Differentiation of Organic and Non-Organic Green Onions: An Experimental Image Segmentation Approach

Nerilou B. Dela Cruz
West Visayas State University
Iloilo City, Philippines
nerilou.delacruz@wvsu.edu.ph

Ma Beth S. Concepcion
West Visayas State University
Iloilo City, Philippines
mbconcepcion@wvsu.edu.ph

Regin A. Cabacas
West Visayas State University
Iloilo City, Philippines
rcabacas@wvsu.edu.ph

Yungcheol Byun
Jeju National University
Jeju, South Korea
yungcheolbyun@gmail.com

Bobby D. Gerardo
West Visayas State University
Iloilo City, Philippines
bgerado@wvsu.edu.ph

In-Ho Ra
Kunsan National University
Gunsan, South Korea
ihra@kunsan.ac.kr

ABSTRACT

Image segmentation is a crucial step in image analysis and in understanding especially complicated backgrounds. However, in the image segmentation research domain, real-world data (RWD) is limited depending on the subject or issue of the research study. This work introduces a real-world green onions image dataset collected from various locations in Iloilo, Philippines, and utilized in an experimental approach of color and texture analysis for differentiation of organic and non-organic. The image dataset undergone similarity measures using Euclidean distance. Furthermore, the results of this study highlight the intent to fill the gaps in the lack of real-world image datasets, which could be helpful in future research domains.

KEYWORDS

Segmentation, Green Onions Dataset, Organic and Non-Organic Differentiation, Real-World Data

1 INTRODUCTION

Nowadays, how food is grown can significantly impact human health [1]. Food nutrition plays an integral part in an individual's day-to-day life, contributing to diet and well-being [2]. However, human health as we all know is vulnerable to any diseases [3]. Thus, the food should contain valuable ingredients to holistically strengthen and nourish the body. In fact, during the Covid-19 pandemic, the World Health Organization [4] advised people to consume healthful food to build and sustain human body immunization. Furthermore, a rapid study [5] shows an increasing attention during the pandemic to opt for healthier quality food safety, and choice.

The increasing awareness of organic products, organic food consumption, and demand for higher prices introduced opportunity for malpractices such as fraudulent food production practices and concerning food safety issues [6-8]. Food authentication, a prominent countermeasure to these issues often is time-consuming, and expensive as methods like spectroscopic (e.g., near or Fourier-transform infrared, nuclear magnetic resonance with chemical pattern recognition) [9] is used. Therefore, this study unveils a non-invasive and inexpensive approach in differentiating organic and non-organic food sources using image segmentation.

In literature, few studies were conducted to classify organic and non-organic food. Work in [10] proposed a method for detecting organic and inorganic beans where the proposed method encountered several problems during the classification process due to the difficulty of variations of image conditions, size, resolution, poses, and rotation. On the other hand, authors in [9] proposed a low-cost sensor using a flashlight and pattern recognition system for diffraction grating organic and inorganic apples. From these studies, the primary issues include the dataset's image quality and background noise. Thus, to provide a solution to these challenges, this study introduces a real-world dataset of organic and non-organic green onions and proposes a framework to differentiate using image segmentation.

The succeeding Section 2 discusses in detail the organic and non-organic green onion dataset including the data collection method and characteristics. Section 3explains the proposed experimental analysis using image segmentation, while the initial results of the experiments are discussed in Section 4. Lastly, concluding statements are presented in Section 5.

2 DATA DESCRIPTION

Numerous studies claim that green onions have antioxidants, nutritional content, and significant compounds such as minor components of macro and micro minerals (e.g., potassium, calcium, magnesium, iron, selenium) and vitamins (e.g., carotene, folate, vitamin A, vitamin C) [11-14]. Thus, green onion is a condiment vegetable and is quite popular in dishes worldwide. Also, it is easy to plant, care for, and grow rapidly [12]. Moreover, it also has sulfur compounds, which plays a vital role in draught resistance [13] [15-17]. However, in the early 2000s, several studies conducted investigations due to that involvement of green onion in diseases and outbreaks [17-18]. For instance, the large outbreak as the infectious source [19-20]. Therefore, several studies have been interested in using green onions as subject of interest for foodborne concentration [21-24].

Due to unavailability of organic and non-organic green onion dataset, in June 2019, in Leon and Lambunao Iloilo, Philippines, the images of green onions were captured and gathered from different farms. The device used was smartphone, Samsung Galaxy Note 5, which has a camera of 16 Megapixels. Moreover, according to [25], the quality of the captured images varies depending on several factors, especially outdoor ones and outdoor scene depended on the weather and the time, which resulted from different illumination and atmosphere. For this study, the World Weather Online [26] was used to retrieve the weather and time during the data gathering as presented in Table 1 shows the number of gathered data from the two-locations mentioned.

Table 1: Data Collection Count

Farms/Sources	No. of Images	Total
Highland Along the road	370	
Highland Backyard	30	44
Inside Greenhouse	309	
Outside Greenhouse	695	1450
Lowland Backyard	239	
Lowland Along the road. Mixed with other vegetables	207	
Grocery Mall	11	22
Public Market	11	

Figure 1: Original Images a.) Highland along the road b.) Highland-backyard c.) Inside Greenhouse d.) Outside Greenhouse e.) Lowland Backyard. f.) Lowland along the road and mixed with other vegetables g.) Public Market (Unidentified Farm) h.) Grocery Mall (Unidentified Farm)

3 PROPOSED WORK

The application of segmentation is to change the representation image into more factual information and make it easier to analyze the features of image regions of particular interest [27]. Mather [28] defined segmentation as "the search for homogenous regions in an image and later the classification of these regions." During image acquisition, the observable challenges of the actual image reality is grasped, such as weather impact on illumination and the noises and obscurity of the background. In several studies [29-31] image segmentation was used to improve the accuracy of the visual categorization. Therefore, the process of segmentation is necessary to validated if image characteristics in the collected dataset will affect future utilization such as in case of image classification. This study, proposes to use two methods for image segmentation: 1) color extraction and 2) texture extraction.

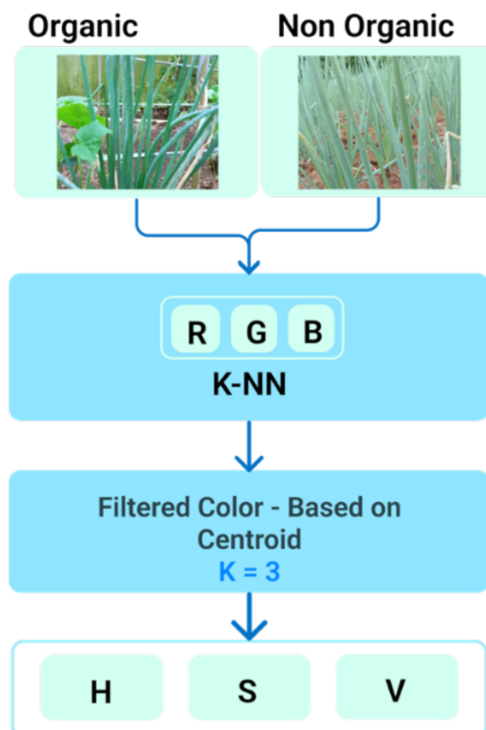

Figure 2: Color Extraction Framework.

Fig. 2 presents the framework for color extraction, wherein, the color space conversion of an image is a procedure that identifies color information. In this work, RGB images of green onions are transformed to Hue (H), Saturation (S), and V for values of such as brightness or contrast adjustment (HSV) colors, which allows the classifier to examine only the crucial pixels in the image. Additionally, one of the primary goals of this study is to distinguish the accurate color information of the color values from RGB color space. To realize this, a k-nearest neighbour (KNN) classifier was applied. Moreover, before converting to HSV color space to select the neighbouring pixels main centroid, the Euclidean distance

metric was defined only from three (3) nearest neighbours. This way, the color information is more inherent to discrimination.
Furthermore, Fig. 3 depicts the framework for texture extraction which can be used in image textures that has a complex visual pattern and governing distribution, especially grey-level color space [32]. The visual pattern usually involves (e.g., perceived lightness, roughness, regularity, linearity, and smoothness) [33]. For the experimental approach, the image was cropped to a specific area or focused on the nearest color and texture visibility. After cropping the images, transformed HSV was utilized to mask the filtered values in the range between the nearest neighbour colors making the foreground to be the only one visible. From the masked foreground, the images transformed to grey and contrast restoration was necessary to enhance the quality of the image from the lousy weather effects [25]. With this method, it can be easy to show essential regions and textures for the following procedure such as Normal Thresholding & Adaptive Thresholding.

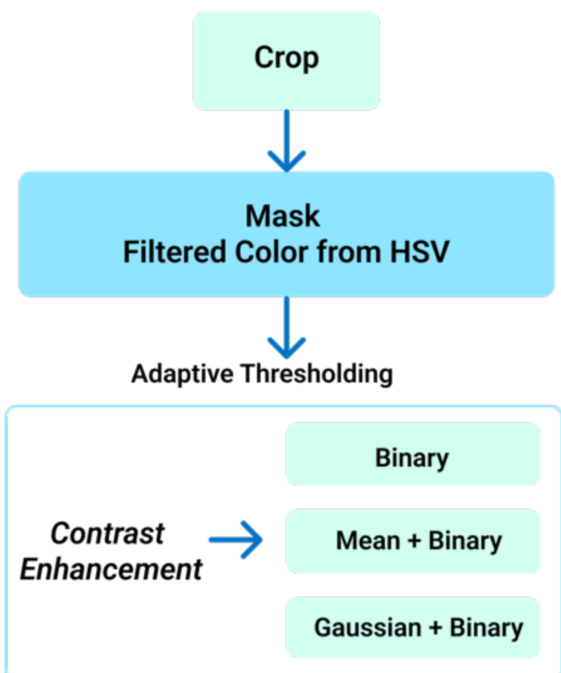

Figure 3: Texture Extraction Framework.

The standard or regular thresholding only uses the binary image and determines the threshold value based on the analyzed histogram.

Then all the grey level values below this T will be classified as black (0), and that above T will be white (1), which lessens the intricacy of the data and simplifies differentiation. Finding a good value of T requires extensive experiments and tuning in most conditions, thus, the used of adaptive thresholding function which is readily available in OpenCV. The adaptive thresholding enhances varying images with different lightning conditions in different areas. Although it may introduce intricacy based on the distinction in pixel intensities of each region which desirable for foreground image objects from the background. In this work, a trial-and-error-based combination of supplying mean and gaussian functions in the adaptive thresholding function was performed. After applying the thresholding procedure, the morphology and contour functions was included. Lastly, a similarity measure using Euclidean distance and adopted the threshold values from the study [34] which indicated seven categories to categorize the similarity between the images. Thus, to differentiate the unidentified between non-organic and organic green onions, and organic and non-organic green onions.

3 EXPERIMENTAL RESULTS & DISCUSSIONS

This section presents the evaluation results from the conducted experiments using color and texture extraction framework and the similarity using Euclidean distance. With the collected 1872 images of green onions contain organic (1450), non-organic (400), and unidentified (22) from two marketplaces, the proponents characterized the dataset according to various factors such as farms environments, weather, time, location, and class type (organic and non-organic). Different illumination, shades, textures, and challenging background can be observed from the dataset. Moreover, the dataset also includes other external factors that may affect future works in classification or image recognition. For instance, poor lightning conditions (i.e., large areas of shadows, highlight areas) which was due to different weather phases, obstructions from other places and distinction from the same color characteristic. For illustration, in the result of Fig. 4, in row number three, another plat leaf was also visible.

Fig. 5 depicts when the parameters used a threshold value minimum of 80 and 255 as the maximum. The experiment used a fixed value of block size set to 101. The differentiation between simple thresholding and adaptive thresholding apparently shows various characteristics using the dataset based on results of the following:

1. The simple thresholding excluded the texture of illumination.
2. The adaptive mean thresholding darkens the texture, and the visibility of illumination is crisp.
3. The adaptive gaussian thresholding flattened and distributed the texture of the illumination under various lightning conditions.

Thus, in Figure 6, the morphology and contours were able to recognize the edges and textures' regions. However, the parameters applied still needed several tuning experiments to recognize the green leaf individually. Moreover, In Tables III, IV, and V , the similarity between unidentified and non-organic, unidentified and organic and lastly organic and non-organic using the Euclidean distance is presented. The unidentified images data from grocery mall and public market was utilized as test data to get the similarity using Euclidean distance difference between organic and non-organic images and the observation are as follows:

1. The grocery mall has low similarity to an indoor organic greenhouse that to a non-organic.
2. The grocery mall has medium similarity to an organic lowland along the road, mixed with other vegetables that the non-organic; and
3. The public market has low similarity to an outdoor organic greenhouse than to a non-organic one.

Therefore, these datasets have similarities to organic image datasets. However, these results still require further experiments. For instance, in the Table V, the results show, non-organic highland-along the road green onions has strong similarity organic green onions (e.g., outside the greenhouse, lowland backyard, lowland-along the road & mixed with other vegetables).

Figure 4: Results of Color Extracted Proposed Framework. Cropped Images (column 1). Masked Images (column 2) and Filtered from HSV (column 3).

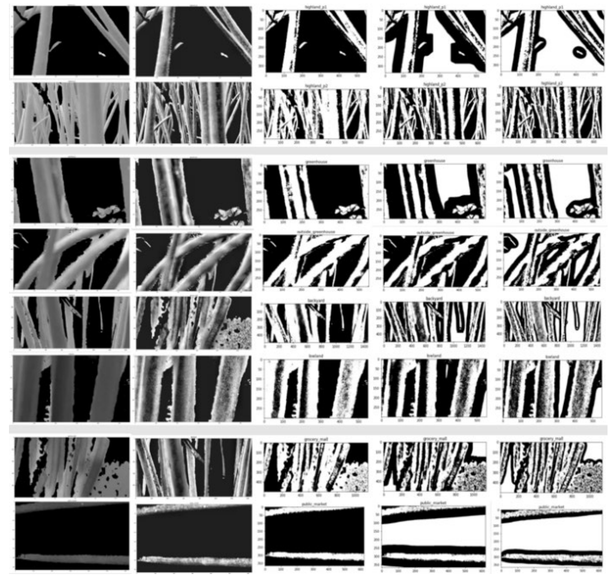

Figure 5: Results of texture Extracted Proposed Framework. Gray Transformed (column 1). Enhanced and Applied Clache Transformed (column 2). Normal Thresholding (column 3). Adaptive Mean thresholding (column 4). Adaptive Gaussian Thresholding (column 5).

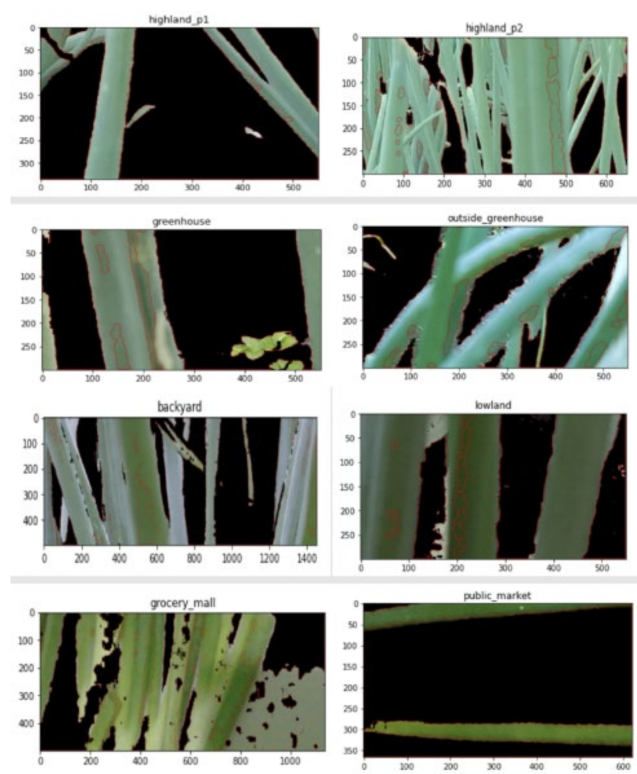

Figure 6: Ground Truth.

Table 3: Unidentified and Non-Organic Green Onions Similarity

Unidentified	Non-Organic	Euclidean Distance	Similarity
Grocery Mall	Highland Along the road	1844080.2	Minimal
	Highland Backyard	1466206.6	Minimal
Public Market	Highland Along the road	3412762.	Low
	Highland Backyard	3030181.	Low

Table 4: Unidentified and Organic Green Onions Similarity

Unidentified	Organic	Euclidean Distance	Similarity
Grocery Mall	Inside Greenhouse	379573.28	Low
	Outside Greenhouse	2314133.8	Low
	Lowland Backyard	2767946.8	Low
	Lowland Along the road. Mixed with other vegetables	4447092.	Medium
Public Market	Inside Greenhouse	1887321.6	Minimal
	Outside Greenhouse	3904849.8	Low
	Lowland Backyard	1353127.9	Minimal
	Lowland Along the road. Mixed with other vegetables	2873116.5	Low

Table 5: Non-organic and Organic Green Onions Similarity

Non-organic	Organic	Euclidean Distance	Similarity
Highland Along the road	Inside Greenhouse	1569491.4	Minimal
	Outside Greenhouse	689712.56	Good
	Lowland Backyard	4498699.	Medium
	Lowland Along the road. Mixed with other vegetables		Medium
Highland Backyard	Inside Greenhouse	1182420.5	Minimal
	Outside Greenhouse	1207214.2	Minimal
	Lowland Backyard	3024077.8	Low
	Lowland Along the road. Mixed with other vegetables		Low

4 CONCLUSIONS

Determining food's safety using image processing methods have become an emerging research topic in the past years and the availability of real-world dataset becomes a motivational factor for these endeavours. Thus, in this work, a real-world green onion image dataset and an experimental approach of image segmentation for colour and feature extraction is presented. In addition, this works provides initial analysis to differentiate the similarity between the categorize datasets, such as organic, non-organic, and unidentified using Euclidean Distance. In the future, the proponent's work will concentrate on extending the similarity differentiation to more sophisticated state-of-the-art algorithms classification such as neural network that is able to classify organic and non-organic green onions, and to add another suitable green leafy plant that could be classify as organic and non-organic using similar strategies.

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REFERENCES

[1] Bostan, I., Onofrei, M., Toderașcu, C., & Lazăr, C. M. (2019). An integrated approach to current trends in organic food in the EU. Foods, 8(5), 144.
[2] Black, C., Moon, G., & Baird, J. (2014). Dietary inequalities: what is the evidence for the effect of the neighbourhood food environment? Health & place, 27, 229-242.
[3] Hanif, R., Iqbal, Z., Iqbal, M., Hanif, S., & Rasheed, M. (2006). Use of vegetables as nutritional food: role in human health. Journal of Agricultural and Biological Science, 1(1), 18-22.
[4] World Health Organization, WHO. (2020). Campaign, "Connecting the world to combat coronavirus" #HealthyAtHome: Healthy Diet
[5] Wachyuni, S. S., & Wiweka, K. THE CHANGES IN FOOD CONSUMPTION BEHAVIOR: A RAPID OBSERVATIONAL STUDY OF COVID-19 PANDEMIC.
[6] Willer, H., & Sahota, A. (2020). The world of organic agriculture, statistics, and emerging trends 2020 at BIOFACH 2020.
[7] Ferreira, G., Tucker, J., Rakola, E., & Skorbiansky, S. R. (2021). Fraud in organic foods. In Food Fraud (pp. 335-350). Academic Press.
[8] Esteki, M., Regueiro, J., & Simal-Gándara, J. (2019). Tackling fraudsters with global strategies to expose fraud in the food chain. Comprehensive reviews in food science and food safety, 18(2), 425-440.
[9] Jiang, Y., & Li, C. (2020). Convolutional neural networks for image-based high-throughput plant phenotyping: a review. Plant Phenomics, 2020.
[10] Naveena .M, Pavithra .B .S, G. Hemantha Kumar. (2017). Classification of Organic and Inorganic Beans using Vision Approaches. International Journal of Engineering Science and Computing. (Vol. 7 Issue No.10).
[11] Imai, S., Tsuge, N., Tomotake, M., Nagatome, Y., Sawada, H., Nagata, T., & Kumagai, H. (2002). An onion enzyme that makes the eyes water. Nature, 419(6908), 685-685.
[12] Štajner D, Milić N, Čanadanović-Brunet J, Kapor A, Štajner M, Popović BM (2006) Exploring Allium species as a source of potential medicinal agents. Phytother Res 20:581–584
[13] Kapoulas, N., Koukounaras, A., & Ilić, Z. S. (2017). Nutritional quality of lettuce and onion as companion plants from organic and conventional production in north Greece. Scientia horticulturae, 219, 310-318.
[14] Khan SA, Jameel M, Kanwal S, Shahid S (2017) Medicinal importance of Allium species: a current review. International Journal of Pharmaceutical Science and Research 2:29–39
[15] McCallum J, Porter N, Searle B, Shaw M, Bettjeman B, McManus M (2005) Sulfur and nitrogen fertility affects flavour of field-grown onions. Plant Soil 269:151–158
[16] Liu X, Gao S, Liu Y, Cao B, Chen Z, Xu K (2019) Comparative analysis of the chemical composition and water permeability of the cuticular wax barrier in Welsh onion (Allium fistulosum L.). Protoplasma1-8

[17] Mead, P. S., L. Slutsker, V. Dietz, L. F. McCaig, J. S. Bresee, C. Shapiro, P. M. Griffin, and R. V. Tauxe. 1999. Food-related illness and death in the United States. Emerg. Infect. Dis. 5:607–625.
[18] Nainan, O. V., G. Xia, G. Vaughan, and H. S. Margolis. 2006. Diagnosis of hepatitis A virus infection: a molecular approach. Clin. Microbiol. Rev. 19:63–79.
[19] Dentinger, C. M., Bower, W. A., Nainan, O. V., Cotter, S. M., Myers, G., Dubusky, L. M., ... & Bell, B. P. (2001). An outbreak of hepatitis A associated with green onions. The Journal of infectious diseases, 183(8), 1273-1276.
[20] Wheeler, C., Vogt, T. M., Armstrong, G. L., Vaughan, G., Weltman, A., Nainan, O. V., ... & Bell, B. P. (2005). An outbreak of hepatitis A associated with green onions. New England Journal of Medicine, 353(9), 890-897.
[21] Park, E. J., Alexander, E., Taylor, G. A., Costa, R., & Kang, D. H. (2008). Fate of foodborne pathogens on green onions and tomatoes by electrolysed water. Letters in applied microbiology, 46(5), 519-525.
[22] Fino, V. R., & Kniel, K. E. (2008). UV light inactivation of hepatitis A virus, Aichi virus, and feline calicivirus on strawberries, green onions, and lettuce. Journal of food protection, 71(5), 908-913.
[23] Zheng, Y., & Hu, Y. (2017). Development of a fast and efficient method for hepatitis A virus concentration from green onion. Journal of virological methods, 249, 161-164.
[24] Gao, S., Liu, X., Liu, Y., Cao, B., Chen, Z., & Xu, K. (2021). Comparison of the effects of LED light quality combination on growth and nutrient accumulation in green onion (Allium fistulosum L.). Protoplasma, 258(4), 753-763.
[25] Narasimhan, S. G., & Nayar, S. K. (2001, December). Removing weather effects from monochrome images. In Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001 (Vol. 2, pp. II-II). IEEE.
[26] WWO, W. (2019). World weather online. Retrieved from https://www.worldweatheronline.com/lambunao-weather-history/iloilo/ph.aspx, https://www.worldweatheronline.com/leon-weather-history/iloilo/ph.aspx
[27] Kuruvilla, J., Sukumaran, D., Sankar, A., & Joy, S. P. (2016, March). A review on image processing and image segmentation. In 2016 international conference on data mining and advanced computing (SAPIENCE) (pp. 198-203). IEEE.
[28] P. Mather, Computer processing of remotely-sensed images, Chichester: Wiley, 1999.
[29] Nilsback, M.E., Zisserman, A.: Automated flower classification over a large number of classes. In: ICVGIP (2008)
[30] Uijlings, J.R.R., Smeulders, A.W.M., Scha, R.J.H.: What is the spatial extent of an object? In: CVPR, pp. 770–777 (2009)
[31] Chai, Y., Lempitsky, V., Zisserman, A.: Bicos: A bi-level co-segmentation method for image classification. In: ICCV (2011)
[32] Gonzales-Barron, U., & Butler, F. (2008). Discrimination of crumb grain visual appearance of organic and non-organic bread loaves by image texture analysis. Journal of food engineering, 84(3), 480-488.
[33] Gonzalez, R. C., & Woods, R. E. (2002). Digital Image Processing, New Jersey (pp. 48-54; pp. 699-816).
[34] Mustafa, A. A. (2015, January). A modified Hamming distance measure for quick detection of dissimilar binary images. In *International Conference on Computer Vision and Image Analysis Applications* (pp. 1-6). IEEE.