Tomayto, Tomahto: A Machine Learning Approach for Tomato Ripening Stage Identification Using Pixel-Based Color Image Classification

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Abstract—The main enterprise of the Philippine agriculture sector is crop cultivation where tomato is deliberated as one of the major crops in the country. With the abundance on tomato production, ripeness classification becomes fairly laborious and challenging, not to mention the subjective visual interpretation of human graders grounded from practical experience that is easily influenced by the environment and prone to error. Thus, this study proposes an automatic tomato ripeness identification using Support Vector Machine (SVM) classifier and CIELab color space via a machine learning approach. Dataset used for modeling and validation experiment in a 5-fold cross-validation strategy was composed of 900 images assembled from a farm and various image search engines. Divided into six classes that represent tomato ripening stages, experimental results showed that the proposed method was successful with 83.39% accuracy in ripeness classification detection. With this machine learning approach and combination of image processing techniques, the agriculture industry could benefit by automating the ripeness estimation which then could save tomatoes from damage.

Keywords— Image Processing, Image Classification, Support Vector Machine, Machine Learning, CIELAB color space

I. INTRODUCTION

Despite the transformation to an industrialized economy, Philippines is still primarily an agricultural country [1] where the gross value of agricultural production is amounted to PhP 429.7 billion during the first quarter of 2019 [2]. Employing 39.8% of the country's labor force [3], the main enterprise of the agriculture sector of the Philippines is crop cultivation [4] such as tomatoes, rice, corn, coconut, sugarcane, pineapple, mango, banana, and abaca, just to name a few. According to Philippine Statistics Authority, tomatoes are one of the major crops in the country [5]. In fact, tomato production reached 95.30 thousand metric tons from January to March 2019 [6]. The tomato (*Solanum lycopersicum*), known as "Kamatis" in the Philippines, has attracted the interest of food markets due to its medicinal impact such as decreasing the risk of various health conditions such as cancer, cardiovascular disease, and osteoporosis, and nutritive values such as phosphorus, iron, calcium, and vitamin C [7]. Lycopene, the major carotenoid in the fruit, is only amassed during the final ripening stage which accounts for 80% of the total carotenoid content [8]. Hence, tomato ripeness estimation has been viewed as a vital process that influences its quality evaluation. In fact, consumers use ripeness as a strand of what defines quality fresh fruits, which is grounded from its visual appearance such as color, size, and shape. Fruits color skin is not only an important determinant

of fruit selling price, but also as a feature of fruit ripeness [9] for numerous agricultural products such as apples [10, 11], bananas [12, 13], lime [14], mangoes [15-17], tomatoes [18, 19], and watermelons [20]. The abundance of harvest made it challenging to consistently determine tomato ripeness, which then becomes a problem when exported to a far place. Besides, farmers and human graders are usually subjective in ripeness visual interpretation grounding it from practical experience and/or ripeness classification charts, and easily influenced by the environment and prone to mistakes [21]. Thus, tomatoes are either unripe or overripe when they arrive at the market. This is the primary reason why tomatoes are often harvested during the "green" stage (See Fig. 1) to endure transportation [22]. Nevertheless, consumers are still less likely to purchase tomatoes when they are not on the "red" stage of ripening.
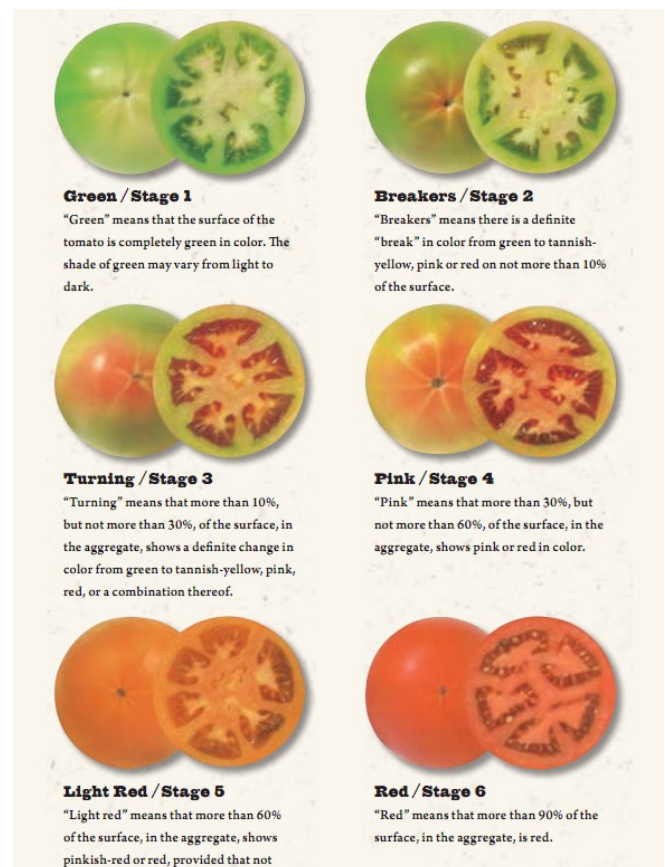

Fig. 1. Maturity and Ripening Stages of Tomatoes Based on United States Standards for Grades of Fresh Tomatoes.

The unceasing development of digital image processing, computer vision, and machine learning have paved a way for agriculture industry to further improve quality inspection and defect sorting [23] of fruits [10-20]. In case of tomatoes, the identification of ripening stage is achievable to categorize by computers using physical parameters like color since there is a positive correlation between color and ripeness of tomatoes [24]. Thus, this study proposes an automatic tomato ripeness identification by means of Support Vector Machine (SVM) classifier and CIELAB ($L*a*b*$) color space via a machine learning approach. Castro *et al.* [25] acknowledged SVM classifier as the best machine learning technique compared to K-nearest neighbor, artificial neural network, and decision tree algorithms, and L*a*b compared to RGB and HSV as the best color space for ripeness level classification of Cape gooseberry; hence, the usage of SVM and $L*a*b*$ color space for this study. The succeeding sections of the paper covered the review of existing research on ripeness classification of fruits and vegetables (Section 2), the materials and methods describing the logistics and phases of the development of the proposed tomato ripeness classification (Section 3), results from the experimental evaluations and its discussion (Section 4), and the conclusion and future research works (Section 5).

II. RELATED WORKS

Xiaobo, Jiewen, and Yanxiao [10], and Cárdenas-Pérez *et al.* [11] developed a computer vision system to identify the classification of apple maturity based on its color parameters. The first study examined three hundred and eighteen apples by using organization feature parameter by genetic algorithm which is expressed by the equation of feature parameter (1). The next study, on the other hand, analyzed one hundred and fourteen apples by calculating the apple color variances (ΔE) on CIELab color space using equation (2). Both studies were successful on classifying apple ripeness level using their own techniques where Cárdenas-Pérez *et al.* received a hundred percent apple ripeness classification accuracy while Xiaobo, Jiewen, and Yanxiao's method was more accurate than back-propagation artificial neural network (BP-ANN).

$$[26] \ x \ \surd \ p_1 + p_3 \qquad (1)$$

$$\surd \ (\Delta L*)^2 + (\Delta a*)^2 + (\Delta b*)^2 \qquad (2)$$

On the other hand, Mendoza and Aguilera [12], as well as Paulraj *et al.* [13] used bananas for their image classification. The former used RGB color space to investigate 100 ripe and 116 unripe bananas and classify the ripeness using Artificial Neural Network while the latter used $L*a*b*$ color space to examine 49 banana samples and classify it according to the 7 ripening stages by instigating computer vision. Interestingly, Mendoza and Aguilera performed more progressive analyses such as brown spot, image texture, and chemical analysis for a more accurate classification model. Perhaps, Mendoza and Aguilera's model was more accurate (98%) than the model developed by Paulraj *et al.* (96%) because of these additional analyses. Brown spot analysis was evaluated from binarized images of banana peel where the number of brown spot was identified from the $a*$ color which signifies brown spots. The texture analysis focused on segmenting the grayscale version of the sample using the average of 4 directions that extracted four textual features. Lastly, chemical analysis was done to determine total soluble solids using a digital refractometer.

Furthermore, similar and more methodologies of machine learning and image processing were performed on mangoes. First, Vélez-Rivera *et al.* [17] utilized $L*a*b*$ color space as well but mixed with HSB. Moreover, Manila mangoes were inspected through its physicochemical properties to estimate its ripening index (RPI). Zheng and Lu [15] utilized CIELAB color space to examine mangoes as well but the classification was performed using a least-squares support vector machine (LS-SVM) classifier. Fractal analysis was the foundation of LS-SVM since it has been successfully used on classification [27], appearance characterization [28], and quality prediction [29, 30] of foods. Nandi, Tudu, and Koley [16] utilized SVM as well but persisted on using RGB instead of converting to other color space to avoid additional calculations. Moreover, the classification performance was calculated and quantified using k-fold (k=6) cross-validation technique via sensitivity, specificity, predictivity, and accuracy measures.

$$Red\text{-}Green = mean(I(:,:,1)) \ / \ mean \ (I(:,:,2)) \qquad (3)$$

$$Red\text{-}Green = mean(I(:,:,1)) \ - \ mean \ (I(:,:,2)) \qquad (4)$$

The ripeness classification of tomatoes has also been part of the proposed systems that utilized computer vision, digital image processing, and machine learning algorithms. Polder, van der Heijden, and Young [18] did compare RGB images with hyperspectral images of tomato to classify its ripeness. Fisher's linear discriminant analysis (LDA) was used as the classification technique which is normally implemented for spectroscopic image classification. An imaging spectrograph with a spectral range of 396 to 736 nm and a 13 μm slit size, was used in the experiment to obtain spectra. Based from the findings of the study, RGB images showed substantial errors when classifying images with little feature variance – another reason why this study used other color space. RGB was used by Goel and Sehgal [19] as well but they had more success with it by using red-green color difference instead of separate red, green, and blue values. To obtain the red-green ratio and red-green difference, equations (3) and (4) were used. As far as the researchers are concerned, they proposed this approach because existing literature on tomato ripeness classification did not take into consideration the light spots (highlights) on tomato surface brought by natural environment illumination [26]. To minimize such case on this study, a computer vision system was setup as shown on Fig. 2. Nevertheless, the white colored pixels were interpolated by the 'tomato colors' from its neighboring segments during background removal. Taofik *et al.* [31] claimed to have a new data acquisition approach in this kind of classification quandary. On developing a model for their 'smart system' designed to detect ripeness of tomato and chili, the image dataset was taken periodically, at 65, 75, 83, and 90 days of planting. Yet, this kind of data acquisition approach was not elaborated in terms of how it helped to increase the classification accuracy. Arakeri and Lakhsmana [21] developed an automated grading system as well with the help of a fruit handling system that was used for moving the tomatoes on the conveyor belt. With the integration of image processing, tomatoes are moved to the respective bins based from its classification: defective or non-defective, and ripe or unripe. The capacity of the machine is 300 tomatoes per hour which is a lot of development on task automation. However, further works are still needed to increase the speed, even the accuracy, especially for image with high specular reflection.

III. Materials and Methods

A. Experimental Setup for Computer Vision System

The image acquisition system for collecting the dataset of tomato images, as an addition for pictures downloaded from image search engines, was a custom-built photography studio designed for food photo shoot. Figure 2 shows this computer vision system (CVS) and the setup of the lighting and studio equipment which was arranged in such a way that the image of tomatoes could avoid unwanted illumination [26]. Instead of a green screen backdrop, a blue screen backdrop (Westcott 131 Wrinkle-Resistant Chroma-Key Backdrop) was used due to the color features of tomato that includes green color. Two 45-watts light bulbs (R20 Incandescent Flood Light 2700K E26 Base) with diffuser (24x36" Softbox Bowens Speedring Kit) were placed at an angle of 45 degrees for both sides to ensure uniform illumination system. Tomatoes are placed on a 24x29 inches table wrapped with blue paper to complement the blue screen backdrop. A digital camera (Nikon D3100) was used to capture tomato images using both automatic and manual settings (f = 3.6; speed = 1/60 or 1/125; no zoom; no flash). The maximum resolution of 14.2 megapixels (4,608 x 3,072) was used to store JPEG images in a desktop computer (Core i5-9600k, DDR3, 1600MHz, 1TB hard drive, 256GB SSD, 8GB RAM) connected to the camera via a USB cable.
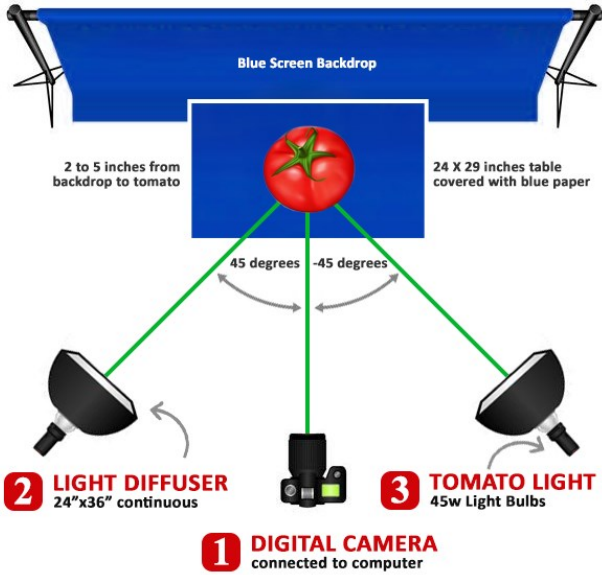

Fig. 2. Computer Vision System for Collecting Tomato Dataset.

B. Preparation of Tomato Images as a Dataset

1) Collection of Tomato Samples

Two image sources of tomato were used to assemble the dataset: image search engines and CVS. Google images and Adobe Stock were utilized for downloading images from the Internet. For CVS, a sample of tomato fruits was collected from Marulas Public Market (14.6738° N, 120.9837° E) for four consecutive weeks (50-100 tomatoes/week) sold by a vendor who imports from a plantation on Laguna. The fruits were then manually classified according to its ripeness stage, and stored inside 25^0C container storages [32]. Image search engines and CVS combined, the total number of sample was 963 tomatoes with different colors and ripeness levels.

$$C = Fg.*mask + Bg.*(\sim mask) \qquad (5)$$

2) Preprocessing of Tomato Images

Following the findings of Castro *et al.* [25] that revealed *L*a*b* color space as the recommended option to work with fruit classification when compared to RGB and HSV, tomato samples were converted first from RGB to L*a*b color space (rgb2lab in Matlab). Wu and Sun [33] also argued that this color space provides uniform color distribution which makes it appropriate for food color measurement. The use of L*a*b color space, where L* (black to white) is the luminance and a* (green to red) and b* (blue to yellow) are the chromatic components, is also considered essential because it matches the colors as perceived by human eyes. After the color space conversion, the digital images were pre-processed using the techniques employed by Garcia *et al.* [34] before segmenting skin color pixels. First, given the large size of images (4,608 x 3,072), each sample was scaled to 1/8th of its image size to speed up the calculations. Next, each sample taken by CVS was applied with a modified Chroma-key method inspired by Sang and Vinh's technique [35] grounded on coarse and fine filter. Using this processing method, the Chroma-key effect was performed on both foreground and background of image using equation (5). On the other hand, downloaded tomato images underwent histogram equalization, noise reduction, lighting correction, and sharpening [34] as the preprocessing techniques before going to image segmentation stage. These were performed in order to have a more accurate and smooth mask (see Figure 3 1b, and 2b) for removing the background.

3) Image Segmentation

For further analysis and understanding of digital images [36] like fruit ripeness classification, image segmentation is customarily a fixed image stage in order to extract a feature or an object of interest which is performed by thresholding, boundary detection or region dependent techniques. Among the aforesaid methods, the simplest and most widely used in image segmentation is thresholding [37]. The techniques in performing thresholding is classified as global (traditional, iterative, and multistage thresholding) and local (Niblack, Sauvola, Bernsen, and Yanowitz and Bruckstein's Method) [38]. Niblack thresholding algorithm, eq. (6), was validated as the better approach at removal of background noise [38]. Hence, tomato image dataset was binarized using Niblack technique to produce better segmentation results. Because of complex and sometimes undistinguishable background and tomato color, the binary-segmented images from CVS (Fig. 3, 2b) were smoother, clearer, and more precise when compared to downloaded images (Fig. 3, 1b). Specular reflection or glare on the tomato surface due to natural lighting conditions was already deciphered by Goel and Sehgal [19] by means of interpolating the neighboring tomato color pixels. As such, the same method was performed for downloaded images. In the case of images from CVS, this was not an issue because the setup of lighting condition was controlled. The resulting binarized images were secluded from the background pixels to eliminate unnecessary and similar colors with tomatoes as these colors could only confuse the classification model and lower the accuracy result. The pixels for tomato were shown in Figure 3 1c and 2c which evidently captured not only the shape feature of the fruit but also its color that will be used for building the tomato ripeness classification model.

$$T(x, y) = m(x, y) + k* \delta(x,y) \qquad (6)$$

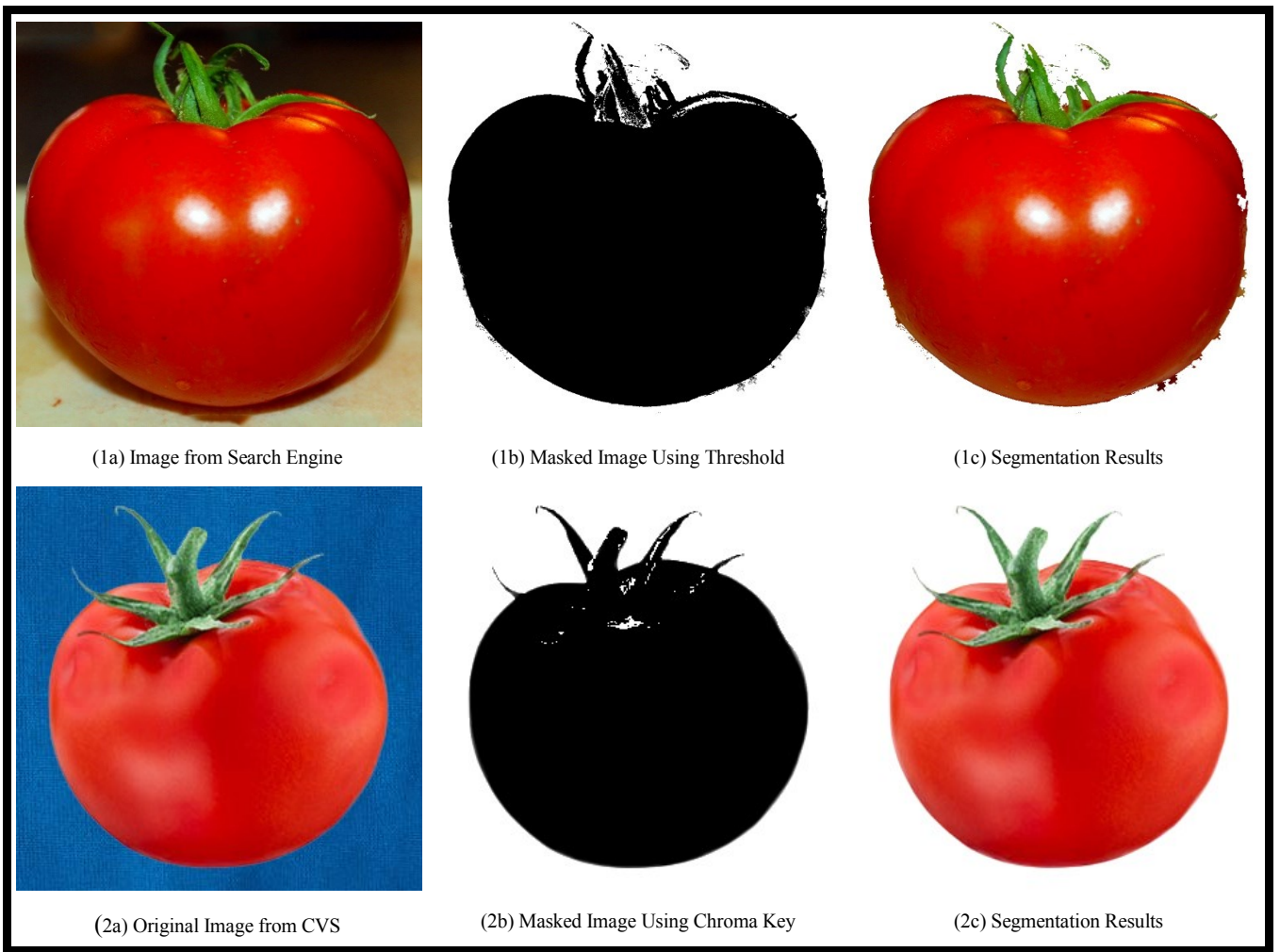|		
(1a) Image from Search Engine	(1b) Masked Image Using Threshold	(1c) Segmentation Results
(2a) Original Image from CVS	(2b) Masked Image Using Chroma Key	(2c) Segmentation Results

Fig. 3. Background Removal of Tomatoes Captured by CVS and Downloaded from Image Search Engines.

C. *Classification of Tomato Ripeness Level*

Features of tomatoes extracted from the previous process were classified according to ripeness level based from United States standards for grades of fresh tomatoes [39]. As shown on Figure 1, the color classification that indicates the stage of tomato maturity of a red fleshed variety of tomatoes includes six ripeness levels: green, breakers, turning, pink, light red, and red. At any ripeness stage, however, tomatoes normally have a mix and color gradient (instead of single solid color) between the neighboring levels. As such, the model accuracy of any color-based image classification could suffer and may produce incorrect predictions. Amirulah, Mokji, and Ibrahim [40] experienced the same dispute for starfruit color maturity classification and proposed a solution by overlapping the hue of adjacent levels where C_i is the fruit ripeness level and C_{i+1} is the adjacent fruit ripeness level, and quantified the area of fruit by dividing the number of pixels of class i that has a color value of less than or equal to H to total pixel of class i, and multiply the quotient to 100. The same approach was performed for the classification of tomatoes grounded from the pixel colors on this study. Apart from the color gradient to the overall skin of the fruit, color gradient spot of the next or previous ripeness level is also part of the classification; for instance, the breakers ripeness stage which is a green-colored gradient but also has a pink or red gradient in certain spots or the pink ripeness stage that still has a green gradient color in certain tomato surface. This is critical to ensure that the color for classification determinant is not focused on single mix.

To classify tomatoes based from its surface color, a non-linear SVM classifier was trained and validated. Castro *et al.* [25] acknowledged SVM classifier with $L*a*b*$ as the best machine learning technique and color space for ripeness classification of a fruit. Nonetheless, SVM was designed for two class problems only. Hence, the application of SVM to a multi-class classification requires a reduction of classes to produce binary problems. Two approaches could achieve the reduction of classes namely "one against all" or "one against one". The first approach is training the binary classifiers to separate each class from others, which is a fast method but usually suffer from marginal errors [41]. The second method is much like the first one but the "one against one" utilizes one optimization problem to obtain the N decision functions which is why it was selected and utilized for the multi-class of tomato ripeness level needed for the classification model.
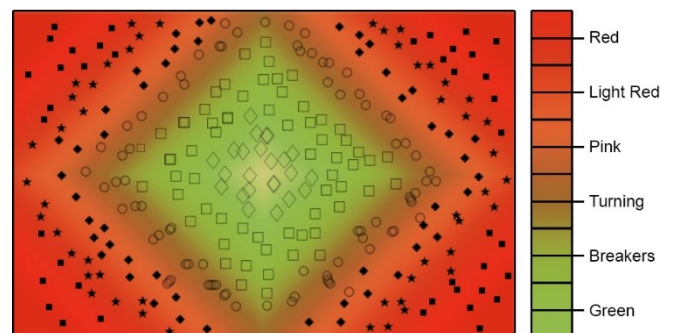

Fig. 4. Visualization of SVM Classification Plot.

TABLE I.   DETAILED ACCURACY RESULTS OF THE TOMATO RIPENESS CLASSIFICATION MODEL

Ripeness Stage	Tomato Samples		Correctly Classified		Accuracy (%)		Precision	Recall	*F*-Measure
	Training	Testing	Training	Testing	Training	Testing			
Green	105	45	101	43	96.19	95.55	0.9600	0.9114	0.9351
Breakers	105	45	94	38	89.52	84.44	0.8800	0.8980	0.8889
Turning	105	45	84	36	80.00	80.00	0.8000	0.8276	0.8136
Pink	105	45	91	38	86.67	84.44	0.8600	0.8600	0.8600
Light Red	105	45	76	35	72.38	77.78	0.7400	0.7450	0.7425
Red	105	45	75	37	71.43	82.22	0.7467	0.7417	0.7442
Total	**630**	**270**	**521**	**227**	**82.70**	**84.07**	**0.8311**	**0.8306**	**0.8307**

IV. EXPERIMENTAL EVALUATION

Using a one-against-one multi-class SVM, a 5-fold cross-validation strategy was performed to 900 colored-images of tomatoes (150 samples per ripeness level) divided into 70:30 ratios for testing and training per ripeness class. Each tomato sample was analyzed based from its $L*a*b$ values to build the classification model. Area Under Curve (AUC), denoting the aggregate measure of performance across all possible tomato ripeness classification thresholds, shows a close value to 1.0 which means that the prediction of the model is close to being correct. In classifying a non-linear dataset, the SVM linear classifier is still a thinkable algorithm so long that the given dataset would be projected into a higher dimension by adding a new dimensionality to transform the dimension into 3D in which the data is linearly separable but dimensionality reduction is through Principal Component Analysis (PCA).

The multi-class SVM classifier for tomato ripeness level yielded a mean accuracy of 83.39%, which is higher than the accuracy achieved by Taofik *et al*. [31] (accuracy = 80%) for the classification of tomato ripeness stage using fuzzy logic technique and RGB color space. The experimental results of Goel and Sehgal [19] (accuracy = 94.29%) utilizing Fuzzy Rule-Based Classification approach (FRBCS), on the other hand, produced a more accurate classification. Therefore, the classifier and color space used, SVM and $L*a*b$, may not be the most precise and accurate when it comes to this particular dataset, unlike the results of Castro *et al*. [25] when tested on cape gooseberry dataset. In classifying the ripening stage of tomatoes using this model, the most accurate is on the green stage which could be explained through the color percentage (almost 100%) of green shades present on the surface. On the other hand, the least accurate ripeness classification is on the light red stage where 60% of tomato surface shows pinkish-red while the remaining is a mix of red and pink shades. The confusion matrix presented a hard evidence that the tomato ripeness classification model had a problem with adjacent neighboring levels especially on the pinkish-red, light red and red stages. Nevertheless, the classification model yielded an acceptable precision, recall, and f-measure (precision = 0.8311; recall = 0.8306; f-measure: 0.8307).

V. CONCLUSION

With the critical role of agriculture in global economy, it is inevitable for technologists and agriculturists to find a way on how to mount machine learning on agricultural sector to drive agrarian productivity and harvest quality which can be observed on today's modern agricultural system operations. The automated process of ripeness estimation, for instance, is not only beneficial for increasing sustainable crop production but also for decreasing pre- and post-harvest waste. Machine learning models built for ripeness classification can be surely beneficial for different domains and applications like sorting

system based from maturity level and crop system to ensure timely harvest, and on the digital agriculture in general. This is the main research motivation of the proposed approach on classifying the tomato ripeness using SVM algorithm.

As indicated earlier, Philippines is an agricultural country where tomatoes are considered as one of the major crops of the country. Therefore, another motivation of this study is to develop an image classifier using machine learning process. The tomato dataset used for experiments were 900 images assembled by downloading images from search engines and capturing photos of tomatoes brought from a market which is directly supplied by a farm using CVS. Divided into 70:30 ratios for testing and training per ripeness class, each tomato sample was analyzed based from its $L*a*b$ values. To ensure high accuracy result, the proposed approach consists of three phases: (1) the experimental setup of CVS, (2) preparation of the tomato image dataset by undergoing pre-processing and image segmentation, and (3) classification of ripeness level using one-against-one multiclass SVM where a 5-fold cross-validation was performed on training and testing dataset.

In conclusion, the proposed machine learning approach using SVM and $L*a*b$ color space applied on classifying the ripeness maturity of tomatoes grounded from the pixel color generated a mean accuracy of 83.39%. Although this is more accurate than existing ones, there are also other classification models and techniques that exceeded this result. Evidently, color space and machine learning algorithm influenced the accuracy of the classification model. Therefore, future works should consider using other algorithms and color space, and try to mix different combination (SVM and RGB, ANN and HSL, to name a few) to determine which one will produce a more accurate model. Additionally, other features than color may also be considered for parameter extraction such as the diameter and age as these are proven indices for maturity of tomatoes [42]. Another direction of research is to assemble a dataset without using artificial background as captured using CVS to preserve natural lighting and background. Lastly, the application of nondestructive testing and non-invasive tools such as smart sensing, colorimetric [43], and hyper spectral imaging camera and systems [44] may be integrated in the machine learning process from dataset preparation to image classification. For information system and mobile application development standpoint, the machine learning model created from this study may be used to develop a real-time detection of tomato ripeness by either uploading a picture on a website application or by using the inbuilt camera of smartphones. In the manufacturing and agriculture perspective, the model can be installed as a core of tomato handling and sorting system. In closing, the image classification model proposed in this paper is a contribution to the agriculture sector, particularly on Philippine agriculture, in terms of providing a valid and accurate method of tomato ripening stage identification.

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