q. Memon, "Efficient Breast Cancer Detection Via Cascade Deep Learning Network," *Int. J. Intell. Networks*, vol. 4, no. January, pp. 46–52, 2023, doi: 10.1016/j.ijin.2023.02.001.

[18] M. Ahmed, N. Afreen, M. Ahmed, M. Sameer, and J. Ahamed, "An Inception V3 Approach For Malware Classification Using Machine Learning And Transfer Learning," *Int. J. Intell. Networks*, vol. 4, no. November 2022, pp. 11–18, 2023, doi: 10.1016/j.ijin.2022.11.005.

[19] A. Lazcano, P. J. Herrera, and M. Monge, "A Combined Model Based on Recurrent Neural Networks and Graph Convolutional Networks for Financial Time Series Forecasting," *Mathematics*, vol. 11, no. 1, 2023, doi: 10.3390/math11010224.

[20] M. Luo, "Multi-Sensor Based Strategy Learning With Deep Reinforcement Learning For Unmanned Ground Vehicle," *Int. J. Intell. Networks*, vol. 4, no. October, pp. 325–336, 2023, doi: 10.1016/j.ijin.2023.11.003.