JOURNAL MEDICAL INFORMATICS TECHNOLOGY
medinftech.org ISSN 2988-7003 (online)

Identification of Rotten Carrots Using Image Processing with Edge Detection and Convolution Techniques

Muhammad Syofian[1*]

[1] *PT. Indonesia Comnet Plus, Indonesia*

ARTICLE HISTORY

Received: 03 January 25
Final Revision: 28 November 25
Accepted: 20 December 25
Online Publication: 31 December 25

KEYWORDS

Convolution Techniques, Edge Detection, Enhancement, Image Processing, Rotten Carrots

CORRESPONDING AUTHOR

14230005@nusamandiri.ac.id

DOI

10.37034/medinftech.v3i4.53

A B S T R A C T

Carrot is one of the agricultural commodities with high nutritional value and a significant market demand. However, its quality can deteriorate due to various factors, one of which is rotting. Early detection of rotting carrots is crucial to prevent economic losses and maintain product quality. The main problem in identifying rotten carrots lies in the need for high precision and the time-consuming nature of manual methods. To address this issue, this research develops an automated method for detecting rotten carrots using image processing techniques. In this study, edge detection and convolution techniques are employed as the primary approaches in image analysis. Edge detection is used to recognize contours and boundaries in carrot images, while convolution techniques are applied to identify patterns of damage and texture differences between rotten and healthy carrots. The research findings indicate that this method is capable of detecting rotten carrots with high accuracy, making it reliable as a tool for sorting and quality assurance in carrot processing.

1. Introduction

Carrots are widely consumed vegetables known for their high nutritional value and health benefits, which has encouraged increased cultivation to support human well-being and food demands [1]. Scientific studies have shown that carrots contain bioactive compounds such as beta-carotene, antioxidants, and dietary fiber, which contribute to improved immune function, eye health, and the prevention of chronic diseases, including cardiovascular disorders and certain types of cancer [2]. These findings indicate that carrots also have potential medicinal value beyond their role as a food source.

Despite their benefits, the quality of carrots can deteriorate during storage and distribution due to various factors, particularly microbial activity that leads to rotting. Rotten carrots experience a decline in nutritional content and visual quality, which directly affects market value and causes significant economic losses for farmers and agricultural industry stakeholders. High agricultural productivity can only be achieved through proper cultivation and post-harvest handling practices, which are essential for maximizing yield and maintaining product quality despite limited land availability [3]. Therefore, early identification of rotten carrots is crucial to minimize losses and ensure that only high-quality products reach consumers.

Conventional methods for identifying rotten carrots rely on manual visual inspection, which requires high precision, is time-consuming, and is prone to human error. These limitations often lead to inconsistent quality assessment and inefficiencies in large-scale agricultural operations. In digital image analysis, objects typically exhibit relatively uniform intensity values, while abrupt changes in intensity indicate object boundaries, commonly referred to as edges [4]. This characteristic can be utilized to distinguish between healthy and rotten carrot surfaces.

To overcome the limitations of manual inspection, this study proposes an automated approach for identifying rotten carrots using digital image processing techniques. Image processing aims to enhance image quality to facilitate interpretation by computer systems and can be applied to static images or video data [5]. These techniques enable rapid processing of large image datasets with consistent and repeatable results, making them suitable for agricultural quality control applications

[6]. The methods employed in this research include edge detection and convolution. Edge detection is used to extract object boundaries by identifying significant intensity variations between neighboring regions [7], while convolution techniques are applied for noise reduction and feature enhancement to highlight texture and surface patterns associated with carrot rot [8].

The main purpose of this study is to develop and evaluate an image processing-based method using edge detection and convolution techniques to accurately identify rotten carrots, thereby improving the efficiency and reliability of automated carrot quality assessment systems and reducing economic losses caused by post-harvest spoilage [9].

2. Research Method

This research was conducted through several structured stages, including data collection, data processing, and image analysis.

2.1. Data Collection

Data collection is a process aimed at obtaining information or data relevant to the research objectives [10]. In this study, image data were collected from a repository available on the Kaggle platform, which is recognized as one of the largest and most comprehensive data sources for scientific analysis, particularly in image processing and computer vision research.

Kaggle provides various datasets that can be freely downloaded and utilized by researchers, facilitating data acquisition and method evaluation. The image dataset used in this research consists of carrot images representing both healthy and rotten conditions. Figure 1 illustrates sample carrot image data used in this study.

Figure 1. Carrot Image Data

2.2. Data processing

Data processing in this research was carried out through 4 structured stages to ensure optimal data quality and relevance including Enlarge, Pre-Processing, Enhancement and Convolution [11]. The overall flow of the image processing stages is shown in Figure 2.

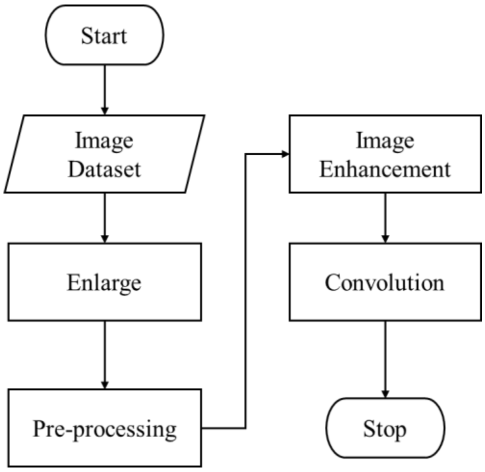


Figure 2. Image Processing Flow

2.2.1 Enlarge

Enlarge is the process of increasing the size or resolution of a digital image to allow for more detailed analysis [12]. This technique is important in image processing applications related to disease identification in carrots, as higher resolution images facilitate the detection of small features and surface irregularities that may indicate rotting or damage.

2.2.2 Pre-prosessing

Preprocessing is the initial step in image processing aimed at enhancing images to prepare them for further analysis [13]. This stage helps standardize images and reduce noise, enabling more consistent and reliable processing results.

In general, data pre-processing includes handling missing data, removing duplicates, and addressing inconsistencies caused by data acquisition errors [14]. In this study, Min-Max filtering is applied as part of the pre-processing stage to enhance image quality and reduce noise. Min-Max filtering is a range-based method with low computational complexity and simple implementation [15], [16]. Min-Max filtering consists of two operations: minimum filtering and maximum filtering. Minimum filtering, also known as erosion, replaces each pixel with the minimum value within a defined neighborhood window, effectively reducing small noise objects [17]. Maximum filtering, or dilation, replaces each pixel with the maximum value in the neighborhood window, enhancing feature visibility and reducing object loss [18].

$$I_{eroded}(x,y) = min_{(i,j)\epsilon W}\{I(x+i,y+j)\} \qquad (1)$$

Where $I_{eroded}(x,y)$ represents the pixel value at coordinates (x,y) after undergoing erosion and dilation operations, where modifications to the shape and structure of objects within the image occur. I(x+i, y+j) denotes the pixel value at coordinates (x+i,y+j) within a natural window centered at (x,y), facilitating localized analysis of image features. The term 'min' indicates the minimum operation, where the smallest pixel value within a specified neighborhood or set is chosen. This operation is crucial in erosion and dilation processes, influencing pixel intensities based on nearby values and thus shaping the overall outcome of these operations.

2.2.3. Enhancement

Enhancement is a process aimed at improving image quality by emphasizing important features and increasing contrast [19]. This stage is used to enhance subtle visual characteristics that may indicate carrot damage or rot, making them more distinguishable [20].

In this process, an Enhancement Intensity Transformation technique is employed that applies intensity limits where pixel values within or outside a specified range [17,55] are retained and temporarily altered, while others are set to 0. Additionally, a value of 200 is added to pixels that meet the criteria, thereby enhancing contrast or making specific features in the imagemoreprominent.

$$G(i,j) = \{T\ jika\ F(i,j) > T\ \} \quad \{F(i,j) Jika\ F\ (i,j) \leq T\ \} \tag{2}$$

Where 'F(i,j)' denotes the original pixel value at coordinates (i,j) in the initial image. Following the thresholding process, 'G(i,j)' represents the pixel value at the same coordinates (i,j) after applying the thresholding operation. The threshold value 'T' is predetermined and used to distinguish between different intensity levels or features in the image. This process involves assigning pixel values based on whether they meet or exceed the threshold value, thereby enabling the segmentation or enhancement of specific features within the image.

2.2.4. Convolution

Convolution is a fundamental technique in digital image processing and computer vision that combines two functions to produce a third function representing feature interactions [21]. In this study, convolution is applied to extract and enhance features that are difficult to detect through manual inspection.

Convolution operates by applying a kernel or filter matrix to each pixel region of the image, enabling feature extraction through weighted summation [22], [23]. This process helps highlight texture patterns and surface abnormalities associated with rotten carrots [24].

$$G(y,x) = \sum_{p=-m2}^{m2} \sum_{q=-n2}^{n2} H(p+m2+1, q+n2+1) \cdot F(y-p, z-q) \tag{3}$$

Where 'G' represents the resulting image from the convolution operation applied to input image 'F' using kernel 'H'. The coordinates (y,x) denote specific pixels within image 'F', while (p,q) refer to coordinates within the kernel 'H'. The variables 'm2' and 'n2' are defined as half the height and half the width of kernel 'H' minus one, respectively. Convolution involves overlaying the kernel 'H' over each pixel (y,x) of image 'F', computing weighted sums of pixel intensities within the kernel's spatial extent defined by (p,q), and assigning the result to the corresponding pixel in image 'G'. This process allows for various image enhancement and feature extraction tasks by emphasizing spatial relationships captured by the kernel 'H'.

3. Result and Discussion

This study aimed to classify carrot images into two categories, namely fresh and decayed carrots, using image processing techniques. Based on the analysis of four carrot images, three images were identified as decayed, while one image was classified as fresh. The identification process involved several sequential image processing stages, including enlargement, pre-processing, enhancement, and convolution.

The enlargement stage played an important role in improving the visibility of fine details related to surface damage or decay. By increasing image resolution, small texture variations and irregularities that indicate carrot deterioration became more observable. This step is particularly beneficial when analyzing image data in which critical features may not be clearly visible at the original resolution.

Pre-processing using Min–Max filtering effectively reduced noise and improved image consistency. Minimum filtering helped preserve small features associated with surface damage, while maximum filtering enhanced significant features and reduced the loss of important structural information. Although visual differences between the original and filtered images may appear subtle, the impact of these processes becomes more evident through histogram analysis.

Table 1 illustrates the results of the enlargement and filtering processes applied to carrot images. The corresponding histograms, shown in Table 2, reveal notable changes in pixel intensity distribution. In the enlargement process, the histogram demonstrates an increase in pixel frequency at certain intensity levels, indicating a higher level of detail due to improved resolution. This enhancement supports more accurate detection of fine surface features.

In contrast, the Min–Max filtering histogram shows a narrower intensity distribution, reflecting effective noise reduction. Lower intensity values become more dominant after minimum filtering, preserving small damaged regions, while maximum filtering increases the prominence of higher intensity values. These changes enhance the contrast between relevant features and the background, thereby facilitating more reliable identification of carrot damage.

Table 1. Process of Enlarging and Filtering Carrot Images

Carrot Image	Enlarge Process	Min-Max Process	Filtering
Image 1			
Image 2			
Image 3			
Image 4			

Table 2. Histogram of Enlargement and Filtering Processes

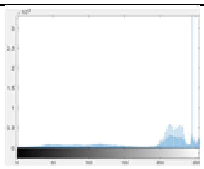
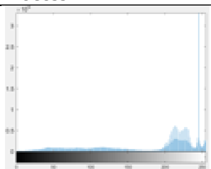
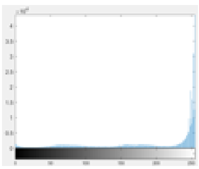
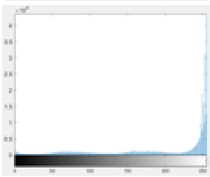
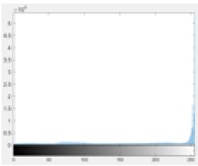
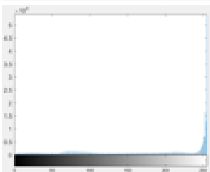
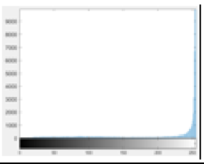
Carrot Image	Enlarge Process	Min-Max Process	Filtering
Image 1			
Image 2			
Image 3			
Image 4			

Image enhancement using intensity transformation techniques further improved image contrast, making disease-related features more distinguishable. The enhanced images contain clearer visual information, which simplifies subsequent analysis and interpretation. The results of the enhancement process are presented in Figure 3, while the corresponding histogram is shown in Figure 4.

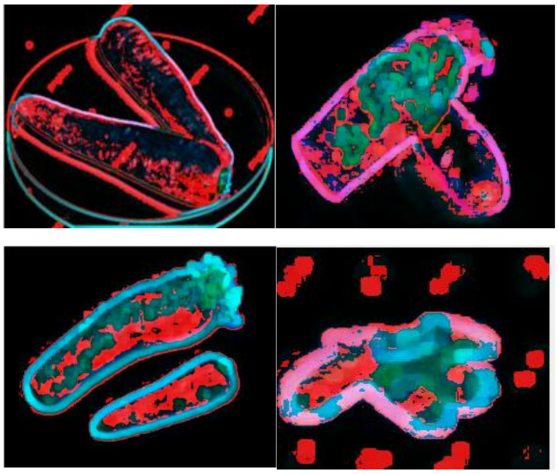


Figure 3. Enhancement Process

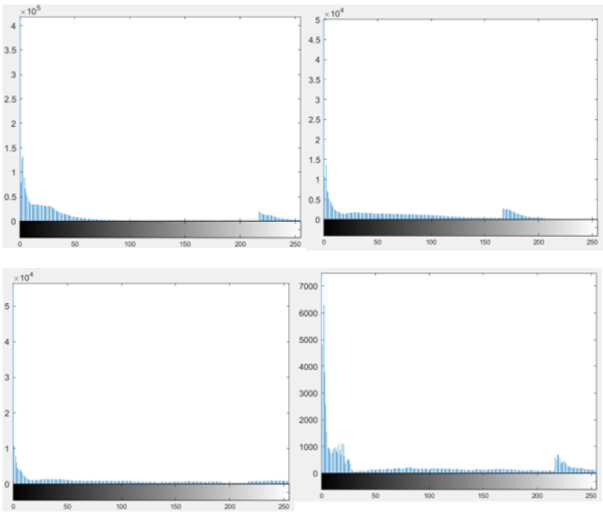


Figure 4. Histogram of Enhancement Process

The histogram of the enhanced image exhibits a wider intensity range and clearer separation between pixel intensity levels. Pixels that meet the predefined threshold criteria are emphasized, resulting in more prominent features that indicate potential decay. This confirms that the enhancement stage effectively improves image interpretability by highlighting important visual characteristics.

The convolution stage produced images with more clearly defined texture patterns and structural features, which are essential for identifying decay-related characteristics in carrots. As shown in Figure 5, convolution emphasizes spatial patterns and surface abnormalities that may not be easily detected using basic image analysis techniques.

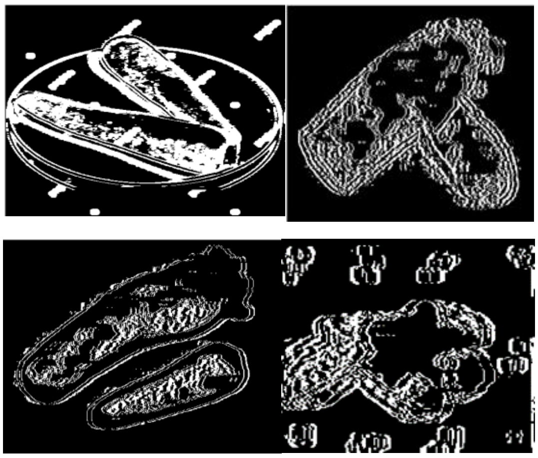


Figure 5. Convolution Process

The histogram corresponding to the convolution process, shown in Figure 6, does not exhibit significant changes compared to previous stages. This observation is expected, as convolution primarily focuses on spatial feature extraction rather than altering the overall pixel intensity distribution. Consequently, improvements achieved through convolution are more evident in the visual representation of texture and edge patterns than in histogram-based intensity analysis.

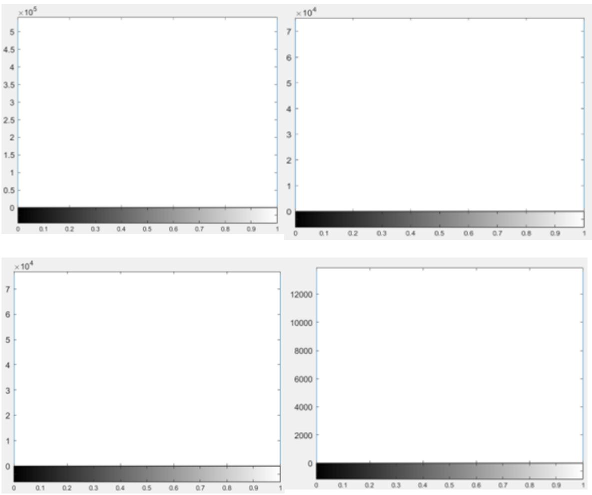


Figure 6. Histogram of Convolution Process

Histogram analysis across all processing stages provides a quantitative means of evaluating the effects of each image processing technique. By examining changes in pixel intensity distribution, histograms offer insights into improvements in image quality and feature visibility that may not be apparent to the naked eye. Histograms describe the distribution of pixel intensities, indicating whether an image appears brighter or darker, and reflect changes caused by image processing operations that influence color and illumination [25].

Overall, this research successfully developed an automated approach for identifying rotten carrots using image processing techniques. The combination of enlargement, pre-processing, enhancement, and convolution demonstrated effectiveness in improving image quality and supporting accurate classification. Histogram analysis at each stage provided valuable insights into how individual processing steps contributed to feature enhancement and decay detection.

The findings of this study are expected to offer a practical and efficient solution for automated detection of rotten carrots, assisting farmers and agricultural industry stakeholders in reducing economic losses caused by post-harvest spoilage. Moreover, the proposed method is not limited to carrots and can be adapted to other agricultural products, offering opportunities for further development in automated sorting systems and agricultural product quality assurance. This research represents a meaningful step toward leveraging image processing technology to support a more efficient and sustainable agricultural sector.

3.1. Limitations of the Proposed Method

Despite its effectiveness, this study has several limitations. First, the image dataset used in this research was limited in size, which may affect the generalizability of the results to broader and more diverse real-world conditions. Variations in lighting, background complexity, and camera quality were not extensively explored and may influence detection performance.

Second, the evaluation of results was primarily based on visual interpretation and histogram analysis, without the inclusion of quantitative performance metrics such as accuracy, precision, or recall. Future studies could incorporate quantitative evaluation and comparative benchmarking to further validate the effectiveness of the proposed approach.

Finally, the current method focuses on offline image analysis and has not yet been implemented in a real-time system. Future research may extend this work by integrating the proposed image processing pipeline into real-time sorting systems and combining it with machine learning techniques for improved robustness and scalability..

4. Conclusion

In conclusion, the proposed method demonstrates that image processing techniques, including enlargement, Min–Max filtering, intensity enhancement, and convolution, can effectively detect surface decay in carrots. The automated approach provides consistent and reliable results compared to manual inspection, contributing to efficient quality control and reduction of post-harvest losses. Future work may address dataset limitations, variable lighting conditions, and real-time implementation to further enhance system applicability.

References

[1] E. Sobari and F. Fathurohman, “Efektifitas Penyiangan Terhadap Hasil Tanaman Wortel (Daucus carota L.) Lokal Cipanas Bogor,” *Jurnal Biodjati*, vol. 2, no. 1, pp. 1-8, May 2017.

[2] F. Al Azami, A. A. Riadi, and E. Evanita, “Klasifikasi kualitas wortel menggunakan metode k-nearest neighbor berbasis Android,” *Jurasik (Jurnal Riset Sistem Informasi dan Teknik Informatika)*, vol. 7, no. 1, pp. 36–39, 2022.

[3] P. H. Marpaung, F. Siburian, and L. P. Nainggolan, “Analisis Yang Mempengaruhi Rotasi Tanaman Ercis (Pisum Sativum L) Ke Tanaman Wortel (Daucus Carota L) Kecamatan Dolat Raya, Kabupaten Karo*,” Jurnal Agroteknosains*, vol. 6, no. 1, p. 81, Apr. 2022, doi: 10.36764/ja.v6i1.757.

[4] K. Anwariyah, “Deteksi Objek Nomor Kendaraan Pada Citra Kendaraan Bermotor,” *JTIM : Jurnal Teknologi Informasi dan Multimedia*, vol. 1, no. 4, pp. 311–317, Feb. 2020, doi: 10.35746/jtim.v1i4.65.

[5] J. Jumadi, Y. Yupianti, and D. Sartika, “Pengolahan Citra Digital Untuk Identifikasi Objek Menggunakan Metode Hierarchical Agglomerative Clustering,” *JST (Jurnal Sains dan Teknologi)*, vol. 10, no. 2, pp. 148–156, Nov. 2021, doi: 10.23887/jst-undiksha.v10i2.33636.

[6] J. Zhang et al., “A comprehensive review of image analysis methods for microorganism counting: from classical image processing to deep learning approaches,” *Artificial Intelligence Review*, vol. 55, no. 4, pp. 2875–2944, Sep. 2021, doi: 10.1007/s10462-021-10082-4.

[7] I. Arief Wisky and Sumijan, “Deteksi Tepi untuk Mendeteksi Kondisi Otak Menggunakan Metode Prewitt,” *Jurnal Teknologi*, vol. 12, no. 2, pp. 34–39, Dec. 2022, doi: 10.35134/jitekin.v12i2.68.

[8] D. Prasetya, Y. D. Lestari, dan A. Budiman, “Perbaikan kualitas citra dengan kombinasi metode contrast stretching dan metode konvolusi,” *Prosiding Seminar Nasional Teknologi Informasi & Komunikasi*, vol. 1, no. 1, pp. 437–442, 2020.

[9] M. Mirbabaie, S. Stieglitz, and N. R. J. Frick, “Artificial intelligence in disease diagnostics: A critical review and classification on the current state of research guiding future direction,” *Health and Technology*, vol. 11, no. 4, pp. 693–731, May 2021, doi: 10.1007/s12553-021-00555-5.

[10] J. Saputra, Y. Sa’adati, V. Y. P. Ardhana, and M. Afriansyah, “Klasifikasi kematangan buah alpukat mentega menggunakan metode k-nearest neighbor berdasarkan warna kulit buah,” *Resolusi: Rekayasa Teknik Informatika dan Informasi*, vol. 3, no. 5, pp. 347–354, 2023.

[11] X. Liang, R. Zhang, M. L. Gleason, and G. Sun, “Sustainable Apple Disease Management in China: Challenges and Future Directions for a Transforming Industry,” *Plant Disease*, vol. 106, no. 3, pp. 786–799, Mar. 2022, doi: 10.1094/pdis-06-21-1190-fe.

[12] S. Avidan and A. Shamir, “Seam carving for content-aware image resizing,” *ACM Transactions on Graphics*, vol. 26, no. 3, p. 10, Jul. 2007, doi: 10.1145/1276377.1276390.

[13] D. Chandra and S. Sembiring, “Meningkatkan Efisiensi Pemrosesan Citra Untuk Klasifikasi Kualitas Biji Jagung Berbasis Tekstur,” *Jurnal Ilmiah Multidisiplin Ilmu Komputer*, Vol. 1, no. 2, pp. 60-73, Feb. 2024.

[14] A. Nurmasani and Y. Pristyanto, “Algoritme Stacking Untuk Klasifikasi Penyakit Jantung Pada Dataset Imbalanced Class,” *Pseudocode*, vol. 8, no. 1, pp. 21–26, Mar. 2021, doi: 10.33369/pseudocode.8.1.21-26.

[15] Z. Wang, Z. Liang, X. Li, and H. Li, “Indoor Visible Light Positioning Based on Improved Particle Swarm Optimization Method With Min-Max Algorithm,” *IEEE Access*, vol. 10, pp. 130068–130077, 2022, doi: 10.1109/access.2022.3228543.

[16] K. Yang, Z. Liang, R. Liu, and W. Li, “RSS-Based Indoor Localization Using Min-Max Algorithm With Area Partition Strategy,” *IEEE Access*, vol. 9, pp. 125561–125568, 2021, doi: 10.1109/access.2021.3111650.

[17] W. A. Saputra, M. Z. Naf’an, and A. Nurrochman, “Implementasi Keras library dan convolutional neural network pada konversi formulir pendaftaran siswa,” *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 3, no. 3, pp. 524–531, Dec. 2019, doi: 10.29207/resti.v3i3.1338.

[18] M. A. Masril and R. Noviardi, “Analisa morfologi dilasi untuk perbaikan kualitas citra deteksi tepi pada pola batik menggunakan operator Prewitt dan Laplacian of Gaussian,” *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 4, no. 6, pp. 1052–1057, 2020.

[19] S. Saifullah, “Segmentasi Citra Menggunakan Metode Watershed Transform Berdasarkan Image Enhancement Dalam Mendeteksi Embrio Telur,” *Systemic: Information System and Informatics Journal*, vol. 5, no. 2, pp. 53–60, Mar. 2020, doi: 10.29080/systemic.v5i2.798.

[20] T. M. Hameedi and G. A. Kaya, “Enhanced Data Hiding Using Some Attribute of Color Image,” *2023 5th International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)*, pp. 1–5, Jun. 2023, doi: 10.1109/hora58378.2023.10156670.

[21] N. Wulan Dari, “Identifikasi Deteksi Tepi Pada Pola Wajah Menerapkan Metode Sobel, Roberts dan Prewitt,” *Bulletin of Information Technology (BIT)*, vol. 3, no. 2, pp. 85–91, Jun. 2022, doi: 10.47065/bit.v3i2.271.

[22] R. J. Pally and S. Samadi, “Application of image processing and convolutional neural networks for flood image classification and semantic segmentation,” *Environmental Modelling & Software*, vol. 148, p. 105285, Feb. 2022, doi: 10.1016/j.envsoft.2021.105285.

[23] A. Pranata and E. Z. Astuti, “Pengolahan citra berbasis deteksi tepi Prewitt pada gambar gigi manusia,” *Eksplora Informatika*, vol. 6, no. 2, pp. 98–105, 2017.

[24] Y. Wu, X. Feng, and G. Chen, “Plant Leaf Diseases Fine-Grained Categorization Using Convolutional Neural Networks,” *IEEE Access*, vol. 10, pp. 41087–41096, 2022, doi: 10.1109/access.2022.3167513.

[25] M. Ikhsan, S. Supiyandi, and A. W. Hakiki, “Analisis perbandingan metode histogram equalization dan Gaussian filter untuk perbaikan kualitas citra,” *Journal of Science and Social Research*, vol. 7, no. 2, pp. 487–492, 2024, doi:10.54314/jssr.v7i2.1865.