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Utilization of Histogram Equalization and Threshold Methods on Finger Veins

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Abstract

Finger vein segmentation requires more accurate visualization to optimize patient services. This study aims to segment the finger vein features using the threshold method and compare those accuracy results. According to the experimental result, the AMT model achieves an accuracy = 57%, AGT accuracy = 62%, and the AMGT model can produce the highest accuracy at 65%. A combination of mean and Gaussian-based thresholding enhances segmentation precision and can harvest a more robust result for detecting features in complex images. The two processes between the Gaussian filter with processing using adaptive mean thresholds can produce more effective results to address finger vein segmentation issues.

Keywords:
Finger, Vein, Segmentation, Histogram, Equalization

1. Introduction

Finger vein segmentation plays a pivotal role in enhancing healthcare services by enabling secure and contactless biometric identification. Unlike external biometric traits, finger vein patterns are internal and unique to each individual, making them difficult to forge and highly reliable for identity verification. This technology is particularly beneficial in medical settings where accurate patient identification is crucial, such as in accessing electronic health records, administering medications, and ensuring the correct delivery of treatments. Moreover, the contactless nature of finger vein recognition aligns with hygiene standards in healthcare environments, reducing the risk of cross-contamination and infection spread [1].

Accurate segmentation of finger vein images is essential for the effectiveness of biometric systems in healthcare. Challenges such as uneven illumination and variations in finger positioning can impede the extraction of clear vein patterns, potentially leading to misidentification. Advanced segmentation techniques, including those utilizing convolutional neural networks (CNNs), have been developed to address these issues by enhancing image quality and accurately delineating vein structures. Implementing these sophisticated methods ensures that biometric systems maintain high accuracy and reliability, which is critical for patient safety and the integrity of healthcare services [2].

Finger vein segmentation remains a challenging task because traditional algorithms often fail to deliver accurate and consistent results. These methods struggle to adapt to variations in illumination, skin texture, and noise, leading to incomplete or erroneous vein extraction. The problem is further exacerbated by the limited availability of large, diverse public datasets and the absence of standardized reference benchmarks, which hinders

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model training, validation, and reproducibility. Consequently, the development of robust segmentation methods for finger vein recognition remains constrained. [3].

Finger vein segmentation faces significant challenges due to low image contrast and intensity inhomogeneity. The vein patterns often exhibit minimal distinction from surrounding tissues, making it difficult for conventional segmentation algorithms to accurately differentiate between foreground (veins) and background. Variations in lighting conditions, skin properties, and sensor sensitivity further exacerbate intensity inconsistencies across the image, leading to incomplete or incorrect vein extraction. These limitations reduce segmentation accuracy and hinder the overall reliability of finger vein recognition systems [4].

The finger vein segmentation problem includes extracting vein patterns from finger images, which is critical for biometric identification. This challenge obscures the vein structures due to low image contrast, uneven illumination, and noise. Effective segmentation requires advanced image processing or deep learning techniques capable of enhancing subtle vascular features while suppressing irrelevant background information. Accurate vein extraction is essential to ensure reliable feature representation and improve the overall performance of finger vein recognition systems [5].

Other issues of finger vein segmentation due to uneven illumination, finger position variations, and inconsistent image quality. It can cause complicate the separation of venous from non-venous regions. These factors introduce noise and distortions that hinder the accurate extraction of vascular patterns, making it difficult for traditional algorithms to maintain robustness and precision across diverse imaging conditions [6].

Many papers have explored various approaches to address The finger vein segmentation problem including neural network and probabilistic graphical model, LadderNet-based algorithm, Kernel Fuzzy C-means (KFCM), and an Active Contour Model (ACM), ResNet, Dilated Convolution, and the Mish activation function [7]. According to the review paper on the new modal biometric method for finger vein fusion and ECG, we undergo this study to analyze the location of veins based on the results of finger vein segmentation using threshold methods. It is to obtain clear visualization and help to establish an objective diagnosis.

2. Related Works

Finger vein recognition is a growing research area in biometric authentication and evaluation studies. Several approaches have been presented to enhance accuracy and efficiency in biometric applications, for instance, an article explored human identification through finger vein and ECG signals, proposing a fusion-based approach for biometric authentication [8] and developed an FPGA-enhanced system-on-chip using a deep learning model for finger vein recognition to advanced computational techniques for biometric applications [9]. Another paper introduced a multilevel threshold image segmentation method using horizontal and vertical multiverse optimization for COVID-19 chest radiography. The approach demonstrated the effectiveness of advanced thresholding techniques in medical image processing, providing insights into our use of adaptive threshold methods for finger vein segmentation [10].

Another work introduced an improved sparrow search algorithm for threshold image segmentation in enhancing segmentation accuracy. The outcomes demonstrate the suggested algorithm can overcome other algorithms by calculating entropy-based image segmentation. According to experiment results on both classical and medical images, the suggested approach enhances the segmentation effect in terms of peak signal-to-noise ratio and feature similarity [11].

An article explored a finger vein segmentation algorithm based on LadderNet, which can extract the centerlines of the veins consistently without being affected by fluctuations in vain width and brightness. The paper constructed LadderNet based on the conventional U-Net structure to simplify the network and reduce the parameters because of the characteristics of the finger vein dataset. According to the test on two benchmark datasets such as SDU-FV and MMCBNU_6000, the experimental results show that the LadderNet-based finger vein segmentation algorithm has achieved superior performance with an AUC of 91.56%, 92.91%, and an accuracy of 92.44%, 93.93% [3].

A recent present study exploits structure-specific contextual clues and iterated graph cut (IGC) method for automatic and accurate segmentation of finger-vein images. The technique utilizes the Gaussian probability model to determine the initial labels and apply a maximum posterior Markov random field (MAP-MRF) framework to update the data models of the object and the background. The study gathered 4 finger-vein databases and compared them with some benchmark methods. The experimental results displayed that the proposed IGC method outperforms the state-of-the-practice approaches in finger-vein image segmentation. The IGC with its deep learning (LSDL) counterpart, can increase the average F-measure value by 5.03%, 6.56%, 49.91%, and 22.89% when segmenting images from four different finger-vein databases [13].

DL is a growing approach to deal with many image classification issues [19][20][21][22][23]. Finger vein segmentation also can be resolved by DL algorithms. A study discussed a finger vein segmentation method and device based on a neural network and a probability graph model. The method comprises the following steps: generating a preprocessed image, generating a gold standard beneficial to neural network training, and taking the dense conditional random field of the Gaussian pairwise potential as an RNN to perform average field approximate reasoning. Finally, the method utilizes fusing the dense Conditional Random Field (CRF) into a neural network and performing training processing of the neural network. After training, the model can generate finger vein segmentation using a dense conditional random field (CRF) [18].

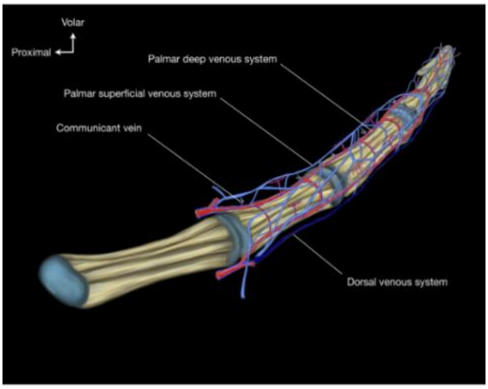
Another paper presented a finger vein segmentation method and apparatus based on a neural network and a probabilistic graphical model. In the model, the dense CRF with a Gaussian pairwise potential as a recurrent neural network (RNN) to establish average field approximate reasoning. It is to obtain the finer vein segmentation using CNN with a forward transfer process. In the training process, the error is transferred back to the neural network during a training process, and after a certain period of training, due to the full use of the advantages of the dense CRF [12].

To address finger vein segmentation issues, hand venous mapping provides valuable insights into the structure of finger veins to support the segmentation approach [14]. Various papers have explored adaptive thresholding techniques and histogram equalization for image binarization and contour detection to reflect the importance of effective segmentation methods for finger vein visualization [15][16][17].

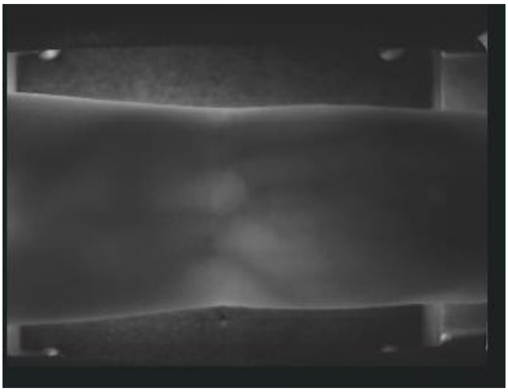
3. Experimental Setup

3.1 Dataset

This study gathered the finger vein dataset from the Kaggle research corpus at https://www.kaggle.com/datasets/ryeltsin/finger-vein/data). To evaluate the effectiveness of different thresholding methods for finger vein segmentation, we conducted a series of experiments using the samples.



Finger cross-session under human skin



Vascular anatomy

Fig. 1. Finger vein dataset

We selected the dataset at random to be processed using adaptive mean thresholds, adaptive Gaussian thresholds, and adaptive mean thresholds with Gaussian blur. To make the entire procedure smoother and more noise-resistant, use block size 15. The data is in bitmap (.bmp) format, so in image processing, histogram equalization is used to optimize the segmentation.

3.2 Proposed Method

1) Histogram Equalization

Visual enhancement of high-frequency spatial information can be done using histogram equalization. Histogram equalization works by modifying the pixel intensity of the image so that the resulting histogram is uniform. Histogram equalization is a technique for increasing the contrast in images of blood vessels in fingers by spreading the intensity of pixel values more evenly so that image details appear clearer.

2) Threshold Image Segmentation

Threshold image segmentation is obtained from information from the image gray-level histogram. This gray level comes from the difference between the target area and the background area, which is compared and then given a threshold that is appropriate for each value at each pixel so that segmentation can be carried out [7].
Formula of threshold $T(x, y)$

$$b(x,y) = \begin{cases} 0 \; if \; I(x,y) \;\; T\,(x,y) \\ 1 \; otherwise \end{cases}$$

where $b(x, y)$ is the binarized image and $I(x, y)$ [0,1] is the intensity of a pixel at position (x, y). Image binarization divides pixels into two groups: white and black.

3) Adaptive Mean Threshold

At the adaptive average threshold, the pixel value is replaced by the average value of all neighbors compared to the actual pixel value. If the actual pixel value is less than the average pixel value, the color will be black, and otherwise, the color will be white.

4) Adaptive Gaussian Threshold

In the adaptive Gaussian threshold, the image is segmented based on the average of the block size between the actual pixels and the neighboring pixel values with a constant value

C. Then this action produces a binary image from a grayscale image with the following equation:

$$T(x,y) = m(x,y) - k * s\ (x,y))$$

T is the threshold value at pixels x and y in a block. While m is the average value of pixels in a block. Then s is the standard deviation, and k is a constant value that has been set to control the sensitivity in the threshold process [11].

5) Adaptive Threshold using Gaussian Blur

In adaptive mean with Gaussian blur, the image is blurred first using a Gaussian filter, and then thresholding the mean is performed. Gaussian blur uses a 5 x 5 kernel with a standard deviation = 0. The formula is as follows:

$$G\ (x,y) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

Where σ is the standard deviation of the normal distribution. x and y denote the horizontal and vertical coordinates of the pixel point, with the origin at the top left corner of the image. Next, after processing using Gaussian blur, continue to the adaptive mean thresholding stage with an average of 15 x 15-pixel blocks around the central pixel and minus 3. If the pixel intensity is smaller than or equal to the local threshold, then the pixel is part of the object (white value = 255). If the pixel value is greater than the threshold, then the pixel is not part of the object (black value = 0).

This study employs a systematic approach to finger vein segmentation, beginning with the collection of high-resolution bitmaps (.bmp) images. The dataset comprises randomly selected finger vein images, which are processed using three thresholding techniques: AMT, AGT, and AMTG. Before applying these thresholding methods, histogram equalization enhances image contrast, allowing for a more uniform distribution of pixel intensities and improving vein structure visibility. This preprocessing step plays a critical role in reducing noise and enhancing segmentation accuracy.

The implementation phase involves applying each thresholding technique using a block size of 15, which balances noise suppression and vein clarity. The experimental workflow includes loading each image, applying histogram equalization, and processing the images with all three thresholding methods. The segmentation results are evaluated based on visual clarity and pixel-wise accuracy against ground truth images.

4. Result and Analysis

In this part, we present the results of various approaches including Histogram, Adaptive Mean Threshold (AMT), Adaptive Gaussian Threshold (AGT), and, Adaptive Mean Threshold using Gaussian Blur (AMTGB).

1) Histogram

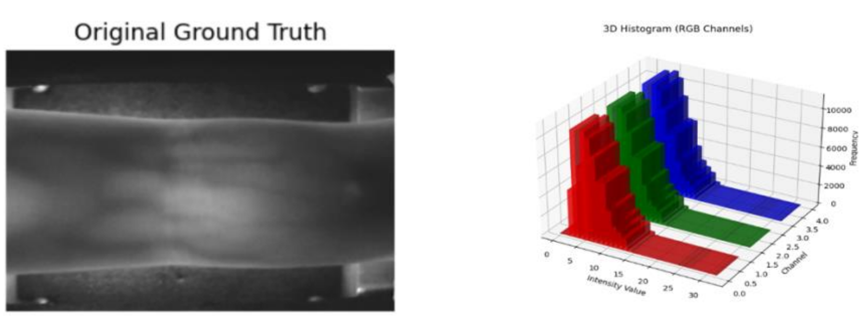


Fig. 2. Histogram of finger vein dataset

The histogram results show that the segmentation graph of the finger vein that indicated by the image being dominated by dark colors where low pixel intensity dominates. In addition, the RGB channel has a uniform pattern so that the segmentation results are consistent.

2) Adaptive Mean Threshold (AMT)

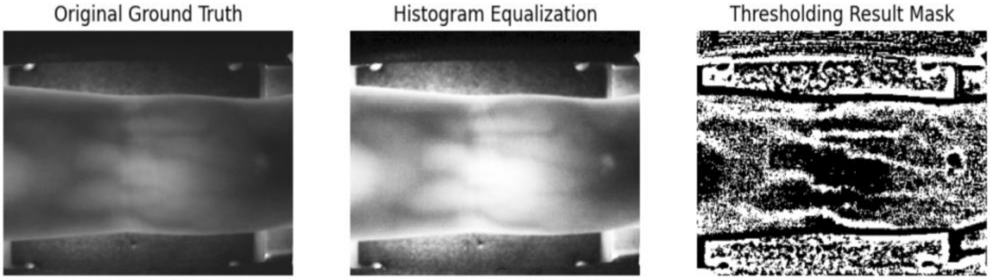


Fig. 3. Result of adaptive mean threshold

There are several stages of segmentation using AMT, namely the original ground truth, histogram equalization, and thresholding result mask. In the original ground truth, it is the initial image that has not been processed. This is indicated by a grayscale image with uneven lighting. Then the histogram equalization is carried out to increase the contrast of the image, which is indicated by a brighter middle structure so that it can be processed to the next stage. Finally, the thresholding result mask is used to produce binary segmentation.

3) Adaptive Gaussian Threshold

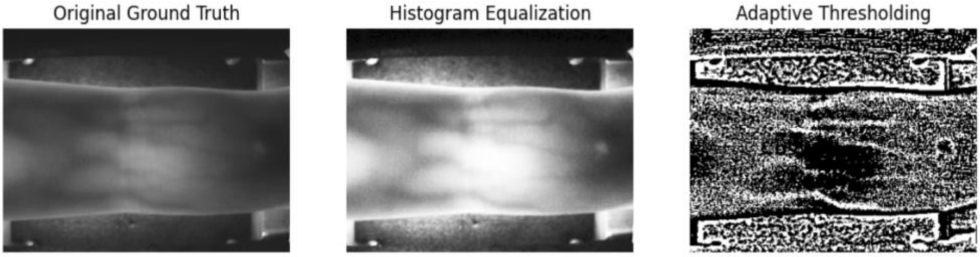


Fig. 4. Result of adaptive Gaussian threshold

4) Adaptive Threshold using Gaussian Blur

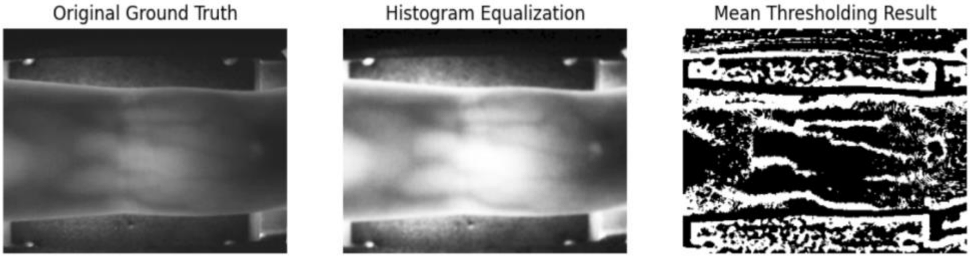


Fig. 5. Result of Adaptive Mean Threshold using Gaussian Blur (AMTGB)

In the original truth results, there are initial conditions of the image with blood vessel areas and other anatomical areas. The lighting conditions are still uneven. Then in the histogram equalization, there is an increase in the image, this is indicated by the increasingly clear fine features that were previously hidden in the shadows. Then in the adaptive thresholding process, the blood vessel structure is more defined and contrasted so that the details of the blood vessels are more visible, pixel value accuracy, FRR, and FAR of each method are as follows in Table 1:

Table 1: Accuracy Comparison of Models

Perform Models	Segmentation Models		
	Adaptive Mean Threshold (AMT)	Adaptive Gaussian Threshold (AGT)	Adaptive Mean using Gaussian Threshold (AMGTB)
Accuracy	57 %	62 %	**65 %**

This study evaluates three segmentation models including AMT, AGT, and AMGT based on their accuracy in image processing tasks. According to the experimental result, the AMT model achieves an accuracy = 57%, AGT accuracy = 62%, and the AMGT model can produce the highest accuracy at 65%. These results indicate that combining mean and Gaussian-based thresholding enhances segmentation precision, offering a more robust method for detecting features in complex images.

The adaptive mean threshold results after histogram equalization produce a clearer mask than the mask results using the adaptive Gaussian threshold. Although the results of the adaptive Gaussian threshold are smoother, in this case, the clarity of the location of the veins is needed for analysis. The adaptive mean threshold using Gaussian blur has smoother and clearer results than the two previous methods. This study confirmed that the adaptive threshold filtered using Gaussian shows more accurate results even though it has a correct level of 1 lower than the mean.

5. Conclusion

In this study, we undergo finger vein identification to analyze the location of veins based on the results of finger vein segmentation using various threshold methods. This study demonstrates that combining adaptive mean and Gaussian-based thresholding significantly improves finger vein segmentation accuracy. Among the three evaluated methods, the Adaptive Mean with Gaussian Thresholding (AMGT) achieved the highest accuracy at 65%, outperforming Adaptive Gaussian Thresholding (62%) and Adaptive Mean Thresholding (57%). These findings confirm that integrating Gaussian filtering with adaptive mean processing enhances the segmentation of complex finger vein patterns. This approach provides a more precise visualization of vein structures, supporting improved biometric identification and more effective patient service applications. Future work will focus on extending this method to larger and more diverse datasets, including different finger types and skin tones, to test generalizability. Moreover, integrating machine learning or deep learning techniques with adaptive thresholding may further enhance segmentation precision.

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References

[1] H. Kolivand, S. Asadianfam, K. A. Akintoye, *et al.*, "Finger vein recognition techniques: a comprehensive review," *Multimedia Tools and Applications*, vol. 82, pp. 33541–33575, 2023, doi: 10.1007/s11042-023-14463-5.

[2] Z. Zhang, P. Liu, C. Su, and S. Tong, "A High-Speed Finger Vein Recognition Network with Multi-Scale Convolutional Attention," *Applied Sciences*, vol. 15, no. 5, p. 2698, 2025, doi: 10.3390/app15052698.

[3] J. Zeng, F. Wang, C. Qin, J. Zhu, Y. Zhai, and B. Zhu, "A Novel Method for Finger Vein Segmentation," in *Lecture Notes in Computer Science*, Springer, Cham, 2019, pp. 589–600, doi: 10.1007/978-3-030-27532-7_52.

[4] J. Zhang, Z. Lu, and M. Li, "Finger-vein image segmentation based on KFCM and active contour model," in *Instrumentation and Measurement Technology Conference*, pp. 1–6, 2019, doi: 10.1109/I2MTC.2019.8826942.

[5] "A Novel Deep Learning Finger Vein Segmentation Algorithm for Identification and Recognition," 2022, doi: 10.21203/rs.3.rs-1723967/v1.

[6] J. Zhang, Z. Lu, and M. Li, "Active Contour-Based Method for Finger-Vein Image Segmentation," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 11, pp. 8656–8665, 2020, doi: 10.1109/TIM.2020.2995485.

[7] S. Jardim, J. António, and C. Mora, "Image thresholding approaches for medical image segmentation—short literature review," *Procedia Computer Science*, Elsevier B.V., vol. 217, pp. 1485–1492, 2023, doi: 10.1016/j.procs.2023.01.439.

[8] K. Su *et al.*, "Human identification using finger vein and ECG signals," *Neurocomputing*, vol. 332, pp. 111–118, Mar. 2019, doi: 10.1016/J.NEUCOM.2018.12.015.

[9] J. K., S. C., and H. M. A., "FPGA-enhanced system-on-chip for finger vein-based biometric system using novel DL model," *Integration*, vol. 98, p. 102231, Sep. 2024, doi: 10.1016/J.VLSI.2024.102231.

[10] H. Su *et al.*, "Multilevel threshold image segmentation for COVID-19 chest radiography: A framework using horizontal and vertical multiverse optimization," *Computer Biology and Medicine*, vol. 146, Jul. 2022, doi: 10.1016/j.compbiomed.2022.105618.

[11] D. Wu and C. Yuan, "Threshold image segmentation based on improved sparrow search algorithm," *Multimedia Tools and Applications*, vol. 81, no. 23, pp. 33513–33546, Sep. 2022, doi: 10.1007/s11042-022-13073-x.

[12] J. Zeng, F. Wang, C. Qin, B. Zhu, J. Zhu, Y. Zhai, J. Gan, and J. Deng, "Finger vein segmentation method and apparatus based on neural network and probabilistic graphical model," 2021.

[13] L. Lei, F. Xi, S. Chen, and Z. Liu, "Iterated graph cut method for automatic and accurate segmentation of finger-vein images," *Applied Intelligence*, vol. 51, no. 2, pp. 673–689, 2021, doi: 10.1007/S10489-020-01828-8.

[14] M. Lhuaire *et al.*, "Venous system mapping of the digits and the hand: An anatomical study and potential surgical applications," *JPRAS Open*, vol. 33, pp. 171–183, Sep. 2022, doi: 10.1016/J.JPRA.2022.04.008.

[15] I. Singh, O. James, T. Sinam, and T. R. Singh, "Local Contrast and Mean based Thresholding Technique in Image Binarization," 2012.

[16] N. A. Rehman and F. Haroon, "Adaptive Gaussian and Double Thresholding for Contour Detection and Character Recognition of Two-Dimensional Area Using Computer Vision," *Engineering Proceedings*, vol. 32, no. 1, 2023, doi: 10.3390/engproc2023032023.

[17] R. M. Dyke and K. Hormann, "Histogram equalization using a selective filter," *Visual Computer*, vol. 39, no. 12, pp. 6221–6235, Dec. 2023, doi: 10.1007/s00371-022-02723-8.

[18] J. Zeng, F. Wang, C. Qin, B. Zhu, J. Zhu, Y. Zhai, J. Gan, and J. Deng, "Finger vein segmentation method and device based on neural network and probability graph model," 2020.

[19] L. S. Sandy, S. Defit, and G. W. N. Gunadi, "Identifying Corn Leaf Diseases Using CNN Algorithm," *ijicom*, vol. 7, no. 1, pp. 99–107, Mar. 2025.

[20] R. L. Satria Putra and M. H. Wathan, "Shallots Classification using CNN," *ijicom*, vol. 3, no. 1, pp. 40–51, Feb. 2022.

[21] R. L. Satria and M. H. Wathan, "ConFruit: Effective Fruit Classification Using CNN Algorithm," *ijicom*, vol. 5, no. 1, pp. 10–18, Aug. 2023.
[22] M. Diqi and S. H. Mulyani, "Implementation of CNN for Plant Leaf Classification," *ijicom*, vol. 2, no. 2, pp. 1–10, Mar. 2021.
[23] Abidin, Hamzah, and M. E. Hiswati, "Efficient Fruits Classification Using Convolutional Neural Network," *ijicom*, vol. 3, no. 1, pp. 1–9, Oct. 2021.