Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 10, No. 2, May, Pp. 197-206

Bamboo diameter detection system based on image processing as a pre-assessment for an automated bamboo splitting technology

Sinta Uri El Hakim[1], Rokhmat Arifianto[2], Sugiyanto*[1], Ilham Ayu Putri Pratiwi[1], Galuh Bahari[1], Radhian Krisnaputra[1]
Department of Mechanical Engineering, Vocational College, Universitas Gadjah Mada, Yogyakarta, Indonesia[1]
Informatics and Computer Engineering, Politeknik Negeri Jakarta, Depok, Indonesia[2]

Article Info
Keywords:
Bamboo Laminated, Bamboo Radius, Canny Edge Detection, Hough Transform, Pre-assesment

Article history:
Received: November 29, 2024
Accepted: February 25, 2025
Published: May 31, 2025

Cite:
S. U. E. Hakim, R. Arifianto, Sugiyanto, I. A. P. Pratiwi, G. Bahari, and R. Krisnaputra, "Bamboo Diameter Detection System Based on Image Processing as a Pre-Assessment for an Automated Bamboo Splitting Technology", *KINETIK*, vol. 10, no. 2, May 2025.
https://doi.org/10.22219/kinetik.v10i2.2170

*Corresponding author.
Sugiyanto
E-mail address:
sugiyanto_t@ugm.ac.id

Abstract
Bamboo is recognized for its eco-friendly attributes and rapid growth, serves as a promising sustainable alternative to wood. However, the high production cost of laminated bamboo remains a major challenge due to labor-intensive processes, particularly manual splitting, which affects efficiency and labor costs. To overcome this issue, this study presents an automated bamboo diameter measurement system that leverages Canny Edge Detection and Hough Transform to ensure precise and uniform slat dimensions. A dataset of 100 bamboo images with diameters ranging from 11 - 13 cm was utilized for training and testing. The system achieved a high accuracy, with a coefficient of determination (R^2) of 0.973, demonstrating strong predictive reliability. Furthermore, Bayesian Optimization was applied to fine-tune parameters, resulting in an optimized configuration for both Canny Edge Detection and Hough Transform. The proposed system reduces dependence on manual labor, thereby lowering production costs and improving overall manufacturing efficiency. Automation in the bamboo splitting process ensures consistent and precise slat dimensions, supporting scalability and enhancing the economic feasibility of laminated bamboo production. The findings of this study provide a practical and sustainable solution to optimize production, making laminated bamboo a more viable and competitive material in the industry.

1. Introduction
The increasing demand for wood-based materials has led to significant deforestation, contributing to environmental degradation and CO_2 emissions [1][2][3]. As a sustainable alternative, bamboo has gained attention due to its rapid growth, high CO_2 absorption, and structural strength, making it a promising substitute for timber in various construction and industrial applications [4][5]. Its rapid growth rate makes bamboo as an efficient and sustainable alternative, suitable for various construction and industrial applications. By integrating bamboo into production processes, the strain on natural forests can be alleviated, fostering an eco-friendlier approach to resource utilization. Among the various bamboo-based products, laminated bamboo has emerged as one of the most sought-after materials due to its high durability, aesthetic appeal, and versatility. This engineered bamboo product is offering a strong and sustainable alternative to hardwood.

Laminated bamboo has garnered increasing attention from various industries due to its potential as an eco-friendly alternative to wood. However, despite the growing interest, laminated bamboo products have yet to achieve widespread adoption. One of the main challenges lies in the relatively high cost of laminated bamboo compared to traditional wood products. This elevated price is attributed to a production process that is both time-intensive and technically complex, encompassing stages such as splitting, planning, gluing, and drying to ensure the production of high-quality laminated bamboo [6][7]. Among the various stages of laminated bamboo production, the splitting process is particularly labor-intensive, requiring precision to produce uniform bamboo slats for subsequent processing. The reliance on manual splitting extends production time and significantly increases costs. To address this challenge, an automated bamboo splitting system is essential to standardize slat dimensions and optimize production efficiency. This process relies on bamboo diameter measurement, ensuring consistency in slat sizing. In this research, an automatic bamboo diameter measurement technique is introduced using Canny Edge Detection. However, since bamboo is not a perfectly circular material, an additional Hough Transform approach is employed to enhance diameter detection accuracy, further improving the automation process. The proposed system leverages advanced image processing techniques to achieve uniform bamboo slat dimensions while optimizing production time and reducing dependence on manual labor. This automation approach is expected to enhance the economic feasibility of laminated bamboo, making it a more viable and sustainable alternative to traditional wood-based materials.

Studies specifically focusing on bamboo diameter measurement have not been conducted previously. However, various methods for measuring the diameter of circular objects have been extensively explored. One notable example is a study by Tao and Chen in 2024, which aimed to measure the diameter of the human pupil to assess mental states [8]. Their research utilized gray-to-gray conversion and threshold segmentation techniques to determine the pupil's diameter. The findings revealed that the pupil exhibited two measurable diameters due to its elliptical shape, rather than being perfectly circular.

In 2024, Yamaguchi et al. conducted a study focused on measuring wood diameter [9]. To calculate the cross-sectional (CS) value, images were transformed into pixel representations. These pixel-based images were then classified into two groups: pixels belonging to the CS and those outside it. Yamaguchi employed threshold variations across pixels to perform this classification. The study analyzed 194 data samples, successfully classifying 124 of them, resulting in a classification accuracy exceeding 60%.

Qi et al. conducted a study to measure the diameter of tomato plant stems using YOLO8-Seg and an RGB-D camera sensor [10]. The primary challenges encountered were the uneven size of the stems along their length and their irregular, non-circular shape. To overcome these issues, Qi enhanced the method by incorporating a bud bounding box, which helped identify the region of interest (ROI) for measurement. This modification streamlined the process of pinpointing the main stem, enabling more accurate diameter measurements.

In 2024, Poyraz et al. implemented a linear normalization technique to enhance the accuracy of grey-to-grey threshold selection and pixel counting for measuring the diameters of ring-type workpieces [11]. The study simultaneously measured both the outer and inner diameters, utilizing high-contrast black-and-white images, which proved advantageous for the grey-to-grey threshold method. The findings indicated that this approach successfully improved the Mean Absolute Error (MAE) rate by 3% to 10%.

In 2024, Zhenglan et al. introduced a deep learning-based method for measuring wood diameters using a dual-network model [12]. This approach integrates the Yolov3 algorithm for detecting logs and the DeepLabv3+ algorithm for segmenting wood images. The proposed model achieved a mean average precision (mAP) of 97.28% and a mean intersection over union (mIoU) of 92.22%. This method allows for automatic and precise measurement of wood diameters, even under varying lighting conditions and log orientations, offering a more efficient alternative to traditional manual techniques.

Pu et al. proposed a novel approach for extrapolating Radar Cross Section (RCS) by integrating 3-D nearfield imaging with Bayesian learning [13]. This method tackles the issue of scatter center instability caused by variations in observation angles using a Bayesian-based adaptive parameter optimization algorithm. The algorithm iteratively refines model parameters to improve the accuracy of RCS predictions. By utilizing 3-D imaging, the scatter distribution of objects can be captured in greater detail, resulting in more precise extrapolation. Simulation and experimental findings confirm that this method offers significantly higher accuracy compared to traditional approaches, positioning it as a superior solution for radar and remote sensing applications.

This study introduces a pre-assessment system designed to determine bamboo diameters, aiming to reduce size inconsistencies during the splitting process. The proposed measurement method leverages image processing techniques, specifically Canny edge detection and Hough transform, applied to a dataset of bamboo images captured with a camera. This dataset is used for both training and testing to ensure precise and accurate diameter measurements. Furthermore, Bayesian optimization is implemented to enhance computational efficiency and improve the accuracy of the measurements. This study is structured into four sections: Section 1 Introduction, Section 2 Research Method, Section 3 Results and Discussion, and Section 4 Conclusion.

2. Research Method

The process of measuring bamboo diameters using image processing is outlined in the flowchart shown in Figure 1. This study employs methods such as Canny edge detection and the Hough Transform. The first step involves collecting image data of bamboo for diameter measurement. Images are captured using a professional camera positioned at a fixed distance from the bamboo to ensure consistency across samples with varying diameters. The bamboo is placed against a plain, colorless background to focus the image on the bamboo stalk. Figure 2 illustrates the image collection process. A total of 100 bamboo samples with different diameters were photographed once each, producing 100 images. The study includes bamboo samples with diameters ranging from 11 cm to 13 cm.

After obtaining 100 bamboo images, the next step involves splitting the dataset into two subsets for model training and testing. In this study, 70% of the images were allocated for training and model development, while the remaining 30% were used to assess the model's performance. The process of detecting circular diameters starts by converting the color images into grayscale, simplifying the visual data for more efficient algorithm processing. The grayscale images are then analyzed using the Canny Edge Detection algorithm to accurately identify object edges, particularly circular boundaries. Once these circular edges are detected, the Hough Transform is utilized to geometrically identify the circle's shape. From the detected results, the largest circle diameter is selected for further analysis, ensuring the focus remains on the primary or most relevant object in the image.

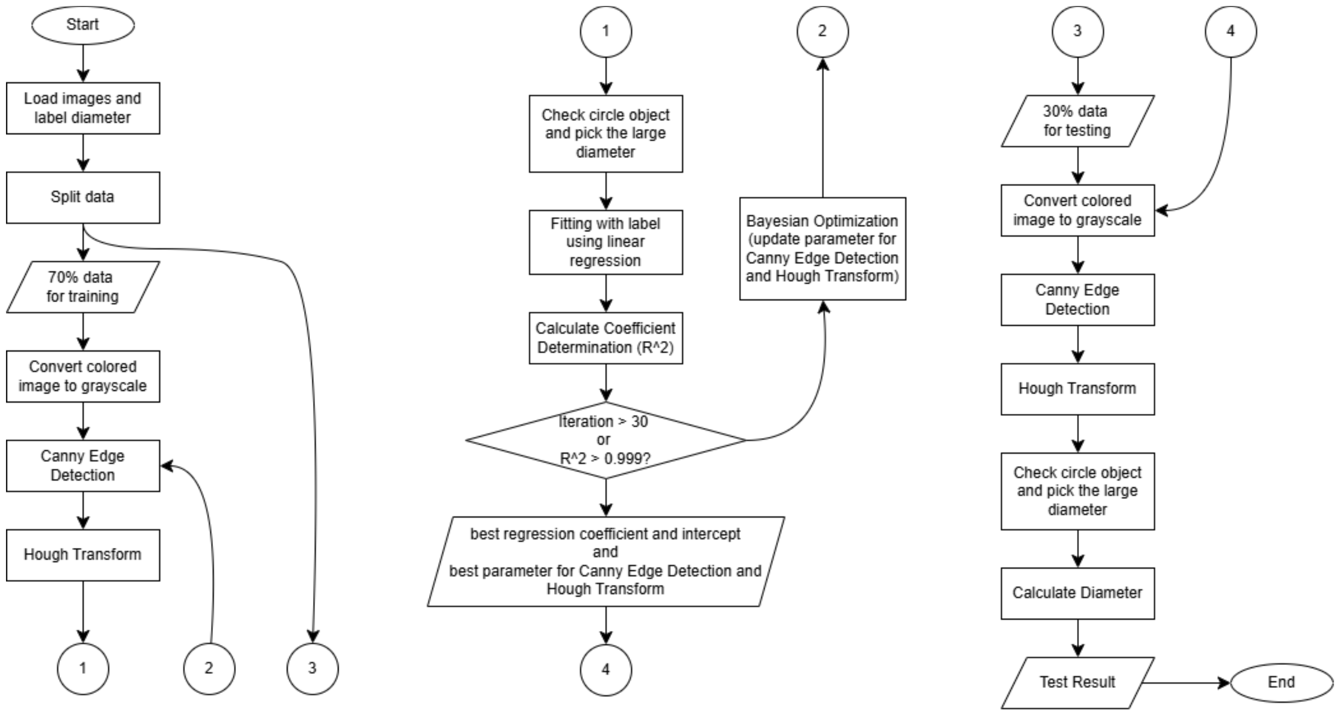

Figure 1. Research Flowchart

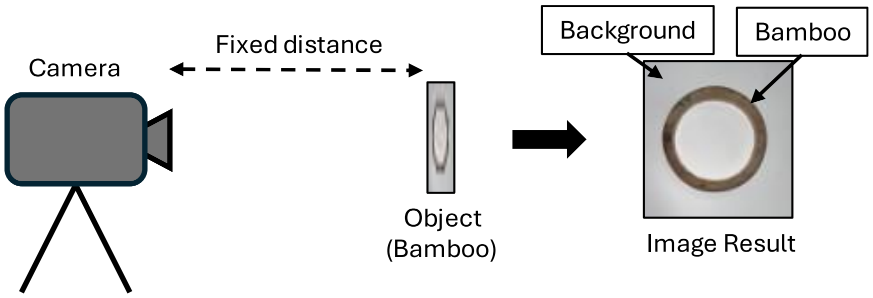

Figure 2. Procedure for Image Bamboo Data Collection

The training phase focuses on optimizing parameters of edge detection algorithms and Hough Transform using Bayesian Optimization. This approach identifies optimal parameters that deliver accurate circle detection. Detected circle diameters are evaluated against labeled data using linear regression to determine model accuracy and consistency. The iterative process continues until one of two conditions is met: a coefficient of determination exceeding 0.999, indicating high accuracy, or a maximum of 30 iterations if optimal results are not achieved earlier. Once optimal parameters are established, the model is tested on evaluation datasets to assess its performance in accurately detecting circle diameters. This process ensures the development of a reliable and highly accurate model capable of detecting circle diameters across various image types.

The combination of Canny edge detection and Hough Transform was chosen for bamboo diameter measurement due to their effectiveness in detecting circular shapes in images with well-defined edges. The Canny algorithm enhances edge contrast, making it easier for the Hough Transform to accurately detect circles corresponding to bamboo cross-sections. Compared to deep learning-based approaches, which require large labelled datasets and significant computational resources, these traditional techniques offer a more lightweight and interpretable solution, making them suitable for real-time or resource-constrained applications. However, their limitations include sensitivity to noise and varying lighting conditions, which deep learning models can often handle better through feature learning.

Bayesian Optimization was selected for hyperparameter tuning due to its ability to efficiently explore the parameter space and converge to an optimal solution with fewer evaluations compared to exhaustive methods like grid search or random search. By leveraging a probabilistic model, Bayesian Optimization identifies promising parameter configurations through acquisition functions, such as Expected Improvement, reducing the number of evaluations needed to reach a high-performing model. The selected parameter ranges were based on prior domain knowledge and experimental observations, ensuring a balance between flexibility and computational feasibility.

This research did not employ data augmentation or cross-validation, which may limit the model's ability to generalize to unseen conditions. Future studies could incorporate these techniques to improve robustness and performance consistency. Additionally, expanding the dataset and comparing more methods, including deep learning and other traditional approaches, could provide better insights into the trade-offs between accuracy, computational cost, and generalization ability, ultimately leading to a more reliable bamboo diameter measurement system.

2.1 Canny Edge Detection

The Canny Edge Detection algorithm is widely recognized as one of the most effective methods for edge detection [14]. Introduced by John F. Canny in 1986 [15], this algorithm is based on three key criteria for edge detection: high Signal-to-Noise Ratio (SNR), precise positional accuracy, and single-edge response [16]. High SNR helps minimize edge detection errors by filtering out noise and identifying false edges. Positional accuracy ensures the detected edges closely align with the actual edges. The single-edge response criterion ensures that the algorithm detects only one edge point at a time, significantly reducing errors in the detection process.

Based on these criteria, the Canny edge detection process involves several steps: smoothing the image using a Gaussian Filter, calculating the image gradient and its direction, applying Non-Maxima Suppression, and identifying edges and their connections using a dual-threshold approach [17], [18]. The detailed procedure for implementing Canny edge detection is described in the following steps [19]:

1) Smoothing Image Using Gaussian Filter

The Canny algorithm uses a 2D Gaussian Filter to smooth images and remove noise. The Gaussian function equation is shown in Equation 1 below.

$$G_{(x,y)} = \frac{1}{2\pi\sigma^2} e^{\frac{(x^2+y^2)}{2\sigma^2}} \tag{1}$$

The gradient vector value is obtained as shown in Equation 2:

$$\nabla G_{(x,y,\sigma)} = \begin{bmatrix} \frac{\partial G}{\partial x} \\ \frac{\partial G}{\partial y} \end{bmatrix} \tag{2}$$

The gradient value ∇G is expressed in a one-dimensional filter equation that operates via convolution on columns and rows. These equations are detailed in Equations 3 and 4:

$$\frac{\partial G}{\partial x} = kx \cdot e^{-\frac{x^2}{2\sigma^2}} \cdot e^{-\frac{y^2}{2\sigma^2}} \tag{3}$$

$$\frac{\partial G}{\partial y} = ky \cdot e^{-\frac{x^2}{2\sigma^2}} \cdot e^{-\frac{y^2}{2\sigma^2}} \tag{4}$$

where k is a constant, which is expressed by Equation 5 as follows:

$$k = -\frac{1}{2\pi\sigma^4} \tag{5}$$

The constant k in Equation 5 is used to perform sequential convolution processes to generate feature extractions P_x dan P_y as shown in Equations 6 and 7. Meanwhile, σ is a parameter of the Gaussian filter used to determine edge detection in bamboo images.

$$P_x = \frac{\partial G(x,y,\sigma)}{\partial x} \cdot f(x,y) \tag{6}$$

$$P_y = \frac{\partial G(x, y, \sigma)}{\partial y} \cdot f(x, y) \tag{7}$$

If $f(x, y)$ represents the original bamboo image, the smoothed bamboo image obtained using the Gaussian Filter can be expressed as shown in Equation 8.

$$F_{(x,y)} = f_{(x,y)} * G_{(x,y)} \tag{8}$$

2) Calculate the Magnitude and Direction of the Gradient
After applying a Gaussian filter to smooth the image, the gradient magnitude and direction of the smoothed bamboo image are calculated using Equations 9 and 10. These calculations help determine the intensity values at each pixel in the bamboo image. The partial derivatives in the x and y directions for the image $I(x, y)$ are derived from $P_x(i, j)$ and $P_y(i, j)$, respectively. These values are then used to calculate the gradient amplitude $M(i, j)$ and the gradient direction $\theta(i, j)$. The gradient direction in the x and y axes indicate the orientation of intensity changes in the image, while the gradient magnitude measures the degree of intensity variation around a given pixel. Equations 9 and 10 define the gradient magnitude and direction.

$$M(i, j) = \sqrt{P_x(i, j)^2 + P_y(i, j)^2} \tag{9}$$

$$\theta(i, j) = arctan\left(\frac{P_y(i, j)}{P_x(i, j)}\right) \tag{10}$$

3) Conduct the non-Maxima Suppression
After calculating the gradient magnitude and direction, Non-Maxima Suppression is applied. This step aims to narrow the edges into thin lines by suppressing pixels that are not part of the primary edge. Pixels that do not have the maximum gradient value in the direction of the gradient are eliminated. The equation for the gradient direction at pixel (i, j) is shown in Equation 11.

$$\xi(i, j) = Sector\big(\theta(i, j), \xi(i, j)\big) = 0,1,2,3 \tag{11}$$

This equation uses four main sectors (0, 1, 2, 3), corresponding to the gradient direction. The pixel value at (i, j) is then compared to the gradient values of its neighboring pixels within a 3x3 window. If the pixel value at (i, j) is greater than those of its neighbors in the gradient direction, it is retained as part of the edge. Otherwise, the pixel value is set to 0 to eliminate noise or false edges.

4) Double Threshold to Detect and Connect Edge
After identifying the main edges, the next step is to apply a double threshold. This step is used to classify pixels based on the strength of the edges. The double threshold is categorized into two thresholds: a high threshold and a low threshold. $T_h(i, j)$ represents strong edge pixels with gradients above the high threshold (τ_h). Meanwhile, $T_l(i, j)$ represents weak edge pixels with gradients between the low threshold (τ_l) and the high threshold (τ_h) whose presence depends on their connection to strong edges. Pixels with gradient values below the low threshold (τ_l) are discarded as they are not considered part of the edge; it is shown in Equation 12.

$$\begin{gathered} \tau_l < M(i, j) < \tau_h \\ T_h(i, j) \\ T_l(i, j) \end{gathered} \tag{12}$$

The Double Thresholding process concludes once all relevant edge pixels have been detected, resulting in a complete representation of the edges in the image. The combination of Non-Maxima Suppression and Double Thresholding ensures that all edge detections are clean, precise, and accurate.

In this study, the Gaussian filter's standard deviation (σ) was not tuned using Bayesian Optimization but was directly set to 1.25 to balance noise reduction and edge preservation. This value was chosen to ensure that edges of the bamboo cross-section remain clear while minimizing noise interference. A lower σ value could retain fine details but might also increase sensitivity to noise, leading to false detections, whereas a higher σ value would smooth out noise but risk blurring important edges, potentially affecting diameter accuracy. By selecting σ = 1.25, the model aims to achieve optimal circle detection performance in real-world bamboo images while maintaining robustness to variations in lighting and background conditions. Future research could explore adaptive σ tuning to further enhance detection accuracy under diverse environmental conditions.

2.2 Hough Transform

The Hough Transform was first introduced by Paul V. C. Hough in 1962 [20] to detect linear lines in images. It was later expanded by Richard Duda and Peter Hart in 1972 to detect other geometric shapes such as circles and ellipses, referred to as the Circle Hough Transform [21], [22]. The effectiveness of the Hough Transform is influenced by several parameters, including the minimum distance between detected circle centers, the accumulator threshold for circle detection, and the minimum and maximum radius of detected circles [23]. The output of the Hough Transform consists of several detected circles whose diameter approximates the size of the bamboo. The result from the Hough Transform includes the center point and radius of the detected circles. The equation for detecting curved lines in the bamboo image is shown in Equation 13.

$$(x - x_0)^2 + (y - y_0)^2 = (r)^2 \quad (13)$$

In this case, the bamboo image is a two-dimensional (x, y) image, where x_0 and y_0 represent the coordinates of the circle's center, and r is the radius of the bamboo circle. The values of $x, y,$ and r are detailed in Equations 14, 15, and 16 as follows:

$$x = x_1 + \frac{x_1 - x_2}{2} \quad (14)$$

$$y = y_1 + \frac{y_1 - y_2}{2} \quad (15)$$

$$r = x_2 - x \quad (16)$$

For a more detailed description of curve line detection and diameter measurement, refer to the illustration shown in Figure 3.

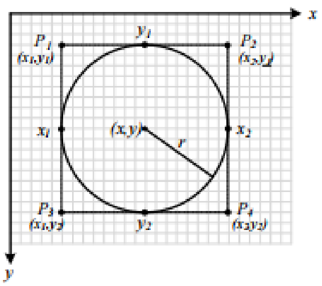

Figure 3. Illustration of Edge Detection and Diameter Measurement Using the Hough Transform Equation [22]

In each iteration, the parameters are updated based on the Expected Improvement equation, allowing Bayesian Optimization to refine the Hough Transform's performance by selecting the most effective parameter values. The Hough Transform then identifies possible circles in the image, and the largest detected diameter is selected. This detected diameter is compared with the actual bamboo diameter, and a linear regression model is built to evaluate accuracy. The initial minRadius and maxRadius values were manually tuned by considering the minimum and maximum possible bamboo diameters in the image. Subsequent iterations then relied on Bayesian Optimization to refine these values, improving detection accuracy while mitigating the Hough Transform's sensitivity to noise and irregular bamboo stalk shapes. This optimization process enhances the robustness of the method, ensuring better performance across varying image conditions.

2.3 Bayesian Optimization

Bayesian Optimization is a probabilistic optimization method used to find the optimal value of a function that is difficult to evaluate directly or has high computational costs. This technique is particularly useful for hyperparameter tuning in machine learning models, as it minimizes the number of evaluations needed to find the optimal solution [24], [25]. In this research, the parameters being tuned include the edge detection threshold (param1), the minimum distance between detected circle centers (minDist), the accumulator threshold for circle centers during detection (param2), and the minimum and maximum diameters of detected circles (minRadius and maxRadius). The Bayesian Optimization process is represented by an objective function, as shown in Equation 17.

$$f: \chi \to \mathcal{R} \tag{17}$$

where, subset $\chi \subseteq \mathcal{R}^d$, meanwhile x value is shown in Equation 18.

$$x^* = \arg\max_{x \in \chi} f(x) \tag{18}$$

The purpose of Bayesian optimization is to find the global optimum of a function $f(x)$ y constructing a probabilistic model for $f(x)$. This model is then used to decide where the next evaluation of the function should be made. As a result, the number of function evaluations required is minimized, which saves computational time and improves accuracy.

In Bayesian optimization, a Gaussian Process is used to model the objective function $f(x)$ generating probabilistic predictions in the form of the mean $\mu(x')$ and variance $\sigma^2(x')$ at each point x. The mean and variance are calculated by using Equations 19 and 20, respectively:

$$\mu(x') = k(x', X)K(X, X)^{-1}y \tag{19}$$

$$\sigma^2(x') = k(x', x') - k(x', X)K(X, X)^{-1}k(x', X)^T \tag{20}$$

The $K(U, V)$ represents the covariance matrix, where each element (i, j) can be computed as $k_{i,j} = k(x_i, x_j)$ with $x_i \in U$ and $x_j \in V$.

The next step is to correlate the detected circle diameter from the Hough transform with the actual diameter. This process results in a regression equation that links the detected pixel diameter from the Hough transform to the real-world diameter in centimeters. The method and parameters obtained are then tested using the previously separated test data. The model built with these optimal parameters is tested on the test data to evaluate its accuracy, using the coefficient of determination. A coefficient of determination close to 1 indicates a high accuracy of the model, while a value closer to 0 suggests a low accuracy.

The adjustable parameters, including the edge detection threshold (param1), the minimum distance between detected circle centers (minDist), the accumulator threshold for circle center detection (param2), and the minimum and maximum diameters of detected circles (minRadius and maxRadius), directly influence the accuracy of circle detection in the image. These parameters determine the sensitivity and precision of the detection process, impacting the ability to correctly identify the bamboo's diameter. Proper tuning of these values ensures that the detected circle closely matches the actual bamboo diameter, minimizing prediction errors and improving measurement accuracy.

In this study, the optimization process aims to find the best parameter configuration by iterating up to 30 times or stopping earlier if the coefficient of determination (R^2) exceeds 0.999. The algorithm evaluates each parameter set based on its impact on diameter prediction accuracy, refining the values iteratively. Convergence is determined when further iterations yield negligible improvements in accuracy, indicating that an optimal solution has been reached. The selection of the next parameter set during optimization is guided by the Expected Improvement acquisition function, which balances exploration and exploitation by prioritizing parameter configurations that are likely to improve the current best solution.

3. Results and Discussion

After performing the training and testing phases with 100 bamboo image data, the edge detection results for the bamboo circle circumference are shown in the graph in Figure 4. Based on the graph, in the initial iterations (Trial 0-10), the objective value fluctuates significantly around the number 1, without showing a significant decrease. However, starting from iteration 10 to 20, the objective value drops drastically, indicating that the algorithm is beginning to find better solutions. After iteration 20, the best value stabilizes close to 0, suggesting that the algorithm has reached or nearly reached an optimal solution. Although there are still some blue points above the red line, representing less optimal solutions, the algorithm consistently maintains its best value throughout the optimization process. This indicates that the algorithm is capable of improving its performance until it finds an optimal solution within a certain number of iterations.

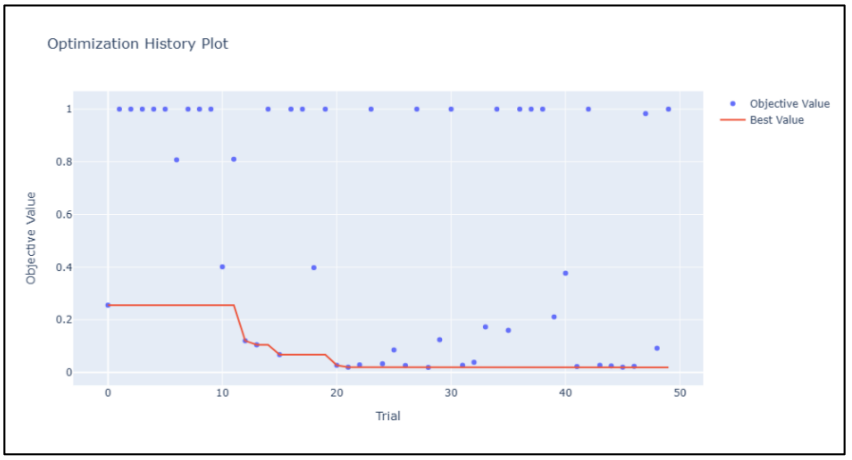

Figure 4. Canny Edge Detection with Hough Transform Plot Parameter Optimization

The optimization results indicate that the best configuration obtained is {'minDist': 12, 'param1': 91, 'param2': 88, 'minRadius': 100, 'maxRadius': 361}. Using these parameters, the model yields a coefficient of determination (R^2) value of 0.9733407129636413. This R^2 value, which is very close to 1, indicates that the model has a high level of accuracy in measuring the bamboo diameter, meaning the model's measurements are very consistent with the actual values.

To evaluate whether the predicted bamboo diameter matches the actual measurements, a comparison is made between the diameter from image processing (x), in pixel values, and the actual diameter (y), in centimeters. This comparison is shown in Figure 5. The plot displays the bamboo diameter measured using image processing on the X-axis, and the actual diameter in centimeters on the Y-axis. The green points on the plot represent the observed data or measurements for each bamboo sample, while the red line shows the linear relationship between the image processing results and the actual diameter. The presence of this linear trend indicates the degree of correlation between the two values, which can be used to assess the accuracy of the model in detecting bamboo diameter. A strong correlation results in a trend line closely following the observed data, suggesting that the method has a high level of accuracy.

Based on the plot shown in Figure 5, the correlation between the actual bamboo diameter and the diameter measured through image processing using Canny and Hough transform is evident. The actual bamboo circle diameter ranges from 11 to 13 cm. In this study, the diameter measurements obtained through image processing closely match the actual values, falling within the 11–13 cm range.

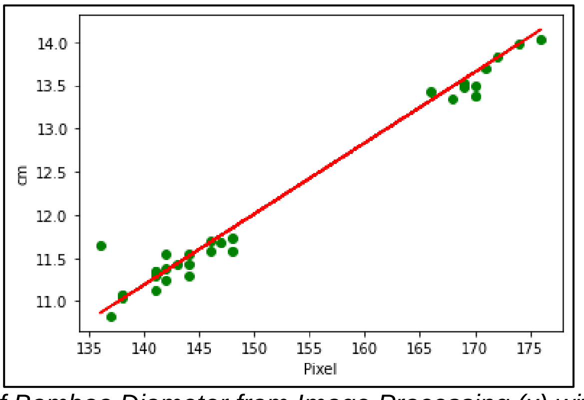

Figure 5. The Comparison of Bamboo Diameter from Image Processing (x) with the Actual Diameter (y) in Centimeters

The results of the image processing using Canny and Hough Transform are shown in Figure 6, illustrating the bamboo diameter detection using image processing techniques. From the image, it is clear that the combination of Canny Edge Detection and Hough Transform is effective in detecting the bamboo circle shape. Moreover, this method can accurately estimate the bamboo diameter based on edge detection and circle recognition. The successful detection demonstrates the potential of the employed method for the automatic and efficient measurement of bamboo diameter.

This research focuses on developing a computationally efficient model using Canny edge detection, Hough transform, and Bayesian optimization, providing a lower-cost alternative to deep learning-based approaches. While deep learning methods may offer higher accuracy, they require extensive datasets, significant computational resources, and longer processing times. A more comprehensive comparison with existing state-of-the-art methods, including traditional edge detection and deep learning techniques, is planned for future work to evaluate accuracy, robustness, and computational efficiency. Although the proposed approach may not achieve the highest accuracy, its efficiency makes it a viable option for real-time or resource-constrained applications. The trade-off between accuracy and computational complexity remains a key consideration, and future research will explore hybrid models that balance these factors effectively.

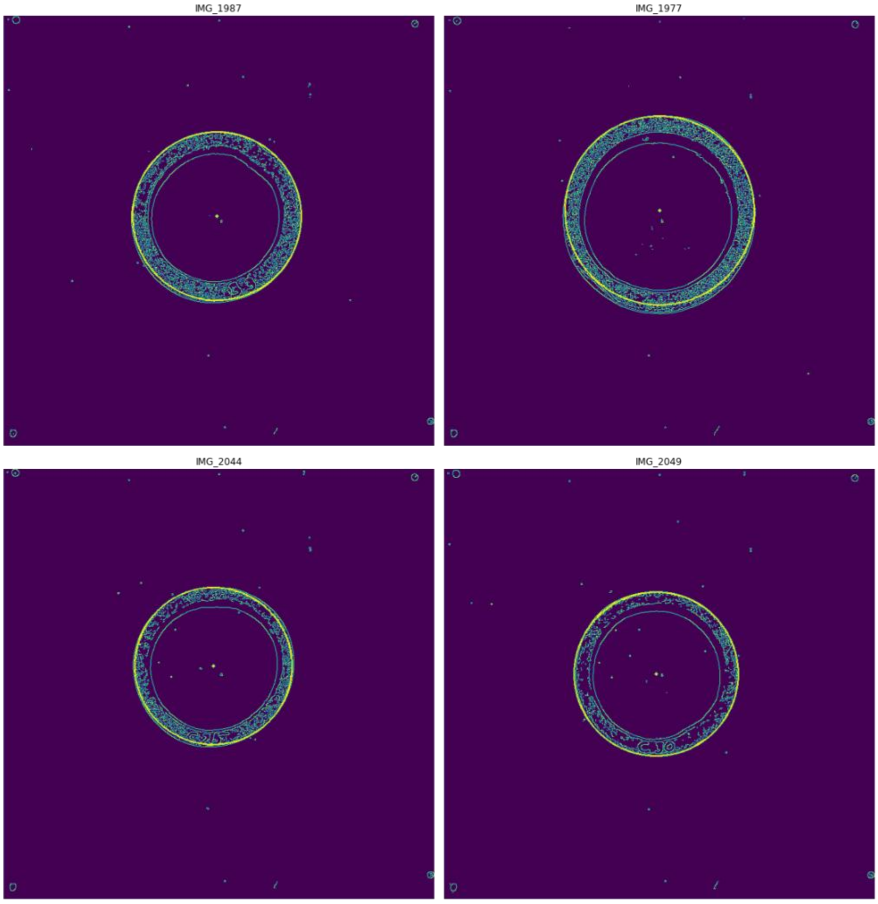

Figure 6. Canny Edge Detection with Hough Transform and Bayesian Optimization Result

4. Conclusion

In this study, the bamboo circle diameter was measured using image processing methods, specifically Canny edge detection and Hough transform. The results of the image processing measurements closely aligned with the actual values, ranging from 11 to 13 cm. To improve the accuracy of the measurements, Bayesian Optimization was applied, with the optimal parameter configuration being {'minDist': 12, 'param1': 91, 'param2': 88, 'minRadius': 100, 'maxRadius': 361}. This configuration yielded a coefficient of determination (R^2) value of 0.9733407129636413. This method is expected to speed up the bamboo splitting process by providing a preliminary assessment based on the diameter measurements.

The next step in improving the model involves testing it in real-world settings using data collected directly from the bamboo splitting system. Acquiring data under actual environmental conditions is crucial to evaluate the model's reliability. Furthermore, the research can be expanded by incorporating additional algorithms to enhance adaptability across different bamboo species, varying image quality, and diverse environmental conditions. The scalability of the method should also be explored, considering its application to larger datasets or real-time processing for industrial use. However, deploying this system in a real-world bamboo production setting presents challenges, such as variations in bamboo shape, lighting conditions, and environmental factors that could impact the model performance. Addressing these issues will be essential for ensuring robust and consistent results in practical applications.

Acknowledgement

This research is supported by Academic Excellent Research Grant (C Scheme) Universitas Gadjah Mada Number 6530/UN1.P1/PT.01.03/2024.

References

[1] P. M. Forster *et al.*, "Indicators of Global Climate Change 2022: Annual update of large-scale indicators of the state of the climate system and human influence," *Earth Syst. Sci. Data*, vol. 15, no. 6, pp. 2295–2327, 2023. https://doi.org/10.5194/essd-15-2295-2023

[2] J. Bredenoord, "Bamboo as a Sustainable Building Material for Innovative, Low-Cost Housing Construction," *Sustain.* , vol. 16, no. 6, 2024. https://doi.org/10.3390/su16062347

[3] D. Behera, S. S. Pattnaik, D. Nanda, P. P. Mishra, S. Manna, and A. K. Behera, "A review on bamboo fiber reinforced composites and their potential applications," *Emergent Mater.*, 2024. https://doi.org/10.1007/s42247-024-00832-9

[4] A. S. Devi and K. S. Singh, "Carbon storage and sequestration potential in aboveground biomass of bamboos in North East India," *Sci. Rep.*, vol. 11, no. 1, pp. 1–8, 2021. https://doi.org/10.1038/s41598-020-80887-w

[5] J. Q. Yuen, T. Fung, and A. D. Ziegler, "Carbon stocks in bamboo ecosystems worldwide: Estimates and uncertainties," *For. Ecol. Manage.*, vol. 393, pp. 113–138, 2017. https://doi.org/10.1016/j.foreco.2017.01.017

[6] N. Nugroho and N. Ando, "Development of structural composite products made from bamboo II: fundamental properties of laminated bamboo lumber," *J. Wood Sci.*, vol. 47, no. 3, pp. 237–242, 2001. https://doi.org/10.1007/BF01171228

[7] E. S. Bakar, M. N. M. Nazip, R. Anokye, and L. Seng Hua, "Comparison of three processing methods for laminated bamboo timber production," *J. For. Res.*, vol. 30, no. 1, pp. 363–369, 2019. https://doi.org/10.1007/s11676-018-0629-2

[8] J. Tao and H. Chen, "A Pupil Diameter Measurement System Based on Image Processing," in *2024 Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC)*, 2024, pp. 1–6. https://doi.org/10.1109/IPEC61310.2024.00011

[9] R. Yamaguchi, R. Watanabe, N. Fujii, D. Kokuryo, T. Kaihara, and Y. Sunami, "Automatic Measurement of Timber Diameter Using Image Processing," *Procedia CIRP*, vol. 126, pp. 44–47, 2024. https://doi.org/10.1016/j.procir.2024.08.259

[10] Z. Qi, W. Hua, Z. Zhang, X. Deng, T. Yuan, and W. Zhang, "A novel method for tomato stem diameter measurement based on improved YOLOv8-seg and RGB-D data," *Comput. Electron. Agric.*, vol. 226, p. 109387, 2024. https://doi.org/10.1016/j.compag.2024.109387

[11] A. G. Poyraz, M. Kaçmaz, H. Gürkan, and A. E. Dirik, "Sub-Pixel counting based diameter measurement algorithm for industrial Machine vision," *Measurement*, vol. 225, p. 114063, 2024. https://doi.org/10.1016/j.measurement.2023.114063

[12] Z. Lu *et al.*, "A Deep Learning Method for Log Diameter Measurement Using Wood Images Based on Yolov3 and DeepLabv3+," *Forests*, vol. 15, no. 5, 2024. https://doi.org/10.3390/f15050755

[13] L. Pu, X. Zhang, J. Shi, S. Wei, T. Zhang, and X. Zhan, "Precise RCS Extrapolation via Nearfield 3-D Imaging With Adaptive Parameter Optimization Bayesian Learning," *IEEE Trans. Antennas Propag.*, vol. 70, no. 5, pp. 3656–3671, 2022. https://doi.org/10.1109/TAP.2021.3137212

[14] M. Nikolic, E. Tuba, and M. Tuba, "Edge detection in medical ultrasound images using adjusted Canny edge detection algorithm," *24th Telecommun. Forum, TELFOR 2016*, pp. 1–4, 2017. https://doi.org/10.1109/TELFOR.2016.7818878

[15] J. Canny, "A Computational Approach to Edge Detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-8, no. 6, pp. 679–698, 1986. https://doi.org/10.1109/TPAMI.1986.4767851

[16] L. Wang, X. Ma, and H. Wang, "Hybrid Image Edge Detection Algorithm Based on Fractional Differential and Canny Operator," in *2018 11th International Symposium on Computational Intelligence and Design (ISCID)*, 2018, pp. 210–213. https://doi.org/10.1109/ISCID.2018.10149

[17] L. Yuan and X. Xu, "Adaptive Image Edge Detection Algorithm Based on Canny Operator," *Proc. - 2015 4th Int. Conf. Adv. Inf. Technol. Sens. Appl. AITS 2015*, no. 2, pp. 28–31, 2016. https://doi.org/10.1109/AITS.2015.14

[18] D. Ji, Y. Liu, and C. Wang, "Research on Image Edge Detection Based on Improved Canny Operator," in *2022 3rd International Conference on Information Science, Parallel and Distributed Systems (ISPDS)*, 2022, pp. 229–232. https://doi.org/10.1109/ISPDS56360.2022.9874064

[19] Y. Li and B. Liu, "Improved edge detection algorithm for canny operator," *IEEE Jt. Int. Inf. Technol. Artif. Intell. Conf.*, vol. 2022-June, pp. 1–5, 2022. https://doi.org/10.1109/ITAIC54216.2022.9836608

[20] P. V. C. Hough, "Method and means for recognition complex patterns," *Us3069654*, p. 6, 1962.

[21] R. O. Duda and P. E. Hart, "Use of the Hough Transformation to Detect Lines and Curves in Pictures," *Commun. ACM*, vol. 15, no. 1, pp. 11–15, 1972. https://doi.org/10.1145/361237.361242

[22] Sutarno, Abdurahman, R. Passarella, Y. Prihanto, and R. A. . Gultom, "Mathematical Implementation of Circle Hough Transformation Theorem Model Using C# For Calculation Attribute of Circle," vol. 172, no. Siconian 2019, pp. 454–458, 2020. https://doi.org/10.2991/aisr.k.200424.070

[23] Y. Mao, S. Wang, L. Chen, F. Han, M. Pang, and H. Li, "Plastic Optical Fiber Dimension Measurement Based on Canny Edge Detection and Hough Line Detection," *2024 IEEE 7th Inf. Technol. Networking, Electron. Autom. Control Conf.*, vol. 7, pp. 375–379, 2024. https://doi.org/10.1109/ITNEC60942.2024.10733135

[24] J. Snoek, H. Larochelle, and R. P. Adams, "Practical Bayesian optimization of machine learning algorithms," *Adv. Neural Inf. Process. Syst.*, vol. 4, pp. 2951–2959, 2012. https://doi.org/10.48550/arXiv.1206.2944

[25] B. Shahriari, K. Swersky, Z. Wang, R. P. Adams, and N. De Freitas, "Taking the human out of the loop: A review of Bayesian optimization," *Proc. IEEE*, vol. 104, no. 1, pp. 148–175, 2016. https://doi.org/10.1109/JPROC.2015.2494218