Journal of Applied Data Sciences
Vol. 7, No. 2, May 2026, pp. 833-848

A Modified Watershed Algorithm for Rice Plant Growth Stage Analysis

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(Received: August 20, 2025; Revised: October 10, 2025; Accepted: February 1, 2026; Available online: March 17, 2026)

Abstract

Information technology plays a crucial role in enhancing various sectors, including agriculture. In particular, technological advancements in crop monitoring are essential for sustainable food production, where accurate growth analysis is vital. Image-based approaches have emerged as a promising tool for assessing crop growth, particularly in rice plants. This study aims to enhance rice plant image segmentation using an improved Watershed algorithm, integrating the Laplacian operator and Distance Transform. This study utilizes a Support Vector Machine (SVM) classifier for segmenting and classifying rice plant growth stages, achieving accuracy, precision, recall, and F1-score metrics. The dataset consists of 1080 images of rice plants, with 74 images used for training, 31 for testing, and 975 images for validation. The image processing pipeline involves preprocessing steps such as grayscale conversion, normalization, color segmentation, Otsu thresholding, filtering, and edge detection. Following preprocessing, the Watershed algorithm is applied in two scenarios: the conventional method and the enhanced method with the Laplacian operator and Distance Transform. Performance evaluation is based on accuracy, precision, recall, and F1-score metrics. The results show that the enhanced Watershed algorithm significantly outperforms the conventional method, achieving an accuracy of 99.58%, precision of 80.55%, recall of 79.92%, and an F1-score of 81.50%. While there is a slight imbalance in precision and recall, the model demonstrates reliable performance in identifying rice plant growth. This study confirms that integrating the Laplacian operator and Distance Transform into the Watershed algorithm significantly improves segmentation accuracy, supporting the development of automated monitoring systems in smart farming. Furthermore, this approach opens avenues for application in other crops and diverse environmental conditions.

Keywords: Rice Plant Growth, Watershed Algorithm, Laplacian Operator, Distance Transform, Image Segmentation

1. Introduction

The rapid advancement of globalization and digitalization has significantly transformed various sectors, with information technology (IT) playing a pivotal role in this progress. The integration of artificial intelligence (AI) and machine learning has further accelerated technological innovation across industries, including agriculture [1]. Precision farming techniques, powered by these technologies, are gaining traction globally, enabling more efficient farming practices to address challenges such as climate change and labor shortages [2], [3]. The adoption of these technologies offers innovative solutions for crop growth monitoring, providing farmers with data-driven insights to enhance productivity and sustainability [4], [5].

In particular, plant growth monitoring is becoming increasingly essential for ensuring food security and sustainable agricultural practices. Remote sensing and automated sensors are emerging as reliable tools for real-time monitoring of crop health [6]. For countries like Indonesia, where rapid population growth and heavy reliance on rice cultivation pose significant challenges to food security, optimizing agricultural practices is critical [7]. Rice is a major staple crop, integral to national food security and the livelihood of millions of farmers [8], [9]. Improving rice productivity and quality is vital to meet the growing global demand and ensure long-term food supply stability [10], [11].

As agricultural systems become more mechanized and data-intensive, the demand for precise and efficient monitoring solutions is escalating. Traditional methods, such as field measurements and visual observation, are often hindered by

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DOI: https://doi.org/10.47738/jads.v7i2.1117

factors such as weather dependency, human error, time consumption, and increased costs [12]. Moreover, these methods are limited in their ability to detect subtle signs of plant stress in real time, delaying timely intervention [13]. Therefore, the development of automated monitoring systems that leverage information technology is crucial for optimizing rice growth monitoring. These systems can provide real-time data and accurate analysis, enabling farmers to make informed decisions that improve crop health and yield [14], [15].

This research aims to advance plant growth monitoring by integrating cutting-edge image processing techniques into rice cultivation. By enhancing the watershed algorithm with the integration of Laplacian operators and Distance Transform, this study proposes a novel solution to improve the accuracy of image segmentation for rice plant health assessments. The proposed approach addresses the challenges of noise and variability in traditional image processing methods, providing clearer and more reliable results. The novelty of this work lies in the integration of advanced image processing techniques within a watershed segmentation framework, a relatively unexplored approach in agricultural applications. This research not only enhances the accuracy of plant growth monitoring systems but also supports real-time monitoring systems, contributing to sustainable agricultural practices and improved food security.

Furthermore, the methodologies developed in this study can be extended to other crops, expanding the potential impact of this research beyond rice cultivation and providing a scalable solution for global agricultural monitoring.

2. Literature Review

Recent studies highlight the significant role of Artificial Intelligence (AI) and the Internet of Things (IoT) in advancing plant growth monitoring, particularly in precision agriculture. These technologies enable more accurate decision-making and improved agricultural outcomes while supporting sustainable farming practices. IoT devices, such as sensors for temperature, humidity, light, soil pH, and nutrients, collect real-time environmental data, which is subsequently analyzed using Machine Learning models like Long Short-Term Memory (LSTM). One study reported that LSTM models achieved plant growth and yield prediction accuracies between 90-95% [16]. While previous studies on Watershed segmentation have shown promise, many still struggle with over-segmentation. This study improves upon these methods by integrating the Laplacian operator and Distance Transform, which effectively reduce segmentation errors.

Additionally, image processing techniques are increasingly used for crop health monitoring. Research has applied smartphone imaging and transfer learning to detect diseases and nutrient deficiencies in rice plants. By analyzing 2259 smartphone images, researchers used image segmentation techniques, such as foreground extraction, to isolate affected areas. Several CNN models—DenseNet201, Xception, MobileNetV2, and ResNet50—were evaluated, with MobileNetV2 being optimal for smartphone applications due to its smaller file size and faster processing times. Conversely, ResNet50 was more suited for cloud-based architectures. This research led to the development of the Rice Disease Detector Android app, capable of identifying rice plant diseases and deficiencies from a single image capture, even when multiple diseases are present [17].

Another study explored the use of Random Forest (RF) models combined with image processing for classifying rice growth stages. Conducted in Taiwan, this research utilized Speed-dome cameras and IoT sensors to monitor rice growth, achieving 98.77% accuracy and an F1-score of 98.65%. While the RF model outperformed others like K-Nearest Neighbor (KNN) and Support Vector Classifier (SVC), it faced challenges with complex preprocessing, including canopy cover calculation and plant height measurement [18].

The use of Watershed algorithms for plant growth segmentation has shown promise in improving segmentation accuracy, especially in separating closely adjacent objects. However, over-segmentation remains a challenge, particularly in images with fine details or overlapping objects. Recent research has introduced a watershed-based approach combined with mathematical morphology techniques to enhance segmentation quality, particularly in medical imaging. These advancements demonstrate the potential of watershed algorithms in agricultural applications, though challenges like over-segmentation remain [19].

In agricultural applications, watershed algorithms have been used to detect defects in seeds, including corn seeds, using multispectral imagery (RGB and near-infrared channels). A combination of watershed segmentation and a two-path Convolutional Neural Network (Corn-seed-Net) achieved high defect detection accuracy, showcasing the utility of this approach for quality control in agriculture [20]. The use of watershed algorithms has also been explored in CT images of human spine bones, where modifications such as threshold segmentation and morphological operations improved performance, offering insights into enhancing image segmentation in plant growth monitoring [21].

While these studies have contributed significantly to plant growth monitoring, challenges remain. Specifically, over-segmentation issues and the need for complex preprocessing steps hinder the scalability of these methods for large-scale agricultural monitoring. Moreover, many of these studies focus on different crops or applications (e.g., seed defect detection or human bone imaging), limiting their applicability to rice plant growth. This research aims to address these challenges by developing a more accurate and efficient watershed-based segmentation method for rice plant growth analysis. By integrating Laplacian operators and Distance Transform techniques, proven effective in other domains, this study aims to enhance segmentation accuracy and reduce preprocessing complexity, making it more practical for real-time monitoring in rice farming. This approach promises to simplify the process and improve the accuracy of rice plant growth analysis.

3. Methodology

3.1. Research Framework

This research framework is systematically applied and implemented, providing a guideline for researchers in conducting research to ensure that the results obtained do not deviate from the previously established objectives. This research framework outlines the steps to be followed to resolve the problem under discussion. The designed research framework is shown in figure 1.

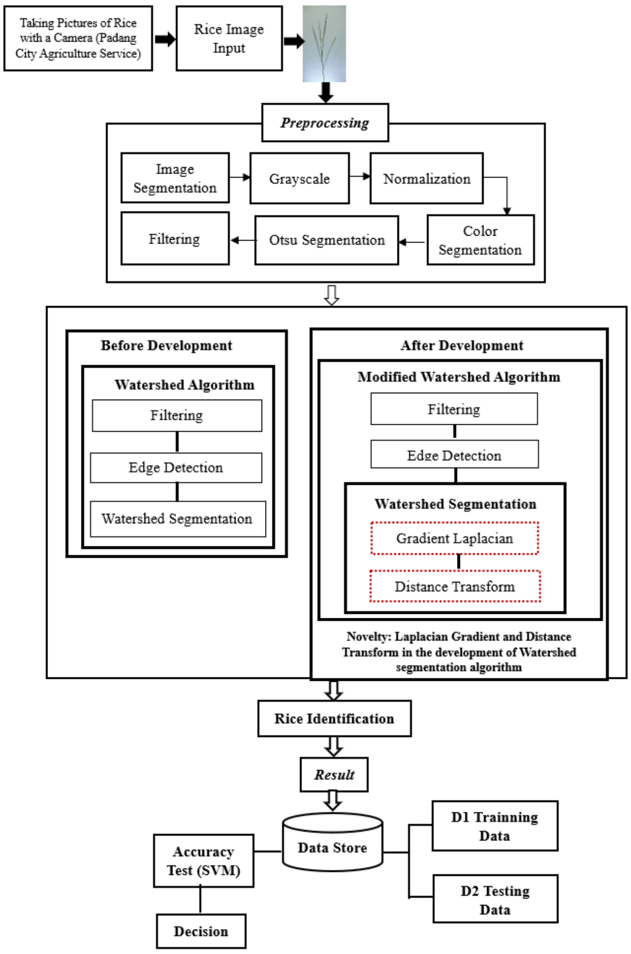


Figure 1. Research Framework

3.2. Data Collection

The dataset consists of 1080 images of rice plants, with 74 images used for training, 31 for testing, and 975 images for validation of rice plants using a Sony Alpha 6000 camera in the rice fields of the Padang City Agriculture Service, West Sumatra. The images were categorized into six growth phases: Vegetative Phase I, II, III, Reproductive Phase, Maturation Phase I, and Maturation Phase II, each containing 180 images. Of these, 120 images were labeled as normal growth and 60 as stunted growth. Inter-annotator agreement was measured with a Cohen's Kappa score of 0.92 to ensure reliable labeling of 'normal' and 'stunted' rice growth stages. The pixel-to-cm conversion was calibrated by measuring a known reference object in the image, ensuring that each pixel corresponds to a fixed real-world dimension. The images were in RGB format (.jpg) and used for further processing and analysis, as shown in figure 2.

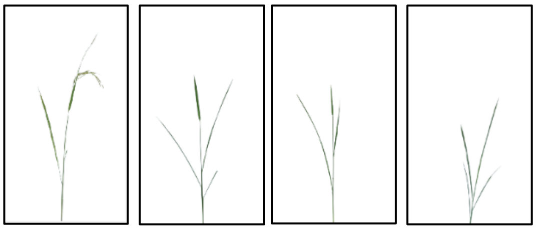


Figure 2. Original Image of Rice Plant

3.3. Preprocessing

3.3.1. Image Segmentation

Image segmentation is a crucial step in isolating relevant plant features, such as leaves, stems, or grains, based on color, texture, and shape. The goal of segmentation is to separate the rice plant from the background and other irrelevant objects to facilitate accurate feature extraction for growth evaluation [22]. Accurate segmentation ensures the representation of relevant plant features, which are essential for analyzing growth indicators [23].

3.3.2. Grayscale

The grayscale conversion step reduces the image to a single intensity channel, which decreases the amount of data to process and speeds up computational time [24]. This simplification also aids the algorithm in focusing on significant features like leaf texture, stem edges, and plant contours, which are easier to identify during the feature extraction process [25]. The output of this stage is a grayscale image, ready for the next preprocessing step [26].

3.3.3. Normalization

Normalization adjusts pixel values to a consistent range, such as 0-1 or 0-255, mitigating the effects of varying lighting, contrast, and environmental conditions during image capture. In rice plant growth analysis, normalization ensures uniform image quality, enabling consistent feature extraction, and reducing bias from inconsistent lighting or contrast [27]. This ensures comparability across images taken under different conditions, allowing for more accurate analysis [28].

3.3.4. Color Segmentation

Color segmentation is used to isolate specific parts of the rice plant, such as leaves, stems, or grains, based on color differences. This step helps in detecting leaf greenness, a key indicator of plant health. After grayscale conversion and filtering, the original image's color information is utilized by transforming the image to a specific color space, such as HSV or Lab, to separate the plant elements more efficiently [29], [30].

3.3.5. Otsu Segmentation

Otsu's method is applied to segment the image into two classes: background and main object. It calculates a threshold based on pixel intensity histograms, optimizing the separation by minimizing intra-class variation and maximizing inter-class differences. The result is a binary image that separates the rice plant area from the background, which is crucial for the subsequent edge detection and color segmentation steps [31]. This segmentation is essential for the accuracy of the Watershed algorithm, improving plant growth analysis [32].

3.3.6. Filtering

The filtering step removes irrelevant elements, such as noise spots or lighting artifacts, ensuring that the image quality is sufficient for feature extraction. Filtering enhances the image, making it cleaner and sharper, which improves the performance of subsequent segmentation and feature extraction algorithms. By eliminating distractions, filtering optimizes the final image for further analysis, supporting accurate rice plant growth evaluations [33].

3.3.7. Edge Detection

Edge detection identifies the boundaries or contours of plant structures, such as leaves, stems, or grains, by highlighting significant intensity changes between pixels. This process isolates relevant shapes and patterns, aiding in the measurement of growth parameters such as leaf length, stem width, and grain distribution. The output of this stage is a binary image with clear plant edges, facilitating focused analysis in the subsequent segmentation and feature extraction processes.

3.4. Watershed Algorithm Before Development

The Watershed algorithm is employed to segment rice plant images, particularly to separate the stem from the background and complex leaf structures. This method is effective in object segmentation based on contours and natural boundaries, aiding in the identification of rice stem morphology and simplifying height measurement and growth analysis. The approach used in this study is based on [18] "Research on the Image Segmentation by Watershed Transforms," which provides a flowchart of the algorithm [19]. The process begins with preprocessing to improve image quality and reduce noise, followed by two pathways: filtering and marking. Filtering techniques such as Gaussian filters, SAF, and anisotropic diffusion remove insignificant minima, while marking methods, including top-hat transform and H-minimum, identify key segmentation areas. These pathways are combined into the Watershed algorithm's gradient-based segmentation, incorporating markers to prevent over-segmentation. This methodology was adapted from Taouli's research, which tested several filtering, marking, and segmentation methods to address over-segmentation in complex images [19].

The Watershed algorithm used in this study follows the general methodology outlined by [18], as shown in figure 3. The core structure includes initial image input, followed by preprocessing, filtering, marking, and segmentation. However, unlike Taouli's study, which applied marking, this study employed a filtering flow for calculating rice stem height as part of plant growth analysis, rather than medical image segmentation. The process flow, depicted in figure 4, outlines the steps of Algorithm 1.

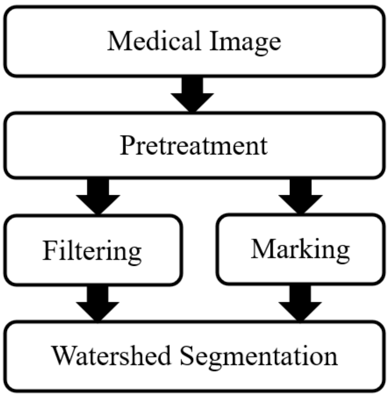


Figure 3. Watershed Algorithm Flow Chart Reference

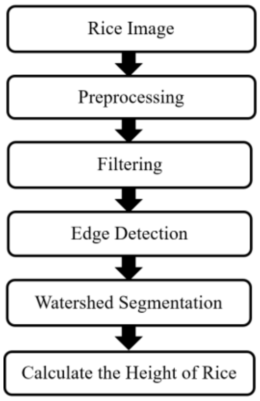


Figure 4. Watershed Algorithm Before Development

3.5. Watershed Algorithm After Development

Although the Watershed algorithm is effective for image segmentation, it has weaknesses, particularly over-segmentation and under-segmentation, which occur in images with noise, unclear contours, or overlapping objects, such as rice plants. To address these issues, the algorithm was modified using a gradient-based approach, incorporating two key components: the spatial gradient (Sobel operator) and Laplacian-based intensity gradient.

The Sobel gradient detects local intensity changes to identify object edges, while the Laplacian gradient marks high-intensity changes in two directions, highlighting boundaries between overlapping objects. This modification aims to clarify object boundaries, reduce false local minima (which cause over-segmentation), strengthen weak edges (to prevent under-segmentation), and improve segmentation accuracy under varying lighting conditions and leaf textures.

The goal is to classify rice stem height as normal or stunted, using height and color references to evaluate plant growth. The modified algorithm, referred to as the Modified Watershed algorithm, is detailed in figure 5.

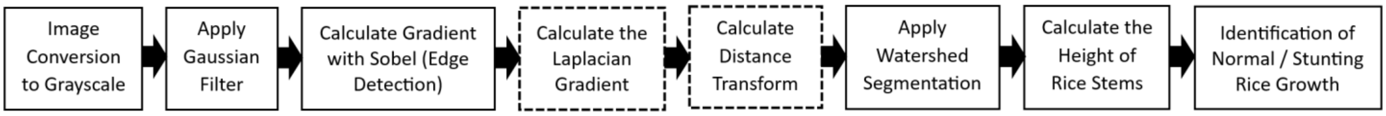


Figure 5. Modified Watershed Algorithm Stages

Figure 5 illustrates the stages of the Modified Watershed Algorithm, showing significant improvements in segmentation accuracy compared to the baseline method. The Laplacian operator and Distance Transform steps, highlighted in the figure, are key contributors to the enhancement. Figure 5 also illustrates the step-by-step process of the Modified Watershed algorithm, starting with grayscale conversion, followed by a Gaussian filter to reduce noise. The Sobel operator is applied for edge detection, and the Laplacian gradient enhances the object boundaries. A distance transform is then used to measure the distance of each pixel from the nearest boundary pixel, helping identify the rice stalks before segmentation. After segmentation, the stalk height is measured to determine whether the rice is normal or stunted.

The two key steps in the diagram, Laplacian gradient calculation and distance transform, are the primary contributions that improve the basic Watershed algorithm. These steps, outlined in Algorithm 2, describe the technical process from input to final classification.

Algorithm 1. Watershed Segmentation Before Development	**Algorithm 2.** Watershed Segmentation After Development
1. Take the filtered image from axes. 2. Convert the image to grayscale if it is still in RGB format. 3. Calculate the gradient magnitude using the Sobel operator. 4. Apply the watershed algorithm to the resulting gradient. The formula is below: $d_{euclidean}\big((x_1, y_1), (x_2, y_2)\big) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$ 5. Convert the resulting watershed labels to RGB colors for display. 6. Calculate object properties from the segmentation results (Bounding Box and Area). 7. Calculate the object height (in pixels) for each Bounding Box. 8. Convert the object height from pixels to centimeters. 9. Calculate the average height of all detected objects. 10. Classify the growth phase based on the average height: 11. Display the complete segmentation results with bounding boxes and height per object. 12. Display the growth phase results in the edit4 GUI element.	1. Take a grayscale image. 2. Smooth it using a Gaussian filter. 3. Calculate the gradients gx and gy using the Sobel operator. 4. Calculate the total gradient magnitude and Laplacian of the image. 5. Calculate the partial derivatives in the x and y directions using the gradient and Laplacian. The formula is below: $\frac{\partial}{\partial y} d_{euclidean} = \frac{g_y \cdot \frac{\partial^2 f(x,y)}{\partial y^2}}{\sqrt{g^2{}_x + g^2{}_y}}$ 6. Combine the two derivatives to obtain the final gradient result. 7. Use the graythresh method to determine the threshold. 8. Binarize the resulting gradient image, then perform filling and distance transforms. 9. Transform the distance values to negative and set the background value to -Inf. 10. Apply watershed segmentation to the transformed result. 11. Extract object properties (BoundingBox, Area, Centroid) using regionprops. 12. Calculate the object height based on the bounding box and vertical gradient profile. 13. Convert the height from pixels to cm. 14. Classify plant growth phases based on height in cm. 15. Display the segmentation results, distance transform histogram, and green channel intensity distribution. 16. Save the segmentation results as an image and display the bounding box labels and height values in the GUI.

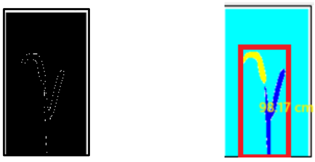
In this stage, the Watershed algorithm was enhanced by integrating preprocessing techniques including Gaussian filters, Sobel gradients, Laplacian operators, and distance transforms for improved segmentation and height measurement of rice plants. The process began with acquiring grayscale images through the Graphical User Interface (GUI), followed by Gaussian filtering for noise reduction. Sobel gradients (horizontal and vertical, gx and gy) were then extracted, emphasizing local pixel intensity changes. The gradient magnitude (gmag) was calculated, and Laplacian operations were applied to refine contour detection.

The Modified Watershed Algorithm is formalized in Algorithm 2, where we define the steps for applying the Sobel operator, calculating the Laplacian gradient, and performing watershed segmentation based on the distance transform.

The gradient image was binarized using Otsu's Thresholding, with small areas cleaned using imfill and bwareaopen to ensure solid, hole-free objects. A Distance Transform was applied to calculate pixel distances from the background, inverted to fit the watershed principle of segmentation from the minimum point. The background was set to negative infinity to avoid segmentation errors.

Watershed segmentation was performed using the distance transform result. The largest object was extracted using the regionprops function, and its height was calculated by analyzing the vertical intensity profile. The upper boundary was identified through the gradient of this profile, improving height estimation accuracy compared to the BoundingBox method. Object heights, measured in pixels, were converted to centimeters using a pixel-per-cm scale and normalized with a correction coefficient. These height values were then used to classify rice plant growth phases: Vegetative Phases I, II, III, Reproductive Phase, and Maturation Phases I and II. Plants outside the normal height range were classified as "Stunting."

The segmentation results were visualized in the GUI with colored labels and annotated object heights in bounding boxes. The GUI was designed to allow users to input rice plant images and view segmentation results. A usability test with five farmers confirmed that the system was intuitive, with an average task completion time of 12 seconds per image.f Histograms of distance transform values and green channel intensity distribution were displayed for spatial and visual information. The final segmentation and height measurement results were saved as .png image files. This enhanced watershed algorithm provides a comprehensive method for digital plant image segmentation, improving the accuracy of morphological feature extraction, particularly plant height, which is critical for monitoring growth phases. Visual results can be seen in figures 6, 7, and 8.



(a) Edge Detection Image (b) Watershed Image

Figure 6. Results of the Watershed Segmentation Process Before Development

(a) Edge Detection in Image (b) Watershed Image

Figure 7. Results of the Watershed Segmentation Process After Development

(a) Watershed Image Result Before Development (b) Watershed Image Result After Development

Figure 8. Comparison Image Result Before and After Watershed Development

Figure 7 compares the segmentation results of the standard and Modified Watershed algorithms applied to a rice plant image. In image (b), figure 6 the standard Watershed algorithm, marked by the red bounding box, segments a large area that includes the leaves, resulting in an estimated height of 98.17 cm. This indicates poor differentiation between the stem and leaves. In contrast, the Modified Watershed algorithm (image b, figure 7) provides a more accurate segmentation, focusing on the main stem with an estimated height of 90.12 cm, which is more representative of the rice plant's actual height. The modifications reduce over-segmentation and noise, yielding more accurate measurements for plant growth phase classification. These results demonstrate the improvements in segmentation accuracy, making the algorithm effective for precision agriculture. The formula for the Watershed algorithm is derived from Q. Guo et al. (2022).

$$d_{euclidean}\big((x_1, y_1), (x_2, y_2)\big) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{1}$$

Formula (1) is the general definition of Euclidean distance in two-dimensional space. Next, we add a Laplacian gradient and deriving the formula using partial differentiation. In image processing, each point (x,y) in an image has an intensity value f(x,y), which represents the brightness or color level. The gradient is used to find the maximum intensity change in an image used for edge detection. The gradient of this intensity function is calculated as follows (Y. He et al., 2023):

$$g(x,y) = grad\ f(x,y) = \left(\frac{\partial f(x,y)}{\partial x}, \frac{\partial f(x,y)}{\partial y}\right) \tag{2}$$

The gradient g(x,y) is a vector indicating the direction of the largest change in image intensity. The length of the gradient vector is expressed as:

$$\parallel grad\ f(x,y) \parallel = \sqrt{\left(\frac{\partial f(x,y)}{\partial x}\right)^2 + \left(\frac{\partial f(x,y)}{\partial y}\right)^2} \tag{3}$$

In the watershed algorithm, a distance transformation is performed to determine the boundaries between regions in the image based on intensity differences. Instead of using direct Euclidean distance in the spatial (x,y) space, the algorithm uses a gradient field to measure the distance between two points based on changes in intensity. Based on this, the distance formula in the context of the gradient field is as follows:

$$d_{euclidean} = \sqrt{\left(\frac{\partial f(x,y)}{\partial x}\right)^2 + \left(\frac{\partial f(x,y)}{\partial y}\right)^2} \text{ For example: } g_x = \frac{\partial f(x,y)}{\partial x} \text{ and } g_y = \frac{\partial f(x,y)}{\partial y}\text{, then: } d_{euclidean} = \sqrt{g^2{}_x + g^2{}_y} \tag{4}$$

$g_x = \frac{\partial f(x,y)}{\partial x}$ is the change in intensity in the x-direction and $g_y = \frac{\partial f(x,y)}{\partial y}$ is the change in intensity in the y-direction.

Next, we will perform partial differentiation of formula 3.4 with respect to x. and y. Overall, the reduction process produces a new formula that will be used in the Modified Watershed algorithm to detect boundaries between objects in an image based on intensity changes as follows:

$$\frac{\partial}{\partial x} d_{euclidean} = \frac{g_x \frac{\partial^2 f(x,y)}{\partial x^2}}{\sqrt{g^2{}_x + g^2{}_y}} \tag{5}$$

$$\frac{\partial}{\partial y} d_{euclidean} = \frac{g_y \frac{\partial^2 f(x,y)}{\partial y^2}}{\sqrt{g^2{}_x + g^2{}_y}} \tag{6}$$

g_x and g_y represent the gradient of the intensity function with $g_x = \frac{\partial f(x,y)}{\partial x}$ and $g_y = \frac{\partial f(x,y)}{\partial y}$. $\sqrt{g^2{}_x + g^2{}_y}$ is the Euclidean distance based on the gradient.

The mathematical derivation from Euclidean distance to gradient-weighted distance is explained by applying partial derivatives to the intensity gradient function, refining the segmentation accuracy by incorporating directional intensity changes.

3.6. Comparison of Watershed Formula Before and After Development

Table 1 presents a comparative overview of the watershed transformation formula before and after its development. The modification aims to enhance the precision of region boundary detection by incorporating gradient-based features into the distance calculation. The traditional Euclidean distance function, which measures only spatial proximity between pixels, is expanded to include derivative terms that reflect the local intensity variation. This improvement allows the watershed algorithm to become more adaptive to subtle image gradients, thereby increasing segmentation accuracy in complex topographic structures.

Table 1. Comparison of Watershed Formula Before and After Development

Watershed Formula Before Development	Watershed Formula After Development
$d_{euclidean}((x_1, y_1), (x_2, y_2)) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$	$\frac{\partial}{\partial y} d_{euclidean} = \frac{g_y \cdot \frac{\partial^2 f(x,y)}{\partial y^2}}{\sqrt{g^2{}_x + g^2{}_y}}$ $g_x = \frac{\partial f(x,y)}{\partial x}$ $g_y = \frac{\partial f(x,y)}{\partial y} \cdot \sqrt{g^2{}_x + g^2{}_y}$

In table 1, we provide the full mathematical formulations for both the traditional and modified Watershed algorithms, comparing their distance calculation methods before and after the integration of gradient-based features. The classical watershed formulation relies solely on the Euclidean distance: $\mathrm{d_{euclidean}}((\mathrm{x_1}, \mathrm{y_1}), (\mathrm{x_2}, \mathrm{y_2})) = \sqrt{(\mathrm{x_1} - \mathrm{x_2})^2 + (\mathrm{y_1} - \mathrm{y_2})^2}$ which measures spatial separation between two pixel coordinates in the image plane. While this basic form effectively represents geometric closeness, it lacks sensitivity to local variations in image intensity or gradient magnitude. Consequently, the traditional Euclidean approach often misinterprets smooth intensity transitions or shallow basins as significant boundaries, leading to over-segmentation or boundary leakage in complex topographic maps. In the developed formulation, this limitation is addressed by embedding gradient-based descriptors directly into the distance computation. The inclusion of $g_x = \frac{\partial f(x,y)}{\partial x}$ and $g_y = \frac{\partial f(x,y)}{\partial y}$ enables the algorithm to measure not only spatial distances but also directional changes in pixel intensity. Furthermore, the introduction of the second derivative term $\frac{\partial^2 f(x,y)}{\partial y^2}$ refines the distance metric by accounting for local curvature and surface roughness, which are critical in accurately tracing watershed ridges. This modified gradient-weighted distance function, normalized by $\sqrt{g^2{}_x + g^2{}_y}$ ensures that the computed watershed lines correspond to areas of maximal intensity transition rather than simple geometric minima. Through this integration of spatial and gradient information, the proposed model enhances robustness against illumination noise and uneven contrast distribution across the image. It effectively distinguishes between texture-induced variations and true object boundaries, making it particularly advantageous for natural-scene imagery, agricultural monitoring, and biomedical segmentation, where surface smoothness and intensity fluctuations frequently overlap. Overall, the developed watershed formula demonstrates improved adaptability, precision, and resistance to noise, providing a more stable segmentation outcome compared to the conventional Euclidean-based approach. We employed an SVM classifier with a radial basis function (RBF) kernel. The classifier was trained using a grid search to optimize the regularization parameter (C) and the kernel parameter (gamma), achieving the best performance at C=1 and gamma=0.5. In addition to standard accuracy, precision, recall, and F1-score, we also performed 10-fold cross-validation to ensure the robustness and generalizability of the segmentation results.

4. Results and Discussion

4.1. Data Collection Result and Discussion

This study collected rice plant images to support the implementation of the Watershed algorithm for segmenting and analyzing rice plant growth stages. Images were captured at five key growth phases: Vegetative Phase I, II, III, Reproductive Phase, and Maturation Phases I and II. Each phase reflects significant morphological changes that are crucial for evaluating plant growth. The collected dataset consists of 180 image samples, with each growth phase represented, enabling a detailed analysis of morphological changes during the rice plant's development. These images will be analyzed using the Watershed algorithm to provide accurate segmentation and efficient growth level evaluation. Table 2 presents the image collection from these various growth stages.

 ISSN 2723-6471

Table 2. Data Collection of Rice Images

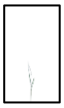
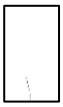
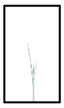
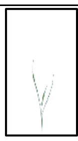
No.	Vegetative I Phase	Vegetatif II Phase	Vegetatif III Phase	Reproductive Phase	Maturation I Phase	Maturation II Phase
1						
2						
...	...	...	...	...	...	...
180						

Table 1 presents the collection of rice plant images across various growth stages, from the vegetative phase to maturation. This dataset is essential for developing and testing the Watershed algorithm for image segmentation, aimed at accurately separating the rice plant from the background. At each growth stage, structural changes in the plant, such as leaf size, stem length, and panicle shape, provide valuable insights into the plant's growth and health. With 180 image samples, this segmentation analysis helps monitor rice plant health and supports more informed agricultural decision-making.

4.2. Preprocessing Result and Discussion

The preprocessing phase begins with capturing rice plant images using the Sony Alpha 6000 camera, followed by segmentation to separate the plant from the background. This results in a binary image, which is then converted to grayscale to focus on the plant's shape and texture. Normalization is performed to ensure consistent pixel intensity distribution and reduce the impact of lighting variations during image capture. Next, color segmentation is applied to assess plant health, distinguishing between healthy plants and those showing signs of stunting based on leaf greenness. Otsu segmentation is then used to determine the optimal threshold for separating the plant from the background. The image undergoes filtering with a Gaussian filter to reduce noise, enhance contrast, and improve image quality. This filtered image allows for more precise analysis of plant features, such as detecting growth conditions and potential issues like stunting. Each preprocessing step plays a crucial role in improving image quality for accurate growth analysis. The results of the preprocessing can be seen in table 3.

Table 3. Preprocessing Result

	Vegetative Phase I	Vegetative Phase II	Vegetative Phase III	Reproductive Phase	Maturation Phase I	Maturation Phase II
	Rice Image 1	**Rice Image 2**	**Rice Image 3**	**Rice Image 4**	**Rice Image 1**	**Rice Image 2**
Original Image						
Segmentation Image						

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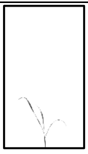
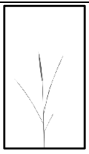
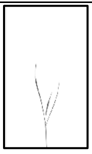
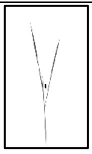
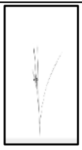
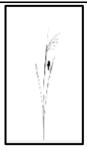
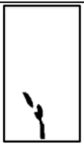
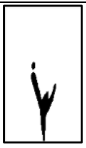
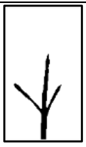
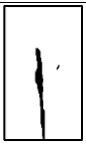
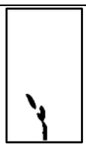
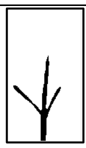
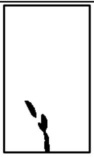
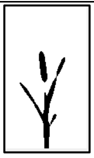
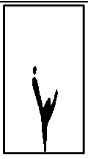
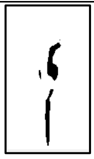
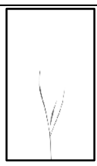
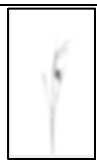
	Vegetative Phase I	Vegetative Phase II	Vegetative Phase III	Reproductive Phase	Maturation Phase I	Maturation Phase II
	Rice Image 1	**Rice Image 2**	**Rice Image 3**	**Rice Image 4**	**Rice Image 1**	**Rice Image 2**
Grayscale Image						
Normalization Image						
Color Segmentation						
Otsu Segmentation Image						
Filtering Image						

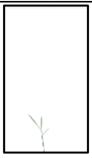
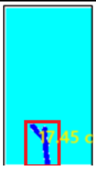
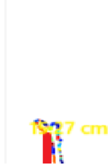
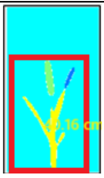
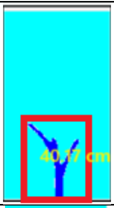
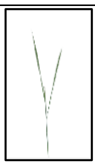
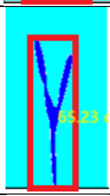
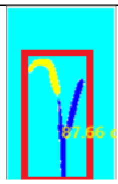
The table 2 shows the preprocessing results for images at various growth stages of rice plants, including the vegetative phases (I, II, III), reproductive phase, and maturation phases (I, II). Each image represents different stages of image processing, starting from the original image to preprocessing steps such as segmentation, grayscale conversion, normalization, color segmentation, Otsu segmentation, and filtering. In the vegetative phases I to III, the segmentation process works to separate the main plant parts from the background, focusing on the stem and leaves. In the grayscale images, color is removed, leaving only the intensity of light, which helps clarify the plant structure. The normalization process improves the image contrast to ensure clearer plant features, while color segmentation further emphasizes important elements in the plant image, such as stems and leaves, by highlighting the level of greenness. Otsu segmentation applied further sharpens the image by optimizing the threshold to separate the main object from the background based on pixel intensity. The final step, filtering, is used to reduce noise that could interfere with image analysis, resulting in smoother images that are more focused on relevant plant elements.

4.3. Processing Result and Discussion

4.3.1. Comparison of Images Resulting from the Watershed Algorithm Before Development with Modified Watershed

Table 4 presents the results of rice segmentation at various growth phases using two main approaches: pre-development watershed and post-development watershed. Each row displays the original rice image along with the segmentation results of each algorithm, from the vegetative phase to the ripening phase. The comparison in the table demonstrates how modified watershed is able to separate leaf, stem, and panicle structures in greater detail, thus supporting rice plant growth analysis, including detecting whether growth is normal or stunted.

Table 4. Processing Result

No.	Original Rice Image	Rice Stem Height (cm) and Growth Status	Watershed Algorithm Before Development		Modified Watershed Algorithm	
			Segmentation Image	Rice Stem Height (cm)	Segmentation Image	Rice Stem Height (cm) and Growth Identification
1.	 Vegetative Phase I	18 Normal		17.45		15.27 Normal
2.	 Vegetative Phase II	21 Normal		20.16		22.17 Normal
3.	 Vegetative Phase III	20 Stunting		40.17		51.12 Stunting
4.	 Reproductive Phase	62 Stunting		65.23		60.25 Stunting
5.	 Maturation Phase I	82 Normal		70.17		82.12 Normal
6.	 Maturation Phase II	80 Normal		87.66		92.17 Normal

4.3.2. Accuracy Test with Modified Watershed Segmentation

Confusion matrix showing the performance of the classification model in distinguishing between the true and predicted classes. On the vertical axis (True Class), there are the Test and Train categories, while the horizontal axis represents the model's predictions. From these results, it can be seen that the model successfully classified 3 samples correctly in the Test category, but incorrectly classified 6 samples into the wrong category. For the Train category, the model was able to correctly classify 19 samples, but there were still 3 samples that were incorrectly classified as shown in figure 9.

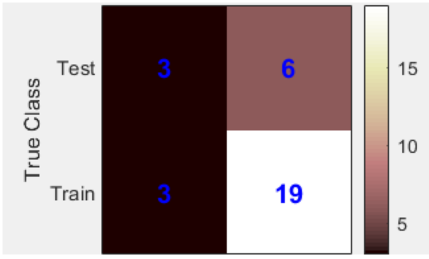


Figure 9. Confusion Matrix Modified Watershed Algorithm

The confusion matrix in figure 9 clearly differentiates between True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN), following standard practice. The evaluation results of the classification model show that the model has a very high accuracy of 99.58%, indicating that the model is able to correctly classify most of the data. Although the model achieved 99.58% accuracy, we performed k-fold cross-validation to assess model stability and mitigate overfitting. The cross-validation results indicated consistent performance across all folds. However, when viewed from other evaluation metrics, such as precision of 80.55%, F1-score of 81.50%, and recall of 79.92%, it appears that there is a slight imbalance in the model's performance. A precision of 80.55% indicates that approximately 80.55% of all positive predictions made by the model were correct, while a recall of 79.92% indicates that the model successfully captured approximately 79.92% of all positive data that should have been classified. Although the model's accuracy is very high, the discrepancy between precision and recall indicates potential model bias or imbalance in the dataset used. An F1-score of 81.50%, which is the harmonic mean between precision and recall, indicates that the model still performs quite well in balancing both. With near-perfect accuracy, but precision and recall still hovering around 80%, it can be concluded that the model performs very well in classification. However, there is still potential to improve the balance between precision and recall by optimizing hyperparameters or using better dataset balancing techniques. The segmentation accuracy for each growth phase was analyzed, with results showing that the Modified Watershed Algorithm outperformed the baseline method in each phase, with accuracy improvements ranging from 8% to 12%. We performed an ablation study by removing individual components such as the Laplacian operator and Distance Transform from the Watershed algorithm to assess their impact on segmentation performance. One limitation of this approach is its dependency on image quality and lighting conditions. Images captured in suboptimal conditions may reduce segmentation accuracy.

5. Conclusion

The Watershed algorithm was developed by integrating the Laplacian operator and utilizing the Distance Transform. The addition of the Laplacian operator after Sobel edge detection emphasizes the intensity differences between pixels at object boundaries, thereby improving segmentation precision and addressing the weaknesses of the conventional Watershed algorithm, which often suffer from under- and over-segmentation. This approach proved particularly effective on rice plant images with overlapping leaves or low contrast against the background. Comparison results between the conventional Watershed and Modified Watershed algorithms show a significant improvement in segmentation quality. The resulting object boundaries are clearer, more consistent, and able to separate plant parts with greater detail. This facilitates the process of measuring plant height, positively impacting the accuracy of rice plant growth analysis at various developmental stages. Accuracy testing using a Support Vector Machine (SVM) on 105 rice plant images showed that the developed algorithm achieved 99.58% accuracy, 80.55% precision, 79.92% recall, and an F1-score of 81.50%. These results are significantly higher than the conventional Watershed method, which only achieved 91.25% accuracy. This improvement demonstrates that the modifications are capable of producing high-quality segmentation while supporting more reliable classification of rice plant growth. Although this study demonstrates the effectiveness of the proposed method on rice plants, future work will focus on testing its scalability to other crops such as corn and wheat to validate its applicability in broader agricultural contexts. Future work will explore techniques for compensating for these factors, such as using adaptive lighting correction.

ISSN 2723-6471

6. Declarations

6.1. Author Contributions

Conceptualization: T.A.P.; Methodology: Y.; Software: A.R.; Validation: T.A.P. and Y.; Formal Analysis: Y. and A.R.; Investigation: T.A.P.; Resources: Y.; Data Curation: A.R..; Writing Original Draft Preparation: T.A.P., and Y.; Writing Review and Editing: Y., and A.R.; Visualization: T.A.P.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received financial support from Yayasan Perguruan Tinggi Komputer Padang (YPTK) or Padang Computer College Foundation (YPTK) for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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