era_ready_ICOIACT2019_Indrabayu_deteksi_kematangan_strawbery.pdf

by

Strawberry Ripeness Classification System Based On Skin Tone Color using Multi-Class Support Vector Machine

Indrabayu
Informatics Engineering Department
Hasanuddin University
Makassar, Indonesia
indrabayu@unhas.ac.id

Nurhikma Arifin
Postgraduate Student of Electrical Engineering Department
Hasanuddin University
Makassar, Indonesia
hikmaarifins@gmail.com

Intan Sari Areni
Electrical Engineering Department
Hasanuddin University
Makassar, Indonesia
intan@unhas.ac.id

***Abstract*— This research aims to build an automatic sorting system for strawberry ripeness into three categories: unripe, partially ripe, and ripe. Manual fruit sorting has many weaknesses and limitations. One of the disadvantages is human error in the sorting process. Therefore, the implementation of artificial intelligence as replacement of human worker can mitigate the problem. Fruit ripeness is identified based on color characteristic, which is the Red, Green, Blue (RGB) value of the object. Multi-Class Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel function is implemented to classify the ripeness. The data was taken using the Logitech C920 web camera which then divided into training and testing data video. In this research, prototype of strawberries sorting is built with real-time video which is never been considered in previous researches. Training data consists of 70 unripe strawberries, 70 partially ripe strawberries, and 70 ripe strawberries. Meanwhile testing data comprises of 30 unripe strawberries, 30 partially ripe strawberries, and 30 ripe strawberries. The result shows that the strawberry ripeness classification system using Multi-class SVM with RBF kernel function produces up to 85.64% accuracy, where the parameters are $C = 7$ and gamma (γ) = 10^{-2}.**

Keywords—strawberry, HSV, RBF, multi-class support vector machine

I. Introduction

The implementation of Industry 4.0 with the application of artificial intelligence and the use of machinery becomes more effective and efficient to replace human tasks, especially in fruit sorting process based on its quality [1]. Sorting strawberries manually has limitations because it is influenced by employee subjectivity and physic ability. Therefore, at some point the classification process becomes inconsistent. Inconsistent classification will affect the quality of the fruit that will be sold or processed in industry. Thus, a solution is needed to maintain the quality of production and the trust of consumers.

Researches on fruit classification have been done widely, especially using computer vision and machine learning. Sidehabi et al. developed fruit sorting machines that classify passion fruit into three categories: unripe, nearly ripe, and ripe. This system using K-means Clustering as a segmentation method and Multi-Class Support Vector Machine (MSVM) as a classification method. The data is taken using a Logitech C270 web camera with input data in 6 sides of passion fruit. The dataset is divided into 93 pieces for training and 30 pieces for testing data. Based on the results of attempts conducted, passion fruit sorting system with RBF kernel function parameters $C = 25$ and $\gamma = 10^{-5}$ can achieve accuracy 93,3% with an average time to sort each fruit is 0.94128 seconds [2].

Li et al. conducted research on fast recognition method for elevating mature strawberries using deep learning approach. Experimental result showed that the average recognition rate of mature strawberries using Caffe-Net can reach 95% accuracy, higher than SVM that only yielded 84% accuracy [3]. Elhariri et al. presented a content-based images classification system to monitor the ripeness level of bell pepper by investigating and classifying the different maturity stages. Experimental result showed that the system has obtained a classification accuracy of 93.89%, using One-against-One Multi-class SVM with linear kernel function and 10-fold cross-validation [4]. Prakash et al. developed a classifier using multi-class SVM with RBF kernel to classify apple. This system was compared with conventional K-Nearest Neighbor (KNN) and Naïve Bayes classifiers. The multi-class SVM classifier with RBF kernel has shown superior classification performance [5].

El-Bendari et al. presented an automated multi-class classification approach for tomato ripeness measurement and evaluation via investigating and classifying the different maturity stages and then compared it with one-against-one (OAO) multi-class SVM with linear kernel, one-against-all (OAA) multi-class SVM with linear kernel and Linear Discriminant Analysis (LDA) algorithm). The result of the experiment showed that the system has obtained ripeness classification accuracy of 90.80% using one-against-one (OAO) multi-class SVM algorithm with linear kernel function, while ripeness classification accuracy of 84.80% using one-against-all (OAA) multi-class SVM algorithm with linear kernel function, and ripeness classification accuracy of 84% using LDA algorithm [6]. Mahendra et al. compared several images processing-based features for Support Vector Machine (SVM) to classify strawberries quality. The compared features were Red Green Blue color models (RGB), Hue Saturation Value color model (HSV), RGB histogram, Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), Oriented FAST and Rotated BRIEF (ORB), and Histogram of Oriented Gradients (HOG). Experimental result showed that SURF achieved the best accuracy up to 90.73% [7].

From previous researches that used SVM method, only Ref. [7] that work on strawberry classification. However, its data collection process was taken in the form of still images and not imitating real condition in industry. The main contribution of this research is the making of prototype with real-time video, thus it is closer to direct implementation according to industry needs.

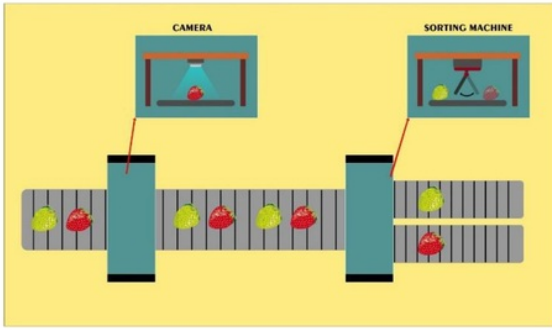

Fig. 1. Illustration of strawberry ripeness classification system

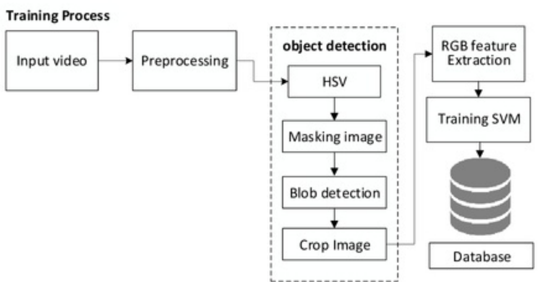

Fig. 2. Block diagram of training data

This research builds an automatic sorting system for industrial automation using the Multi-class SVM algorithm with RBF kernel. Based on previous researches, RBF is proven as the best SVM kernels that handle non-linear data. This system will classify the maturity of strawberries based on the RGB model into three categories: unripe, partially ripe, and ripe.

II. Proposed Method

The proposed design of the strawberry ripeness classification system is illustrated in Fig. 1. The proposed system will sort strawberries that meet ripeness standards. Unripe and partially ripe strawberries are categorized as strawberries that do not meet the standards while ripe strawberries are categorized as strawberries that meet the standards. This system is implemented on a prototype which uses a conveyor belt, box, and a camera. The data is taken using camera Logitech C920 with a resolution of 1920x1080 pixels, 15-megapixel snapshots, and 30 fps bitrate. The camera is installed in the box with predetermined lighting conditions using LED strips. The distance between the camera and strawberries is 25 cm. The strawberry sorting system is processed using python programming language. The dataset is divided into training and testing data.

A. Training Data

Block diagram of training data can be seen in Fig. 2.

- *Input Data*: Input data in the training process are video frames that consist of 70 unripe strawberries, 70 partially ripe strawberries, and 70 ripe strawberries. The best frame from training data is selected, so not all frames are used. Examples of frames used in the training data process can be seen in Fig. 3.

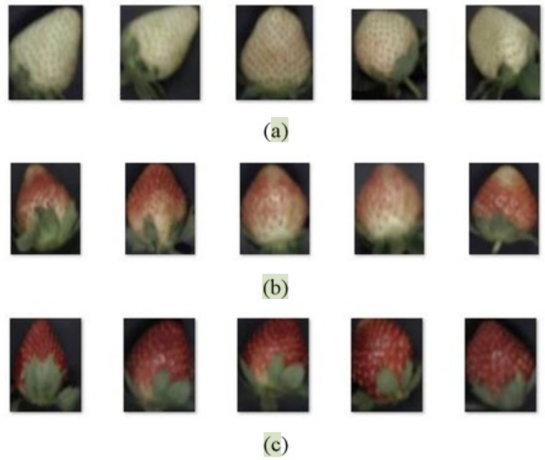

Fig. 3. Strawberry frames in the training process: (a) unripe strawberries; (b) partially ripe strawberries; and (c) ripe strawberries

- *Preprocessing:* In this process, the image is resized from 1920x1080 to 1280x720 pixel to reduce the execution time and cut the memory usage.

- *Convert RGB to HSV*: After the image went through the preprocessing, RGB image is converted to HSV. Digital images use RGB color models as color reference standards, so it is necessary to convert RGB to HSV models [8]. The HSV color space has three components: Hue, Saturation, and Value [9]. The hue (*H*) of a color refers to which pure color it resembles. All tints, tones, and shades of red have the same hue. Hue is described by a number that specifies the position of the corresponding pure color on the color wheel, as a fraction between 0 and 1. The saturation (*S*) of color describes how white the color is. A pure red is fully saturated, with a saturation of 1; tints of red have saturations less than 1, and white has a saturation of 0. The value (*V*) of a color, also called its lightness, describes how dark the color is. A value of 0 is black, with increasing lightness moving away from black. RGB to HSV conversion is described as follows.

1. Determine the RGB image (1)
2. Find max and min value for each *R*,*G* and *B* channel (2)

$$Cmax = MAX(R,G,B)$$
$$Cmin = MIN(R,G,B)$$

3 Calculate *H* Value

$$H = \begin{cases} 60\left(\dfrac{G-B}{Cmax - Cmin}\right), & if\ Cmax = R \\ 120 + 60\left(\dfrac{B-R}{Cmax - Cmin}\right), & if\ Cmax = G \\ 240 + 60\left(\dfrac{R-G}{Cmax - Cmin}\right), & if\ Cmax = B \end{cases} \quad (3)$$

If image data type is 8 bit, then:

$$H1 = \frac{H}{2}$$

4. Calculate S value

$$S = \begin{cases} \dfrac{Cmax - Cmin}{Cmax} \\ 0 \end{cases} \tag{4}$$

5. Calculate V value

$$V = Cmax \tag{5}$$

Example of strawberry image conversion from RGB to HSV can be seen in Fig. 4.

- *Image Masking*: In image masking process, HSV images are converted to binary images. Masking is a binary image consisting of a value of 0 and not 0 [10]. The masking process aims to separate the foreground and background images by utilizing the threshold process which takes the optimal range of lower and upper values from HSV. Based on the results of attempts conducted, the optimal lower and upper values of HSV can be seen in Table 1.

TABLE I. VALUE RANGE OF *HSV*

Value	*H*	*S*	*V*
Minimal	0	31	37
Maximal	49	168	212

- *Blob Detection*: The next process is to determine the area of the object to apply the bounding box (*bbox*). Blob detection will analyze the area and shape of the blob object from an image that becomes the focus of the detection. The example of object inside a *bbox* and the object after cropping can be seen in Fig. 5.

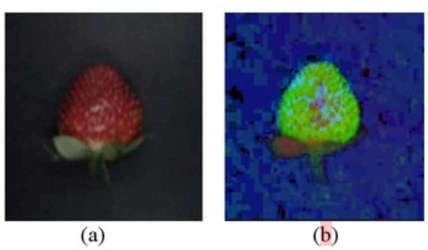

Fig. 4. (a) RGB frame of strawberry; (b) HSV frame of a strawberry after conversion

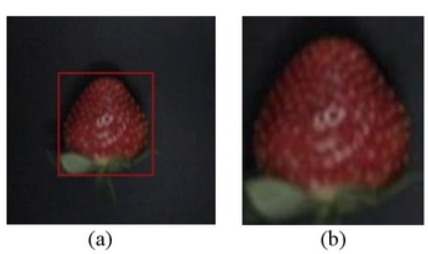

Fig.5. (a) Strawberry frame with *bbox*; (b) Strawberry frame after cropping

- *Feature Extraction*: At this stage, the feature extraction process is carried out. Feature extraction in this study will take the average value of Red, Green, and Blue ($\bar{R}\bar{G}\bar{B}$) in the image as a differentiator between objects.
- *Feature Labelling*: The value of $\bar{R}\bar{G}\bar{B}$ feature is labeled into three class categories (C), which are unripe ([illegible]), Partially Ripe (*PR*), and Ripe (*RP*). The range of minimum and maximum values of the feature $\bar{R}\bar{G}\bar{B}$ can be seen in Table II.

TABLE II. THE RANGE OF $\bar{R}\bar{G}\bar{B}$ VALUE

C	$\bar{R}$	$\bar{G}$	$\bar{B}$
1	56.824457-103.067	59.20913-98.28762	50.40640-79.81763
2	65.60592-114.8516	54.93678-97.06655	46.25921-80.54918
3	49.22717-92.92438	34.754802-71.30653	30.19935-56.48504

- *Database*: After the labeling process is done, the file is saved in CSV format to be used in the classification process.

B. Testing Data

Block diagram of testing data can be seen in Fig 6.

- *Input Data*: Input data in the testing process are video frames that consist of 30 unripe strawberries, 30 partially ripe strawberries, and 30 ripe strawberries.
- The preprocessing stages to feature extraction stage in the testing process are identical to those in the training process.
- *Classification using Multi-Class Support Vector Machine*: After the feature extraction process, the next step is to classify strawberry using SVM algorithm. This algorithm will classify strawberry ripeness to three categories: unripe, partially ripe, and ripe. The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data using only the attributes of test data. Four kernels in SVM are linear, RBF, sigmoid and polynomial [2]. RBF is one of the SVM kernels that can handle non-linear data. So, RBF kernel is used in this study.

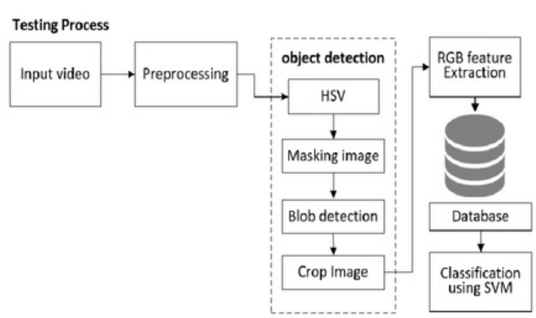

Fig. 6. Block diagram of testing data

Based on the experiment, the RBF kernel results in high classification accuracy compared to other kernels. C and gamma (γ) are the two parameters in the RBF kernel [11]. These parameters are very influential on the level of accuracy so it is necessary to find the optimal value of these parameters in order to produce an accurate classification model. The following equation can be used to calculate the RBF kernel.

$$K(x_n, x_i) = \exp(-\gamma\|x_n - x_i\|^2 + C) \quad (6)$$

$$f(x_i) = \sum_{n=1}^{n} a_n y_n K(x_n, y_n) + b \quad (7)$$

where x_n is the support vector data, a_n is the Lagrange multiplier, and y_n is the membership class label (+1, -1) with n = 1,2, 3, ..., N [2]. The examples of classification results can be seen in Fig. 8.

III. Result and Discussion

In this step, each frame of a video is tested for each class, where one class contains 70 strawberries. The initial step is to conduct experiments to find the optimal values of the C and gamma (γ) parameters of the RBF kernel. The C parameter defines the margin distance and the γ parameter defines the acceleration of the function. To obtain an accurate classification with the highest accuracy, the system has to be experimented with different values of C and γ. The experiment was carried out in 50 trials. The C value is modified from 1 to 10 and the γ value is modified from 10^{-5} to 10^{-1}. The experiment shows that the optimal value of C is 7 and γ is 10^{-2}. Experimentation results to find an optimal value of C using $\gamma = 10^{-2}$ is shown in Table III.

Based on the experiment, the optimal parameter values are $C = 7$ and $\gamma = 10^{-2}$. The highest overall accuracy yielded using these optimal parameters is 85.64%. The accuracy for Unripe (*UR*), Partially Ripe (*PR*), and Ripe (*RP*) classes are 97.07%, 62.94%, and 96.27%, respectively. In this system, the detection error is caused by several conditions, i.e. leaves that partially cover the strawberries, the background included in the bounding box, and color similarity between strawberries. Some of these factors cause the detection results to be inaccurate and unstable. The examples of the detection error are shown in Fig. 9

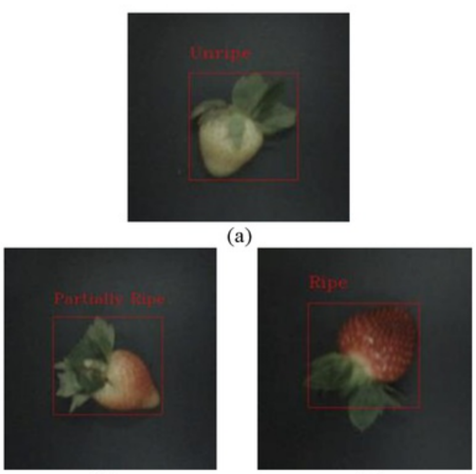

Fig. 8. Examples of classification results in the testing process (a) unripe; (b) partially ripe; (c) ripe

IV. Conclusion

This strawberry ripeness level classification system uses multi-class support vector machine algorithm with RBF kernel, with a value of $C = 7$, and $\gamma = 10^{-2}$. This shows that the high parameter values used in the kernel does not necessarily produce good accuracy. Video data used in the training process include 70 unripe strawberries, 70 partially ripe strawberries, and 70 ripe strawberries, while data in the testing process include 30 unripe strawberries, 30 partially ripe strawberries, and 30 ripe strawberries. This system yields the highest accuracy of 85.64%.

TABLE III. EXPERIMENTATION ON C VALUE USING GAMMA=10^{-2}

	C	Class	PREDICTION *UR*	*PR*	*RP*	Total	Accuracy [%]	Average Accuracy [%]
ACTUAL	1	*UR*	900	9	7	916	94.33	84.31
		PR	115	485	223	823	78.95	
		RP	21	21	951	993	97.65	
	2	*UR*	898	9	9	916	98.03	84.15
		PR	97	477	249	823	57.95	
		RP	16	19	958	993	96.47	
	3	*UR*	898	9	9	916	98.03	84.93
		PR	79	497	247	823	60.38	
		RP	28	15	950	993	96.37	
	4	*UR*	898	910	891	916	98.03	85.14
		PR	83	503	237	823	61.11	
		RP	14	23	952	993	96.27	
	5	*UR*	899	11	6	916	98.14	85.55
		PR	80	513	230	823	62.33	
		RP	13	25	955	993	96.17	
	6	*UR*	896	13	7	916	97.81	56.81
		PR	76	519	228	823	63.06	
		RP	13	26	95	993	9.56	
	7	*UR*	895	13	8	916	97.07	85.64
		PR	74	518	231	823	62.94	
		RP	11	26	956	993	96.27	
	8	*UR*	891	15	10	916	97.27	85.29
		PR	75	513	235	823	62.33	
		RP	11	26	956	993	96.27	
	9	*UR*	888	18	10	916	96.94	84.94
		PR	82	507	234	823	61.60	
		RP	11	26	956	993	96.27	
	10	*UR*	886	20	10	916	96.72	84.91
		PR	81	509	233	823	61.84	
		RP	11	27	955	993	96.17	

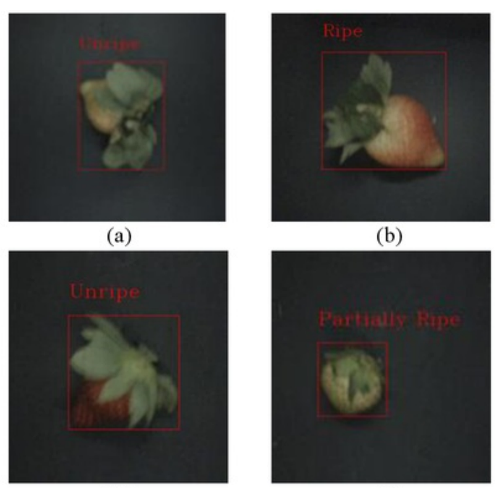

Fig. 9. Examples of detection error

The development of this research is to optimize the detection process by using other algorithms so that the system can adjust the bounding box shape of the object without taking the background.

ACKNOWLEDGMENT

This work is supported by Artificial Intelligence Laboratory, Department of Informatics, the Faculty of Engineering, Hasanuddin University and is funded by DIKTI as a part of magister grade scheme.

REFERENCES

[1] D. H. M. Yahya, M. Kes, "Industrial Era 4.0: Challenges and Opportunities for the Development of Indonesian Vocational Education," p. 27, 2018.

[2] S. W. Sidehabi, A. Suyuti, I. S. Areni, and I. Nurtanio, "The Development of Machine Vision System for Sorting Passion Fruit using MultiClass Support Vector Machine," Journal of Engineering Science and Technology Review, vol. 11, no. 5, pp. 178–184, Oct. 2018.

[3] X. Li, J. Li, and J. Tang, "A deep learning method for recognizing elevated mature strawberries," in *2018 33rd Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, 2018, pp. 1072–1077.

[4] E. Elhariri, N. El-Bendary, A. M. M. Hussein, A. E. Hassanien, and A. Badr, "Bell pepper ripeness classification based on support vector machine," in *2014 International Conference on Engineering and Technology (ICET)*, 2014, pp. 1–6.

[5] J. Suriya Prakash, K. Annamalai Vignesh, C. Ashok, and R. Adithyan, "Multi class Support Vector Machines classifier for machine vision application," in *2012 International Conference on Machine Vision and Image Processing (MVIP)*, Coimbatore, Tamil Nadu, India, 2012, pp. 197–199.

[6] N. El-Bendary, E. El Hariri, A. E. Hassanien, and A. Badr, "Using machine learning techniques for evaluating tomato ripeness," *Expert Systems with Applications*, vol. 42, no. 4, pp. 1892–1905, Mar 2015.

[7] O. Mahendra, H. F. Pardede, R. Sustika, and R. B. Suryo Kusumo, "Comparison of Features for Strawberry Grading Classification with Novel Dataset," in *2018 International Conference on Computer, Control, Informatics and its Applications (IC3INA)*, Tangerang, Indonesia, 2018, pp. 7–12.

[8] B. Y. Budi Putranto, W. Hapsari, and K. Wijana, "Image Color Segmentation with HSV detection to detect objects," *Journal of Informatics*, vol. 6, no. 2, Feb 2011.

[9] O. R. Indriani, E. J. Kusuma, C. A. Sari, E. H. Rachmawanto, and D. R. I. M. Setiadi, "Tomatoes classification using K-NN based on GLCM and HSV color space," in *2017 International Conference on Innovative and Creative Information Technology (ICITech)*, Salatiga, 2017, pp. 1–6.

[10] U. Qidwai and C. H. Chen, *Digital Image Processing: An Algorithmic Approach with MATLAB.* CRC Press, 2009.

[11] C.-W. Hsu, C.-C. Chang, and C.-J. Lin, "A Practical Guide to Support Vector Classification," p. 16.

era_ready_ICOIACT2019_Indrabayu_deteksi_kematangan_s...

ORIGINALITY REPORT

%19	%11	%16	%11
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	slides.com Internet Source	%2
2	docplayer.net Internet Source	%2
3	Oka Mahendra, Hilman F. Pardede, Rika Sustika, R. Budiarianto Suryo Kusumo. "Comparison of Features for Strawberry Grading Classification with Novel Dataset", 2018 International Conference on Computer, Control, Informatics and its Applications (IC3INA), 2018 Publication	%2
4	www.ijarcce.com Internet Source	%2
5	Esraa Elhariri, Nashwa El-Bendary, Ahmed M. M. Hussein, Aboul Ella Hassanien, Amr Badr. "Bell pepper ripeness classification based on support vector machine", 2014 International Conference on Engineering and Technology (ICET), 2014	%1

Publication

6 J. Suriya Prakash, K. Annamalai Vignesh, C. Ashok, R. Adithyan. "Multi class Support Vector Machines classifier for machine vision application", 2012 International Conference on Machine Vision and Image Processing (MVIP), 2012 — %1

Publication

7 www.ijetmas.com — %1

Internet Source

8 doaj.org — %1

Internet Source

9 "Intelligent Computing, Networking, and Informatics", Springer Nature, 2014 — %1

Publication

10 San Jose, L.A.. "Analysis of an inventory system with exponential partial backordering", International Journal of Production Economics, 200603 — <%1

Publication

11 Gajendra Jung Katuwal, John Kerekes, Rajeev Ramchandran, Christye Sisson, Navalgund Rao. "Automatic fundus image field detection and quality assessment", 2013 IEEE Western New York Image Processing Workshop (WNYIPW), 2013 — <%1

Publication

12	research.ijcaonline.org Internet Source	<%1
13	Nashwa El-Bendary, Esraa El Hariri, Aboul Ella Hassanien, Amr Badr. "Using machine learning techniques for evaluating tomato ripeness", Expert Systems with Applications, 2015 Publication	<%1
14	Submitted to TAR University College Student Paper	<%1
15	espace.library.uq.edu.au Internet Source	<%1
16	Submitted to The Hong Kong Polytechnic University Student Paper	<%1
17	epdf.tips Internet Source	<%1
18	Submitted to Xianjiatong-Liverpool University Student Paper	<%1
19	Submitted to Mansoura University Student Paper	<%1
20	Beke-Szikszay Tibor-Laszlo, Corneliu Marinescu, Danila Adrian. "Software Control Method for a Solar Tracking System", 2018 International Conference on Applied and Theoretical Electricity (ICATE), 2018	<%1

Publication

21	Submitted to Asia Pacific Instutute of Information Technology Student Paper	<%1
22	polen.itu.edu.tr Internet Source	<%1
23	Jiaxin Wu. "Prioritisation of candidate Single Amino Acid Polymorphisms using one-class learning machines", International Journal of Computational Biology and Drug Design, 2011 Publication	<%1
24	jtsiskom.undip.ac.id Internet Source	<%1
25	Agus Winarno, De Rosal Ignatius Moses Setiadi, Adli Azhar Arrasyid, Christy Atika Sari, Eko Hari Rachmawanto. "Image watermarking using low wavelet subband based on 8×8 sub-block DCT", 2017 International Seminar on Application for Technology of Information and Communication (iSemantic), 2017 Publication	<%1
26	Submitted to Heriot-Watt University Student Paper	<%1

EXCLUDE QUOTES	ON	EXCLUDE MATCHES	< 5 WORDS
EXCLUDE BIBLIOGRAPHY	ON		