Research Article

Implementation of Polynomial Regression on Coconut Charcoal Making System Integrated with IoT and Cloud in Real Time

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Abstract: Polynomial regression is an analytical method often used to model non-linear relationships between independent and dependent variables. This method is effective in various fields of application, such as prediction, estimation, and analysis. In this study, polynomial regression was applied to facilitate the coconut charcoal manufacturing process to predict the duration of drying time based on the measured temperature. Polynomial regression is implemented with Internet of Things (IoT) technology, where temperature data obtained from sensors is sent in real-time to a mobile application. This application provides convenience for users in monitoring and managing the coconut charcoal drying process, thereby enhancing the efficiency and quality of the final product. This integration shows excellent potential in optimizing the production process using data-driven innovative technology.

Keywords: Polynomial regression; Internet of Things; mobile application; coconut charcoal; innovative technology

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1. Introduction

Indonesia is one of the largest coconut-producing countries in the world, along with other countries such as the Philippines, India, and Malaysia, as well as several countries in Africa, South America, and the Pacific islands. World coconut production reaches nearly ten million hectares in 92 countries, with 75% of the production coming from Asian countries [1]. Despite its immense potential, inadequate coconut utilization can cause coconut waste to threaten the environment.

Currently, the utilization of coconuts is still focused on processing the pulp, such as producing coconut oil and Virgin Coconut Oil (VCO) [2]. However, there are other parts of the coconut that also have economic value and the potential to be processed into value-added products, such as the shell or husk. The coconut shell is the part that separates the coconut fruit from its fibers. Typically, the shell is discarded by consumers, leading to environmental pollution [3]. However, the coconut shell can be utilized to make charcoal briquettes.

Charcoal briquettes are an example of biomass. Charcoal briquettes are an example of biomass. Biomass is material derived from plants that can be used as fuel directly or indirectly [4]. Therefore, biomass is a renewable source and environmentally friendly energy source. As global energy demand continues to increase, efforts to reduce carbon emissions are necessary, making the use of biomass as a renewable energy source highly relevant. Scientists have proposed that to avoid catastrophic consequences of climate change, global emissions need to be reduced by 7.6% per year until 2030 [1]. This is reinforced by the fact that most of the energy sources used in Indonesia currently come from non-renewable sources, such as fossil fuels. This situation could trigger high subsidies that the government must provide if global oil prices rise sharply, as they are now approaching $100 per barrel [5]. This further underscores the importance of exploring cleaner and more sustainable energy sources.

This study implemented a polynomial regression method to facilitate the coconut charcoal manufacturing process. This method is used to predict the duration of carbonization time based on the measured temperature. Polynomial regression models the relationship between an independent and dependent variable when the relationship is non-linear. It allows for more flexible modeling compared to simple linear regression, as it can adjust for more complex changes in the data [6].

The implementation of polynomial regression in this study is integrated with Internet of Things (IoT) technology. Utilizing IoT on temperature sensor devices connected to the network will facilitate real-time temperature monitoring [7]. These temperature sensors are installed on the coconut charcoal heating equipment to collect temperature and time data. This data is then analyzed using the polynomial regression model to predict the optimal carbonization duration. This prediction assists users in performing the carbonization process and avoids over or under-carbonization, which can affect the quality of the produced charcoal briquettes.

Subsequently, the temperature data and carbonization time predictions are sent in real-time to a mobile application. This application is designed to make it easier for users to monitor and manage the coconut briquette drying process remotely [8]. The application allows users to view temperature data and carbonization time predictions. This integration demonstrates how technology can assist in agricultural production and waste processing, providing more efficient and environmentally friendly solutions.

With this innovation, the economic value of coconut waste will increase as the briquettes themselves have a market value [9]. This innovation also supports efforts to reduce carbon emissions and utilize renewable energy sources. The application of technology in the production process shows potential in optimizing available natural resources and contributing positively to the environment and energy sustainability in the future. This study provides an example of how a multidisciplinary approach combining agriculture and technology can yield sustainable solutions.

2. Theory

2.1 Coconut Briquettes

Coconut charcoal briquettes present an innovative solution for effectively utilizing coconut shell waste. With significant potential as an environmentally friendly alternative fuel, these briquettes not only help reduce waste but also transform discarded coconut shells into a valuable energy source. By converting waste into high-value products, coconut charcoal briquettes contribute to sustainable practices and offer a renewable energy option that supports both environmental conservation and economic growth [10].

The goal of coconut charcoal briquette production is to provide a renewable energy source while empowering local communities through economic growth generated by the production and sale of briquettes. The benefits of coconut charcoal briquettes are diverse, encompassing environmental, financial, and social perspectives. Environmentally, using coconut charcoal briquettes helps reduce carbon emissions and air pollution due to their cleaner combustion process compared to coal [11]. From an economic perspective, producing coconut charcoal briquettes can provide an additional source of income for local communities, particularly for coconut farmers who can utilize their shell waste [12]. In addition, coconut charcoal briquettes have a high calorific value and a long burning duration, making them an efficient and cost-effective fuel [13].

Given their significant potential, coconut charcoal briquettes offer a dual benefit: they address the issue of coconut shell waste while also providing a sustainable alternative fuel that is both environmentally friendly and economically advantageous for the community. By converting waste materials into valuable energy resources, these briquettes contribute to waste reduction and promote the use of renewable energy sources. Additionally, the production and use of coconut charcoal briquettes can stimulate local economies by creating new opportunities for income generation, particularly in regions where coconut shells are abundant. This not only fosters environmental sustainability but also supports community development and economic resilience.

2.2 Hardware Design System

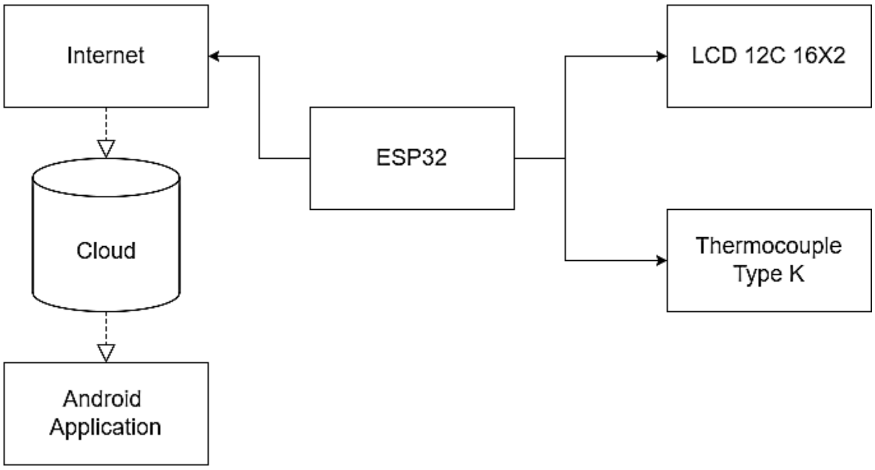

Figure 1. Hardware Design System

Figure 1 explains the workflow of this research system. The tool used in this research is a temperature measurement system designed to monitor the coconut charcoal-making process. This system consists of several main components: the ESP32 microcontroller, a K-type thermocouple with a MAX6675 module, and a 16x2 LCD. The K-type thermocouple measures the temperature during the coconut shell carbonization process. The MAX6675 module then converts the temperature data from the thermocouple into a digital signal that the ESP32 microcontroller can read [14]. ESP32 is a microcontroller that will receive temperature data and process it to be displayed on the 16x2 I2C LCD screen. The I2C LCDs the temperature in real-time, allowing users to monitor and ensure that the temperature remains within the optimal range during the coconut charcoal-making process.

In addition to displaying temperature data, the ESP32 can send data to the cloud via Wi-Fi, allowing remote monitoring and data storage in the Firebase cloud [15]. Implementing the tool in the coconut charcoal manufacturing process can help maintain the quality of the final product as it reduces the risk of errors due to inappropriate temperatures during the carbonization process. With this tool, the coconut charcoal manufacturing process becomes more efficient and controlled and produces high-quality products that can increase economic value and environmental sustainability.

2.3 ESP32

ESP32 is the main component of this research, serving as the chip that connects all the sensors used in the system. This microcontroller is programmed with code stored in the memory available on the ESP32, allowing the microcontroller to perform all the necessary operations. In addition, the ESP32 has an operating voltage range between 2.2 and 3.6V, and under normal operating conditions, this chip will operate at a voltage of 3.3V [16]. This ESP32 microcontroller collects and processes data from various connected sensors, such as a K-type thermocouple with an MAX6675 module for temperature measurement. The temperature data obtained from the thermocouple is converted into a digital signal by the MAX6675 module before being sent to the ESP32 for further processing [17]. The temperature measurement results are then displayed in real-time on the 16x2 I2C LCD screen.

ESP32 can send data to the cloud via Wi-Fi, enabling remote monitoring and data storage in cloud databases such as Firebase [18]. This is particularly beneficial in implementing coconut charcoal making, where precise temperature monitoring is crucial to ensure the carbonization process runs optimally and produces high-quality products. Thus, this tool improves efficiency and control in the coconut charcoal manufacturing process and contributes to increased economic value and environmental sustainability through advanced and affordable technology.

2.4 Type K Thermocouple

Type K thermocouple sensors measure temperature over a fairly wide range. These sensors have excellent sensitivity and have been used in various industrial environments due to their reliability under extreme conditions and wide temperature variations [19]. In this system, the type K thermocouple sensor is connected to the MAX6675 module, capable of measuring temperatures from 0℃ to +1024°C [20]. The MAX6675 module is a processor of the temperature signal read by the thermocouple, converting the analog signal into a digital signal through an ADC (Analog to Digital Converter) converter built into the module [21].

2.5 Software Design

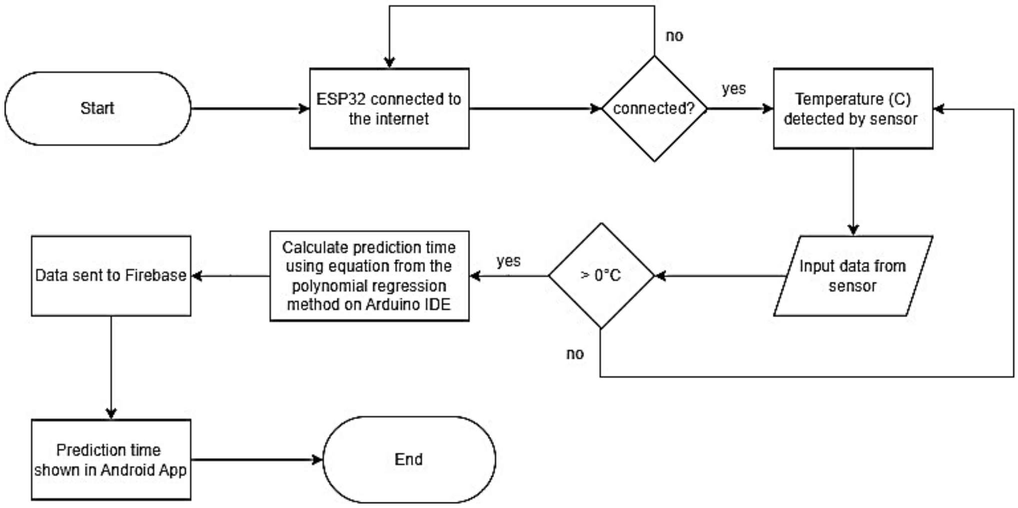

Figure 2. Flowchart Software Design System

Figure 2 illustrates the system workflow in this study. The process starts with connecting the ESP32 to the internet. If the internet connection is successful, the sensor detects the temperature (C) and inputs the temperature data into the system. If not connected, the system will continue to try to connect the ESP32 to the internet. After the temperature data is detected, the system verifies whether the detected temperature is more significant than 0°C. If the temperature exceeds 0°C, the system will calculate the prediction time using the equation from the polynomial regression method implemented in the Arduino IDE. The predicted data was sent to Firebase for storage. The data is then displayed to the Android application, which allows users to view the prediction time in real-time. This process ends after the prediction time is shown in the Android application.

2.6 Polynomial Regression

Polynomial regression is a linear regression in which the relationship between the independent variable (x) and the dependent variable (y) is modeled as an nth-degree polynomial [22]. Polynomial regression is suitable for describing nonlinear relationships between x values and the corresponding conditional mean y. The general formula for polynomial regression is as follows equation 1.

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots .. + \beta_n x^n \quad (1)$$

Where y is a dependent variable, x is an independent variable, *β_0,β_1,β_2,… β_n* is the regression coefficient, and n is the polynomial degree.

In polynomial regression, two primary metrics are used to evaluate the model: Mean Squared Error (MSE) and R-squared value (R2). The following is an explanation of each of these metrics:

2.7 Mean Squared Error (MSE)

(MSE) is the mean square of the error between the value predicted by the model and the actual value of the data. MSE gives an idea of how far the model's predicted value is from the actual value in terms of the square of the error [23]. The smaller the MSE value, the better the model predicts the data. The MSE formula is as follows equation 2. where n is the total of sample data, y_i are actual values from data-i, $\hat{y}_i$ is prediction values from data-i.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (2)$$

2.8 R-Squared (R2)

R-squared (R2) or the coefficient of determination, measures the proportion of variability in the data that can be explained by the regression model [24]. R2 takes values between 0 and 1. Models with higher R2 are considered better at explaining the relationship between the dependent variables. Where y_i are actual values from data-i, $\hat{y}_i$ is prediction values from data-i, and $\bar{y}_i$ is the average of actual values from all data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (3)$$

3. Method

A dataset consisting of 5057 temperature and time data points was used to determine the most appropriate polynomial regression degree for each temperature, based on the smallest difference between the average actual time and the predicted time. The first step involved calculating the average time for each temperature in the dataset. This average time served as the reference value for comparing the prediction results of various polynomial regression degrees. Next, polynomial regression models were analyzed from degree 2 to degree 10 for each temperature. Each degree produced different time predictions. Subsequently, the difference between the average actual time and the predicted time for each temperature, as generated by each polynomial model, was calculated. In this way, the polynomial degree with the smallest difference for each temperature can be determined. This degree is considered the most appropriate because its predictions are closest to the average actual time. The results of this analysis are presented in Table 1.

Table 1. Polynomial Degree Data

No	T	Amm. of Data	$\bar{t}$	Deg. 2	Deg. 3	Deg.4	Deg. 5	Deg.6	Deg. 7	Deg. 8	Deg. 9	Deg.10	Best Deg.
1	120,75	78	3,38	0,92	-2,85	0,80	4,12	4,99	4,80	4,42	4,01	3,68	10
2	120,50	50	3,50	1,88	-1,68	1,63	4,49	5,16	5,02	4,77	4,53	4,38	10
3	120,25	42	4,63	2,84	-0,52	2,47	4,88	5,37	5,27	5,14	5,06	5,06	5
4	120,00	26	5,56	3,79	0,63	3,31	5,30	5,63	5,57	5,54	5,59	5,72	7
…	…	…	…	…	…	…	…	…	…	…	…	…	…
307	27, 75	1	88,64	62,94	84,17	2,85	79,23	87,17	84,14	83,01	83,35	84,44	6

Through this approach, the most suitable polynomial degree for each temperature in the dataset was successfully identified. The chosen degree provided the most accurate time predictions, allowing for the optimal polynomial regression model.

In the data analysis process to determine the most appropriate polynomial degree for time prediction based on temperature data, several other factors were used as evaluation criteria. These factors include Mean Squared Error (MSE), R-squared (R^2), accuracy, and prediction visualization. Each factor provides information about the performance of polynomial regression models from degrees 2 to 10 and offers a clear depiction of the prediction curves for each degree. Below are the comparison results of MSE, R-squared, accuracy, and data visualization from degrees 2 to 10.

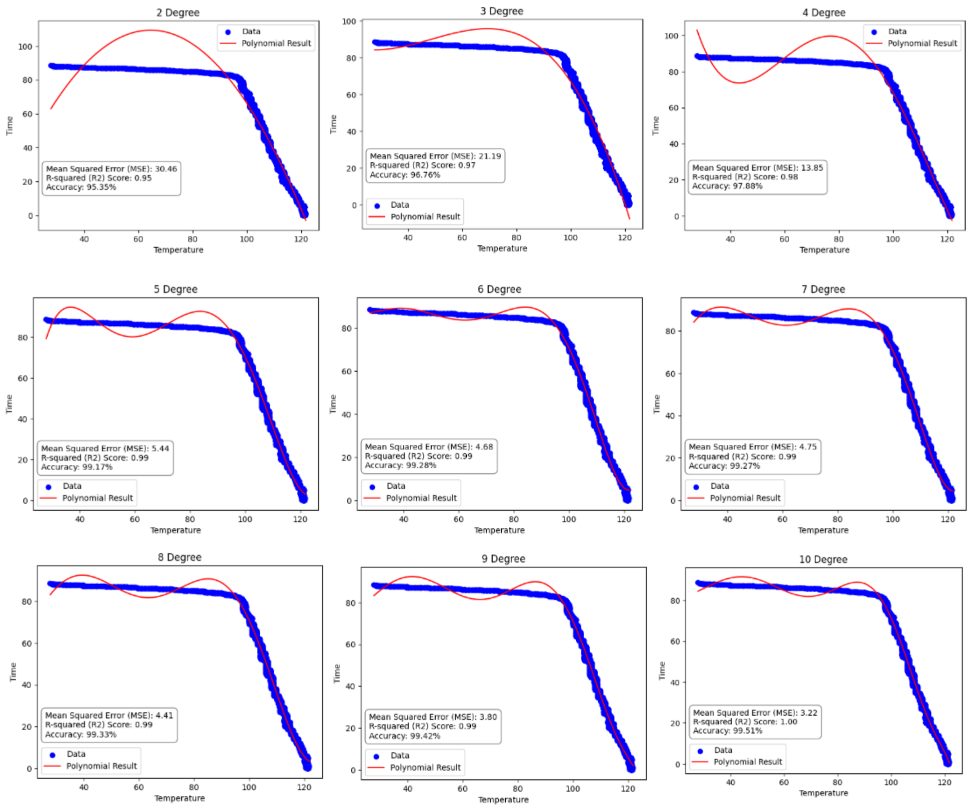

Figure 3. Degree Curve from 2-10 Degree

Figure 3 visualizes where the best model was selected by evaluating MSE, R^2, accuracy, and prediction visualizations. Each degree of the polynomial regression was assessed for its predictive performance through these metrics. Visualization of the predictions offered a clear representation of how each polynomial degree models the prediction curve, aiding in the visual comparison and selection of the most appropriate model based on the available data. This approach ensures that the chosen model is not only statistically robust but also provides an intuitive understanding of its predictive capabilities.

Considering the MSE, R^2, accuracy, and prediction visualizations, the 10th-degree polynomial regression model was selected as the best for predicting time-based on temperature. This model exhibits the smallest prediction error, forms a curve that is closest to the actual data and shows high accuracy. Further visualization of the predictions confirmed that the 10th-degree model provides the best fit for the data, making it the most appropriate choice. The 10th-degree polynomial regression equation supports this decision by capturing complex data patterns and delivering accurate predictions. Implementing this equation in the Arduino IDE will enable more precise time predictions based on temperature, thereby enhancing the performance and reliability of the tool.

4. Result and Discussion

4.1 Polynomial Model

After analyzing the temperature and time data, as much as 5057 data were analyzed using polynomial regression from degree 2 to 10. The decision was made to use degree 10 as the best model. This selection is based on several important factors, including Mean Squared Error (MSE), R-squared (R^2), accuracy, and prediction visualization. The following is a more detailed explanation of this decision.

Table 2. Data Distribution 2-10 Degree

Degree	2	3	4	5	6	7	8	9	10	Total
Total Data	272	134	337	501	772	186	199	207	2.449	5.057

Based on **Table** 2. Data Distribution 2-10 Degree, Table 2, the 10th-degree polynomial model has the largest amount of data, with 2,449 out of a total of 5,057 data points. This indicates that temperature data with the 10th-degree polynomial model has the smallest difference from the average actual time for the various observed temperatures.

a. Mean Squared Error (MSE)

MSE measures the mean squared error of the prediction. In this analysis, the 10th degree provides the lowest MSE value, 3.22, compared to the other degrees. The lower MSE value indicates that the 10th-degree model has a smaller prediction error, making it more accurate in modeling the relationship between temperature and time [25].

b. R-squared (R^2)

i. The R^2 value indicates how well the polynomial regression model explains the variability of the data. The 10th-degree polynomial has a relatively high R^2 value, approaching 1.00., suggesting that the model can capture the variability of the data and provide a better explanation of the relationship between temperature and time [24].

ii. Accuracy is measured based on how close the model predictions are to the actual values. Degree 10 showed the highest accuracy at 99.51%, with the slightest difference between the predicted and actual time averages for various temperatures. With higher accuracy, the 10th degree is considered more reliable in providing precise predictions.

c. Prediction Visualization

a. The prediction graph of degree 10 shows a better ability to form a curve closest to the actual data. The prediction visualization shows that degree ten balances flexibility and model fit to the data.

d. Degree 10 Polynomial Regression Equation

The 10th-degree polynomial regression equation obtained is:

$$\begin{aligned} y = & -3.027154768823266e-16x^{10} + 1.4821485582020052e-13x^{9} + \\ & -2.8575840957978992e-11x^{8} + 2.709176396087686e-09x^{7} + \\ & -1.263056173780334e-07x^{6} + 2.318137574234441e-06x^{5} + \\ & 1.4790077371335862e-07x^{4} + 5.34117044842422e-09x^{3} + \\ & 1.3569687512139095e-10x^{2} + 9.488204883082852e-09x + \\ & 78.2335622527153 \end{aligned} \quad (4)$$

The 10th-degree polynomial regression equation is obtained from the programming code that prints a polynomial equation with coefficients for each power of x, namely the 10th power to the 1st power and a constant or intercept. This equation is used to predict time-based on the temperature in the implemented device that runs on the Arduino IDE. According to the results of the analysis, this implementation will increase the reliability of the device in monitoring temperature and predicting time.

4.2 Coconut Charcoal Result

Figure 1 displays the Android application used for monitoring the carbonization time. It shows that at a temperature of 69.75 degrees Celsius, the required time is approximately 81.87 minutes.

Figure 1. Mobile Application Display Monitoring Process

Figure 2. Mobile Application Display when the Prediction Process has Completed

Figure 2 illustrates the Android application's feature that displays a "Finish" notification when the temperature exceeds 120 degrees Celsius. This alert indicates that the carbonization process is complete and that the system has reached the optimal temperature threshold.

Figure 3. Raw Coconut Charcoal Result

Figure 3 showcases the raw coconut charcoal, highlighting the initial state of the material after the carbonization process. This stage displays the charcoal's basic form before any additional processing. And Briquettes Result is shown in Figure 7.

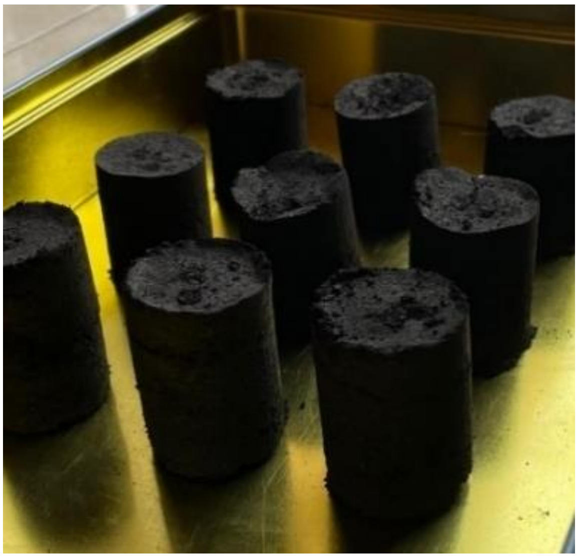

Figure 4 Briquettes Result

Table 3. Latest Research on Coconut Waste, Polynomial Regression, Internet of Things, Real-Time Database, and Cloud to obtain Research GAP

No	Research Topic	Methods Used	Analysis Obtained	Interviewee or Researcher, year	Source on reference
1	Exploring the potential of coconut shell biomass for charcoal production	The study used physicochemical analysis and elemental analysis (EDX, XRF) to evaluate coconut shell biomass for thermochemical conversion.	The world production of coconut accounts for almost ten million hectares in 92 countries, with 75% of the mass production from Asian countries	R. Kabir Ahmad, S. Anwar Sulaiman, S. Yusup, S. Sham Dol, M. Inayat, and H. Aminu Umar, 2022	[1]
2	*Pemanfaatan Tempurung Kelapa Menjadi Briket Arang Sebagai Bahan Bakar Alternatif*	The methods involve training participants to produce coconut shell charcoal briquettes through processes like shell removal, pyrolysis, grinding, printing, drying, and testing for cooking use.	Coconut processing typically focuses on coconut meat for products like oil and VCO, but other parts of the coconut can also be utilized.	Yuliah, M. Dzikri, Masri, E. Darmawan, and A. Yuliana, 2022	[2]
3	*Analisa Desain Kompor Biomassa Berbahan Bakar Tempurung*	The methods involve a literature review, observation, biomass stove design, fluid flow simulation,	The design of the biomass stove, created using SolidWorks software,	Ahmad Yunus Nasution, Fernando Hiro,	[3]

No	Research Topic	Methods Used	Analysis Obtained	Interviewee or Researcher, year	Source on reference
	Kelapa Menggunakan Ansys	and the calculated stove specification.	demonstrated its effectiveness.	Louis Tarigan, 2022	
4	Fabrication and characterization of rice husk and coconut shell charcoal-based bio-briquettes as an alternative energy source	The methods involve preparing briquettes from rice husk and coconut shell charcoal with varying compositions and adhesive, then carbonizing, pressing, drying, and measuring their heat energy content.	Biomass is material derived from plants that can be either directly or indirectly be utilized as fuel in huge so that it can be one of the alternative energy source of fuel oil (fossil).	Y. Yuliah, M. Kartawidjaja, S. Suryaningsih, and K. Ulfi, 2022	[4]
5	*Pelatihan Briket Arang Sebagai Alternatif Energi*	This community service study involves observations to identify issues related to coconut shell waste. Subsequently, socialization and training were carried out on how to produce briquettes from coconut shells.	The study successfully produced coconut shell charcoal briquettes as intended. The training gained knowledge of how to make briquettes as an alternative energy.	Faridatul Mukminah, TriWoro Setiati, Padriyansyah, 2023	[5]
6	Improving Meat Expiration Time Prediction Using The Internet Of Things And Polynomial Regression	The study employed IoT-based sensors to detect NH_3 levels in meat, which were then processed using polynomial regression to predict the meat's expiration time, with results accessible via an Android application.	The relationship between the two variables is parabolic, so it is more suitable to use polynomial regression than linear regression.	I. G. D. Nugraha, G. T. Wijaya, and K. Ramli, 2022	[6]
7	*Perancangan Prototype Monitoring Suhu Berbasis Internet Of Things (IoT)*	The study used an ESP32 as a microcontroller and a DHT22 as a temperature sensor to monitor temperature and humidity. The data is then sent to a cloud server and displayed through the Blynk application.	The simulation of temperature and humidity monitoring through the Blynk application has successfully provided a practical solution for real-time monitoring, even from a distance. This demonstrates that Internet of Things (IoT) systems can transmit data in real-time.	Muhammad Ali Ridla, M. Fahrizal Rahman, 2024	[7]

No	Research Topic	Methods Used	Analysis Obtained	Interviewee or Researcher, year	Source on reference
8	*Prototipe Sistem Pemantauan dan Peringatan Dini Gangguan Aliran Air PDAM berbasis Arduino, Firebase Realtime DB, dan Android*	This research uses an Arduino module to record water flow. The data is then sent to the Firebase Realtime Database and stored. Firebase Cloud Messaging will then send the data to send user notifications.	The application can display a graph of the water flow rate per second to prevent disturbances that can be prevented in advance. However, this system depends on the stability of the internet network.	I Putu Arya Dharmaadi, Dewa Made Sri Arsa, Gusti Made Arya Sasmita, 2021	[8]
9	*Analisis Briket Fiber Mesocarp Kelapa Sawit Metode Karbonisasi Dengan Perekat Tepung Tapioka*	In this study, the process includes preparing briquette raw materials, burning palm mesocarp fiber, screening, mixing, molding, and drying the briquettes.	The results obtained include the comparison of moisture content with the solvent, the ash content of the briquettes, the burning time of the briquettes, and the burning rate of the briquettes. This information helps determine the best briquette with economic value.	Istianto Budhi Rahardja, Cenda E Hasibuan, Yudi Dermawan, 2022	[9]
10	Characterization of charcoal briquettes made from rubber rods and coconut shells with tapioca as an adhesive	The study used a randomized design to test different ratios of rubber rods and coconut shell charcoal with tapioca adhesive to produce briquettes, evaluating their water content, ash content, volatile matter, bound carbon, and calorific value.	Briquette is an alternative renewable fuel used to reduce gas and other fuel energy consumption. The raw material for making briquettes can come from agricultural waste.	F Hamzah et al, 2023	[10]
11	The Development of Sustainable Energy Briquettes Using Coconut Dregs Charcoal and Tapioca Flour as Adhesives	The study involved drying, carbonizing, grinding, mixing, molding, and oven-drying coconut dregs with tapioca flour, followed by evaluating the briquettes' quality based on moisture content, ash content, and density using ASTM standards.	Biomass can replace fossil fuels for heat and electricity, reduce global CO2 emissions, and has lower sulfur content than coal, making it more environmentally friendly.	Dina Asmaul Chusniyah et al, 2022	[11]

No	Research Topic	Methods Used	Analysis Obtained	Interviewee or Researcher, year	Source on reference
12	The Opportunity Export of Coconut Shell Charcoal Briquettes from Indonesia in the International Market	The study used data from books, journals, and websites, analyzed through liberalism, nation-state analysis, and interdependence theory, to assess the export potential of coconut shell charcoal briquettes in the international market.	Besides being used for consumption domestic, commodity coconut is also exported which can be produced in foreign exchange for commodity and can made as a source of income economy.	Karin Sonaya Maudina, Sahri Sahri, Tajidan Tajidan, Addinul Yakin, 2022	[12]
13	The Calorific Value Experiment on Coconut Shell, Bamboo and Mixed Charcoal Briquette	The study measured and compared the calorific values and remaining ash content of charcoal briquettes made from coconut shells, bamboo, and mixed materials to evaluate their suitability as household energy sources.	Coconut shell charcoal briquettes provide higher heating energy and produce less ash, making them more environmentally friendly compared to other charcoals.	P. Siharath et al , 2024	[13]
14	Optimization of Water Conservation Through IoT Sensor Implementation At Smartneasy Nusantara	The study used an IoT-based system with the ESP8266 WeMOS D1 R2 microcontroller and Max6675 temperature sensor to remotely monitor and control a water pump, activating it based on temperature thresholds with a 100% success rate	The temperature value will be captured by the Max6675 Thermocouple sensor, then the Max6675 The thermocouple will send the temperature data to the ESP8266 WeMOS d1 R2.	A. Abdurrafi, D. Maulana, and N. T. Kurniadi, 2023	[14]
15	Cloud Storage for Object Detection using ESP32-CAM	This study optimizes cloud-based object detection for IoT systems using ESP32-CAM, achieving an F1 score of 98.7% and an accuracy of 89.58%.	It serves as the brains of the system, allowing vital information on object detection to be collected and transmitted in real time	I. Imron, B. Satria, S. Karim, and F. Ramadhani , 2024	[15]
16	Towards Sustainable Smart Living: Cloud-Based IoT	The study developed a cost-effective IoT home automation system using the ESP32 microcontroller, Blynk	With an operational voltage range spanning 2.2 to 3.6V,	U. E. Etuk, G. Omenaru, S. J. Inyang, and I. Umoren , 2023	[16]

No	Research Topic	Methods Used	Analysis Obtained	Interviewee or Researcher, year	Source on reference
	Solutions for Home Automation	cloud server, and various sensors and relays for remote control and enhanced functionality.	the ESP32 ensures the smooth execution of the project's activities		
17	Eight Channel Temperature Monitoring using Thermocouple Sensors (Type K) Based on the Internet of Things using ThinkSpeak Platform	This study analyzes the accuracy of a thermocouple sensor in a laboratory incubator, finding a maximum error of 3.98%.	This research used max6675 as the signal amplifier thermocouple sensor, where the thermocouple used type K	C. Prastyadi, B. Utomo, H. G. Ariswati, D. Titisari, S. Sumber, and A. S. Kumar, 2023	[17]
18	Tsukamoto Fuzzy Inference System on the Internet of Things-Based for Room Temperature and Humidity Control	This study develops an IoT-based system for remote fan control and monitoring but finds the fan alone insufficient for cooling, recommending the use of exhaust fans or air conditioners.	The WiFi module contained in the ESP32 is used to access data changes in the database in real-time	Sunardi, A. Yudhana, and Furizal , 2022	[18]
19	Experimental Design, Characterization, coupling, and calibration of type k thermocouple	This study demonstrates that type-K thermocouples can be used for low-voltage applications, with higher temperatures yielding higher power outputs.	the types of thermocouples were considered. It should be noted that the higher the sensitivity of the thermocouple	O. C. Igwilo, , G Mathurine, I. A. Onyegbadue, and R. U. Azike, , 2023	[19]
20	*Rancang Bangun Sistem Pengukuran Alat Thermobath sebagai Alat*	The study designed a Thermo bath cooling system using an Arduino Uno, K-type thermocouple, and pressure transmitter, achieving high accuracy in	With this measurement system, a type-K thermocouple temperature sensor with the MAX 6675 module is used, offering a	Y. Wishnu Pandu Prayudha, S. Fadhil, and S. Novianto, 2022	[20]

No	Research Topic	Methods Used	Analysis Obtained	Interviewee or Researcher, year	Source on reference
	Kalibrasi Temperatur dengan Sistem Arduino Uno	temperature and pressure measurements through calibration.	reading range from 0℃ to +1024°C.		
21	Design And Implementation Of Temperature Measuring Device Using Max6675 And Thermocouple On Wet Cooling Tower	The study involves making the design of a PCB, incorporating an Arduino Mega, a MAX6675 module, and a thermocouple sensor. The sensor was then installed on a cooling tower, followed by data collection and testing.	The results of the thermocouple sensor on the Wet Cooling Tower show normal performance according to statistical testing, including normal distribution, standard deviation, and reliability. All data and values obtained have met the established standards	K. Umurani, Rahmatullah, A. R. Nasution, and M. S. Zufri, 2024	[21]
22	House price prediction using polynomial regression with Particle Swarm Optimization	This paper enhances housing price index prediction models by combining multiple regression with particle swarm optimization (PSO) to improve accuracy and detect price inflection points.	In statistics, polynomial regression is a form of regression analysis in which the relationship between the independent variable x and the dependent variable y are modeled as an nth-degree polynomial in x	Chenhao Zhou, 2021	[22]
23	Implementation of Tensor Flow in Air Quality Monitoring Based on Artificial Intelligence	This paper develops models using various algorithms to predict key air pollutants and evaluate their accuracy in monitoring air quality.	Root mean square error is the process of calculating the square root of the mean square of the variations between the expected value and the actual value	U. Rahardja, Q. Ainia, D. Manongga, I. Sembiring, and Iqbal Desam Girinzio, 2022	[23]
24	The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE, and RMSE in regression	This study argues that the coefficient of determination (R-squared) is a more informative and reliable metric for evaluating regression analyses than SMAPE, MSE, RMSE, MAE, and MAPE, recommending	The coefficient of determination (Wright, 1921) can be interpreted as the proportion of the variance in 137 the dependent variable that is predictable from the independent variables.	D. Chicco, M. J. Warrens, and G. Jurman, 2021	[24]

No	Research Topic	Methods Used	Analysis Obtained	Interviewee or Researcher, year	Source on reference
	analysis evaluation	its use as a standard metric across scientific domains.			
25	Study on Accuracy Metrics for Evaluating the Predictions of Damage Locations in Deep Piles Using Artificial Neural Networks with Acoustic Emission Data	This study proposes a method for selecting the best accuracy metric for predicting damage locations in deep piles using acoustic emission data.	the smaller the MSE value is, the higher the accuracy of the prediction model.	A. Jierula, S. Wang, T.-M. OH, and P. Wang, 2021	[25]

5. Conclusion

Considering the MSE, R^2, accuracy, and visualization of the prediction, the 10th degree was selected as the best model for predicting time based on temperature. This model shows the slightest prediction error, has a better ability to form a curve closest to the actual data, and has high accuracy. Further prediction visualization confirmed that the 10th-degree model best fits the data, making it the most appropriate choice. The 10th-degree polynomial regression equation further reinforces this decision with its ability to capture complex data patterns and provide accurate predictions. Implementing this equation in the Arduino IDE will allow for a more precise prediction of time-based on temperature, improving the performance and reliability of the tool.

6. Suggestion

Based on the findings of this study, the current prediction system is limited to coconut charcoal. To enhance the relevance and applicability of the system, it is recommended that future development expand its scope to include various types of carbon materials, not just coconut charcoal. This expansion will enable the system to provide more comprehensive and accurate predictions for different types of charcoal, improving its utility in various industrial and research applications. Implementing a more universal system could broaden its usage and benefits across multiple sectors and support the development of more effective and efficient alternative carbon fuels.

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