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Visual Classification of Lettuce Growth Stage based on Morphological Attributes using Unsupervised Machine Learning models

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***Abstract*—Food shortage is a serious problem facing the world and is prevalent in urban areas. The scarcity of food is mainly caused by crop failure. Environmental factors offered by the rural areas determine the condition of crops to be produced. This scenario pomps, the explication of urban farming. However, urban farming requires all-out monitoring and control. This study specifically solves the predicament of identifying the developmental growth of plants from seed leaf to amend the techniques of plant science and cultivation management. With a view to this, the paper shows coupled color-based superpixels and multifold watershed transformation in segmenting the lettuce image from the background. To fathom it out, a comparative analysis of three unsupervised machine learning algorithms: Self Organizing Map (SOM), Hierarchical, and K - means algorithms were conducted. These were done by modeling each algorithm from the features extracted from morphological computations of the lettuce images raised in a smart aquaponics setup. Each of the models was optimized to increase cross and hold-out validations. The results showed that K – means algorithm having the parameters of algorithm = 'auto', copyx= 'True', init = 'K- means++', maxiter = '1000', nclusters = '3', ninit = '15', n_jobs = '1', precompute_distance = 'auto', random_state = '10', tol = '0.000001', verbose = '1', leaf_size = '10' was the most effective model for the given dataset, yielding a high precision and recall unsupervised clustering percentage of 91%.**

Keywords*— *smart aquaponics, machine vision, phytomorphological profile, Morphological computations, Superpixels, Machine Learning, Unsupervised Algorithm, Clustering, K – means Clustering, Self Organizing Map, Hierarchical

I. Introduction

Greater part of the world's population nowadays lives in urban areas. The leading cause of it, is the increasing population growth, and lack of economic growth [1].

Urban Agriculture is one of the proposition that address this problems and drive forward the livelihoods contrived by these disadvantages [2]. However it also has negative impacts such as food security and demanding monitoring and control system. The system must comply to plants' requirements and automatic response to environmental factors [3]. Consequential to this is the innovation of Aquaponics System for Urban Farming [4].

Aquaponics is a compound system of two food production domestication: aquaculture, the practice of farming aquatic organisms; and hydroponics, the cultivation of plants in water without soil. It is a cycle of life which organic wastes are generated for the utilization of the adjacent disparate system [5]. Distinctively, bacteria makes use the fish waste and plants intuit and imbibe the resulting nutrients, with the purified water then returning to the fish tanks. However, its operation can be challenging on the subject of monitoring and control for healthy growth of fish and plant [6].

Hereby, data acquisition, monitoring and control systems are well-considered, enhanced, and brought forth to the farm system [7]. One of the critical issues in plant science, cultivation management and farming techniques is distinguishing the development growth stages of plants from seed leaf. Specialization in plant morphology (Phytomorphology) is necessitated for monitoring the growth stage of a plant [8]. The main objective of the study is to achieved the optimized machine learning model in clustering the lettuce images samples into three growth stages (vegetative, head development, and harvest) among the unsupervised machine learning algorithm : Self Organizing Map (SOM), Hierarchichal Clustering (HC), and K – means Clustering (K-means). Specifically, this is attained through the images collected from the vision-based system installed in the smart aquaponic farm setup which are processed to extract the most important Phytomorphology characteristic of the image [9].

II. Related Studies

A. Lactuca Sativa

Lettuce (*Lactuca Sativa*) plant development involves three distinct growth stages separated and ranged based on the number of days planted, namely, vegetative, head development and for harvest [10]. From sowing period up to germination phase that is predominantly takes 280 hours (approx. 12 days) is the vegetative growth stage. Following that, head development growth stage starts once the lettuce is transplanted, which commonly last for 500 hours (approx. 21 days). In the fullness of time, harvest growth stage happens 1080 to 1560 hours (approx. 45-65 days) after sowing the lettuce seed.

B. Machine Vision

A thorough literature review of image preprocessing, segmentation and feature extraction using machine vision affirms to lessen the threats and requisition of the detection and classification systems [11]. It also authenticates the efficiency and high accuracy compared to other methods. But still, the automated vision-based detection and classification methods is in its infancy stage. In current days, farm monitoring is still contingent on the instinctive human decisions showing low accuracy due to the vision limitations of human eye and lacking in knowledge and specialization. Unfolding the issue, Machine vision can be considerate field that involves making a machine ‘‘see” [12].

C. Superpixels Technique

Ascribed to the impediment of the vision system, such as, limited spatial information erroneous representation of abstraction of the original image, superpixels technique emerges. It administers advances and development in machine vision [13], image preprocessing, segmentation [14] and classification. In preference to single standard pixel, superpixel comprises supplemental spatial information, whereof, it provides accurate and precise representation of the original image. Another benefit of it is the reduced computational cost in segmentation. It uses both lines and curves in creating its focal regions [15].

D. Unsupervised Machine Learning

Unsupervised Machine Learning Algorithm is a branch of advanced machine learning algorithm that deals in grouping or further detailed to clustering. These algorithms are capable to detect and discover the potentially interesting and new cluster structures in a dataset. Additionally, these algorithms can be implemented when class label data is unavailable. In this classification system, class label description is irrelevant, yet it is limited into 3 clusters representing 3 growth stage of lettuce (vegetative, head development, and harvest). Being in the case of discovering the class labels that best describe a set of data, unsupervised machine learning should be implemented in place of supervised methods [16].

III. Methodology

This section discusses in particular the distinctive technicalities and information about the hydroponics setup, data gathering and lastly the consequential processes in determining the growth stage of lettuce plant.

Figure 1. Hardware Architecture of the lettuce growth stage identification for data gathering.

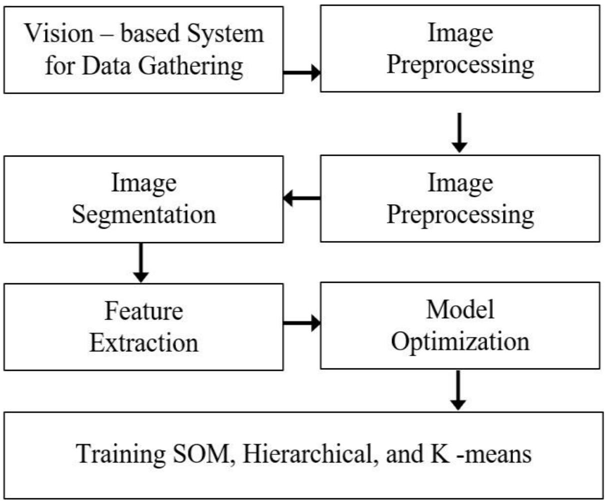

Figure 2. Overall Software Architecture of lettuce growth stage identification

A. Hydroponic Setup

Advanced cultivation style was established in an existing setup using primarily the nutrient film technique.

Figure 3. Growth Bed Setup for Lettuce Cultivation

Shown in figure 2 is the hydroponic setup of the aquaponic system implemented in Rizal, Philippines. An average of four to six lettuce seeds are planted on a rockwool (1x1 in size) and fixed into a container. Each plant container is implanted onto the hole at the top of a polyvinyl chloride (PVC) pipe. The water source will be coming from the pond water constituting the nutrients coming from the organic waste or effluents of tilapia and carp biologically living in the pond. The monitoring and control of the pH and electrical conductivity level of these nutrients were maintained using control systems. There are three layers of growth bed. A total of 141 lettuces were planted in the setup.

B. Dataset Description

Aforementioned, there are three lettuce plant growth stages: vegetative, head development and for harvest. There are disproportion in the data size number of the stages: vegetative has 60 sample images, head development has 150 images, and harvest has 90 images. This was supported by the literature explaining that duration varies in each growth stage of the lettuce [17]. The dataset designated only features that is significant in vision-system growth stage identification such as, number of leaves, biomass area and perimeter, convex area, convex hull (CH) area and perimeter, major and minor axis length of the biomass, major axis length of the dominant leaf, length of plant skeleton, biomass compactness, convexity, and solidity, and the ratio of plant skeleton and perimeter.

C. Image Segmentation

Image segmentation was used in the system to preferably analyze the particular region of color interest in the vision system [18]. It is a process of division or segmentation of an n-dimensional image into manifold pixel segments or image object. This section discusses the established algorithm controlled by the coupled superpixels overlaying and multifold watershed transformation without thresholding to segment the whole lettuce plant which is the image object in focus.

1) Superpixels

Color features using superpixels were used for progressive segmentation of the lettuce images [19]. Superpixel takes advantage because it utilizes geometrical segment of the image larger than the lines and curves provided by the regular pixel [20]. Images were implemented with 50, 100, 50 and 1000 superpixel regions for experimentation and as a result, enhanced images with 1000 superpixel offers the visual positive identification manually and visually. Figure 4 shows the original image in the left side and the overlaid image in 1000 region in the right side.

Figure 4. Superpixel region boundaries and result for 1000 regions.

2) Multifold Watershed Transformation

In modifying and adjusting the segmented image, the researchers delves into watershed ridge lines of the digital image by employing the multifold watershed transformation. The conceptualization of the algorithm technique emerges when the algorithm perceives the illuminated pixels in the image as high eminence and the unilluminated pixels as low eminence [21]. In this setup, there are six-leveled watershed transformation to foremost enhance the segmentation of the lettuce image.

Final watershed transformation was overlaid to mask the original image and produce the immitation of the region of interest (ROI). The result of the sixth watershed transformation is the segmented lettuce pixels as shown in Figure 5.

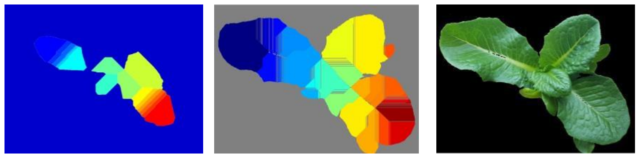

Figure 5. Watershed transformations first, fourth, and sixth segmented lettuce pixels (from left to right).

3) Morphological Feature Extraction

Provided by the image morphological profile (IMP), feasibility of observing, computing and quantifying of the phytomorphological variation of lettuce plant can be done by morphological feature extraction. Disembodied with the background , the masked image goes through region properties computation for segmented leaf and whole biomass, and convex hull generation and flood-fill operation for whole biomass properties [22]. Variation of colors (ncolors) can be set to acquire the conventional masking of the image figure 6 shows different settings in the ncolors and masking selection

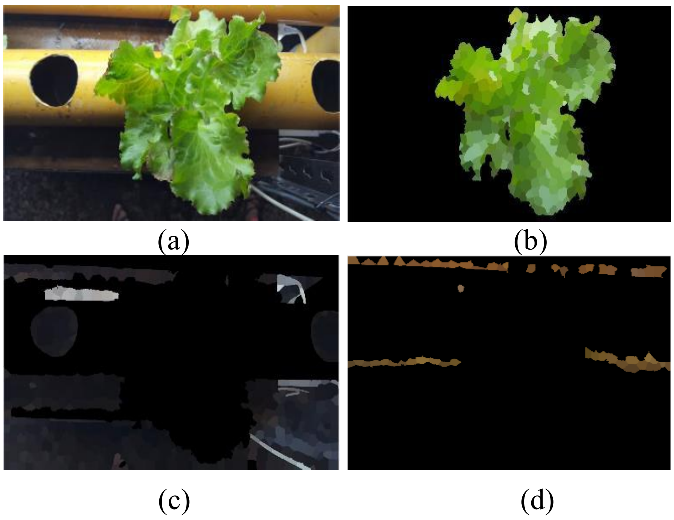

Figure 6. Images produced in variations of different settings in superpixel segmented image. (a) original image (b) intact result of masking (c) Meagreaness in color limitation (d) Sophistical choice of masking.

D. Feature Extraction

The gathered phytomorphological features are the number of leaves, biomass area and perimeter, convex area, convex hull area and perimeter, major and minor axis length of the biomass, major axis length of the dominant leaf, length of plant skeleton, biomass compactness, convexity, and solidity, and the ratio of plant skeleton and perimeter.

E. Optimized Machine Learning Models

The extracted features from the morphological operations were used as the dataset to train the three algorithms; Self Organizing Map (SOM), Hierarchical Clustering (HC), K-means Clustering (K-means). In contact with the setup, the data were fitted independently one at a time with the three algorithms using the default parameters. The paper implements two setup: holdout validation and k-folds 10-fold stratified cross-validation for comparison and juxtaposition [23].

IV. Results and Discussion

The model performance of the initial model and optimized model were scored in both holdout validation and 10-fold stratified cross-validation.

Table 1. Classification scores of the clustering algorithm in default parameters utilizing holdout validation in training and testing.

Model	Holdout Validation Training						Holdout ValidationTesting					
	Correct			Incorrect			Correct			Incorrect		
	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest
SOM	48	100	48	0	20	24	10	24	15	2	6	3
Hierarchical	48	112	72	0	8	0	10	30	18	2	0	0
K-means	48	115	72	0	5	0	10	30	18	2	0	0

Table 2. Classifications scores of the three algorithms in 10-fold validation

Model	Cross-Validation k=10 folds Training						Cross-Validation k=10 folds Testing					
	Correct			Incorrect			Correct			Incorrect		
	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest
SOM	41	94	47	7	26	25	10	23	12	2	7	6
Hierarchical	45	103	59	3	17	13	11	26	14	1	4	4
K-means	45	105	59	3	15	13	11	26	14	1	4	4

Table 3. Optimized holdout classification score of the three algorithms.

Model	Optimized Cross-Validation k=10 folds Training						Optimized Cross-Validation k=10 folds Testing					
	Correct			Incorrect			Correct			Incorrect		
	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest
SOM	42	97	48	6	23	24	12	23	12	0	7	6
Hierarchical	47	108	63	1	12	9	12	27	15	0	3	3
K-means	45	110	63	3	10	9	11	27	16	1	3	2

Table 4. Progressed approach of optimizing the model

Model	Optimized Holdout Training						Optimized Holdout Testing					
	Correct			Incorrect			Correct			Incorrect		
	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest	Vegetative	Head Development	Harvest
SOM	48	100	48	3	22	25	10	24	15	2	6	3
Hierarchical	48	112	72	1	10	1	10	30	18	2	0	0
K-means	48	115	72	1	6	1	10	30	18	2	0	0

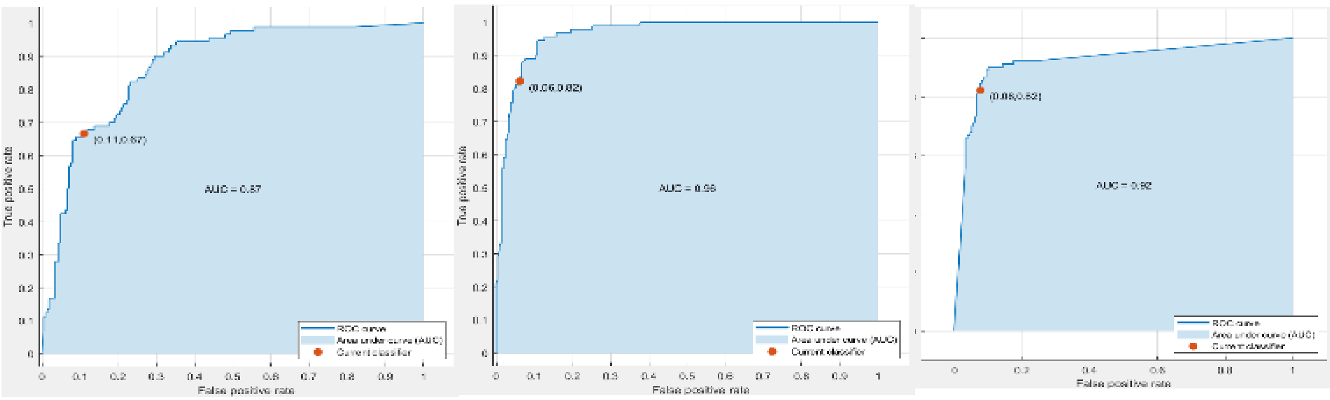

Figure 7. Receiving Operating Characteristic Curve of SOM, Hierarchical, K-means in 10-folds stratified validation

Table 1 shows the classification scores of the clustering algorithm in default parameters utilizing holdout validation in training and testing. This shows that K – means clustering predominantly achieved the best model for holdout with a little disparity together with other clustering algorithms. All of the algorithms in default parameters is also tested using the 10-fold stratified cross-validation to avoid overfitting which may result to poor classification performance. Table 2 shows the classifications scores of the three algorithms in 10-fold validation. In this scenario, K-means still subjugates the other algorithms. Observing the results, K-folds disclose the consistency of percentage accuracy of the three different algorithms indicating a more realistic results.

For visualization, figure 7 use ROC curve to effectively show the effectiveness of K-means.

Each of the algorithms were optimized to determine the best performing parameters. Table 3 shows the optimized holdout classification score of the three algorithms. Distinctively, all of the three algorithms improved their accuracy. Within sight of the data, K -means makes progress that is nearly exquisite to the borderline. Table 4 presents the progressed approach of optimizing the model because of its improved parameters and K-fold validation of data. In essence K – means, with the optimized parameters of of algorithm = ‘auto’, copyx= ‘True’, init = ‘K-means++’, maxiter = ‘1000’, nclusters = ‘3’, ninit = ‘15’, n_jobs = ‘1’, precompute_distance = ‘auto’, random_state= ‘10’, tol = ‘0.000001’, verbose = ‘1’, leaf_size = ‘10’ has the highest precision and accuracy**.** In figures 8, 9, and 10 are the confusion matrices for the optimized models.

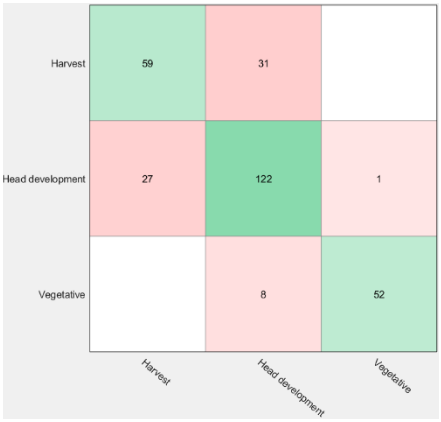

Figure 8. Optimized SOM algorithm showing 77.7% of accuracy

This figure also shows accuracy scoring of the model, 66% in harvest, 81% in Head Development, 87% in Vegetative for True Positive Rates. While, 69% in harvest, 76% in Head Development, 98% for positive predicted value.

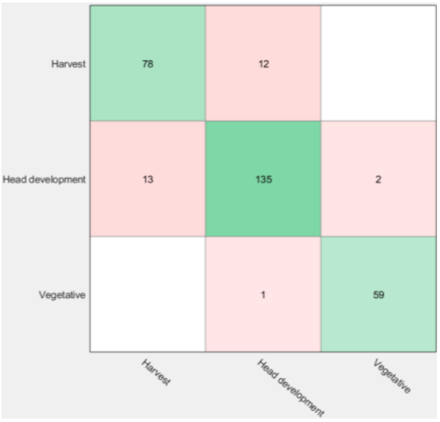

Figure 9. Optimized Hierarchical showing 77.7% of accuracy

This figure also shows accuracy scoring of the model, 88% in harvest, 92% in Head Development, 93% in Vegetative for True Positive Rates. While, 90% in harvest, 90% in Head Development, 95% for positive predicted value.

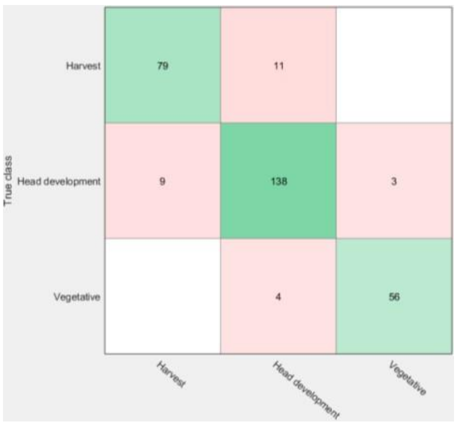

Figure 10. Optimized K-means clustering algorithm showing 91.0% of accuracy

This figure also shows accuracy scoring of the model, 87% in harvest, 90% in Head Development, 98% in Vegetative for True Positive Rates. While, 86% in harvest, 91% in Head Development, 97% for positive predicted value.

Model	% Accuracy			
	Default Parameter		Optimized Parameter	
	Holdout	K Folds	Holdout	Kfolds
SOM	87.34	76	91.33	77.7
Hierarchical	94.98	86.7	98.67	90.7
K-means	96.75	87.3	99.17	91

Table 5. Tabulated Percentage Accuracy of the algorithms used and their optimized models

Table 5 shows the listing of the training and testing accuracy characterized by each machine learning model in their default parameters and the optimized machine learning model. The K – means clustering model performed as the most accuracte model in holdout and k-folds with 96.75% and 91.0% correct classification of lettuce growth stages respectively. Thus, making it the best optimized machine learning model in the sense that this model is consistent in providing correct classifications supported by its performance and accuracy.

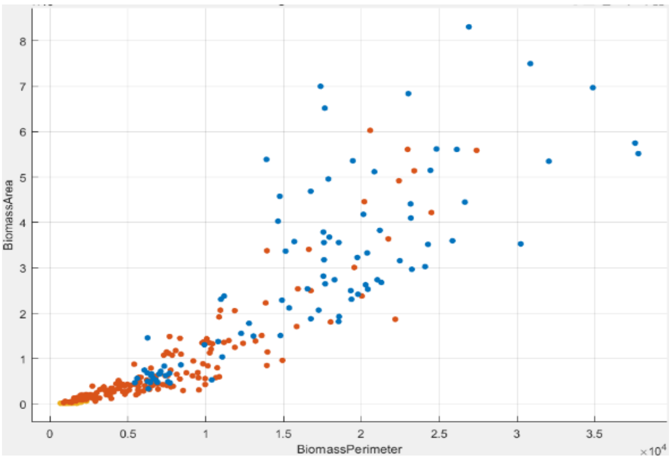

Figure 11. Normal discriminance of K-means clustering Biomass Perimeter vs. Biomass Area

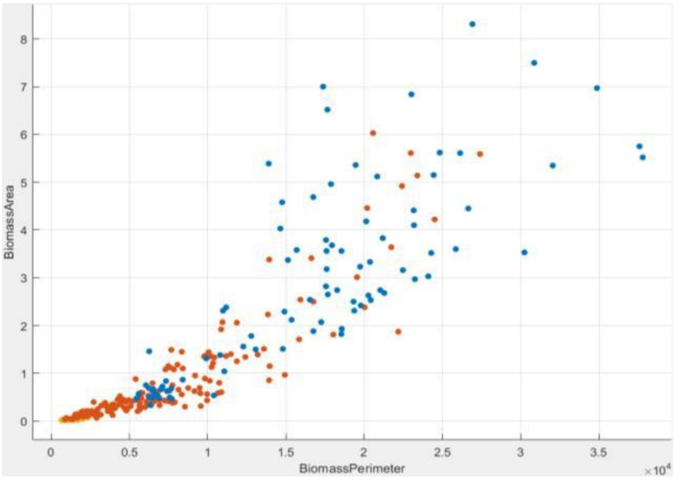

Figure 12. Normal discriminance of K-means clustering Biomass Perimeter vs. Biomass Major Axis Length

Figures 12 and 13 shows a visualization of the clusters using the optimized model of K-means clustering and how they are enhanced using the graph of linear separation of normal discriminance. The graph is based on the most significant feature of the dataset such as: biomass perimeter, biomass area and biomass minor axis length.

V. Conclusion

The comparative investigation was attained effectively and competently by employing the morphological extracted features acquired from the enhanced machine vision-based image preprocessing using superpixels with K-means clustering and Multifold Watershed Transformation to train the Self Organizing Map (SOM), Hierarchical, and K – means clustering algorithms The trained models were further optimized to increase the performance of each algorithm. Analyzing the models in comparison to one another resulted to a conclusion that the K – means algorithm having the parameters of algorithm = 'auto', copyx= 'True', init = 'K-means++', maxiter = '1000', nclusters = '3', ninit = '15', n_jobs = '1', precompute_distance = 'auto', random_state = '10', tol = '0.000001', verbose = '1', leaf_size = '10' was the most effective model for the given dataset, yielding a high precision and recall unsupervised clustering percentage of 91%. Future works constitutes further enhanced segmentation of leaves from stem. Feature selection can also be considered to better optimize the model and reduce the computational time.

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References

[1] D. D. Wachholz, "Urban Agriculture as a Sustainable Livelihood Strategy in Khayelitsha, Cape Town: A Critical Appraisal of the Harvest of Hope Marketing Project," p. 134, 2017.

[2] D. T. Armanda, J. B. Guinée, and A. Tukker, "The second green revolution: Innovative urban agriculture's contribution to food security and sustainability – A review," *Glob. Food Sec.*, vol. 22, no. August, pp. 13–24, 2019.

[3] R. Khan, Z. Aziz, and V. Ahmed, "Building integrated agriculture information modelling (BIAIM): An integrated approach towards urban agriculture," *Sustain. Cities Soc.*, vol. 37, no. August 2017, pp. 594–607, 2018.

[4] T. Y. Kyaw and A. K. Ng, "Smart Aquaponics System for Urban Farming," *Energy Procedia*, vol. 143, pp. 342–347, 2017.

[5] I. Aquaculture, "Integrated Aquaculture and Aquaponics," *Sustain. Food Agric.*, pp. 251–257, 2019.

[6] D. Karimanzira and T. Rauschenbach, "Enhancing aquaponics management with IoT-based Predictive Analytics for efficient information utilization," *Inf. Process. Agric.*, vol. 6, no. 3, pp. 375–385, 2019.

[7] J. D. Alejandrino, R. S. Concepcion, S. C. Laugico, E. T. Trinidad, and E. P. Dadios, "Feasibility of Television White Space Spectrum Technologies for Wide Range Wireless Sensor Network: A survey," *2019 IEEE 11th Int. Conf. Humanoid, Nanotechnology, Inf. Technol. Commun. Control. Environ. Manag. HNICEM 2019*, pp. 2–7, 2019.

[8] J. M. Ladrido, J. Alejandrino, E. Trinidad, and L. Materum, "Comparative survey of signal processing and artificial intelligence based channel equalization techniques and technologies," *Int. J. Emerg. Trends Eng. Res.*, vol. 7, no. 9, pp. 311–322, 2019.

[9] R. S. Concepcion, A. A. Bandala, R. A. R. Bedruz, and E. P. Dadios, "Fuzzy Classification Approach on Quality Deterioration Assessment of Tomato Puree in Aerobic Storage using Electronic Nose," pp. 1–6, 2020.

[10] P. J. M. Loresco, I. C. Valenzuela, and E. P. Dadios, "Color Space Analysis Using KNN for Lettuce Crop Stages Identification in Smart Farm Setup," in *TENCON 2018 - 2018 IEEE Region 10 Conference*, 2018, pp. 2040–2044.

[11] Z. Iqbal, M. A. Khan, M. Sharif, J. H. Shah, M. H. ur Rehman, and K. Javed, "An automated detection and classification of citrus plant diseases using image processing techniques: A review," *Comput. Electron. Agric.*, vol. 153, no. August, pp. 12–32, 2018.

[12] S. C. Lauguico, R. S. Concepcion, D. D. MacAsaet, J. D. Alejandrino, A. A. Bandala, and E. P. Dadios, "Implementation of Inverse Kinematics for Crop-Harvesting Robotic Arm in Vertical Farming," *Proc. IEEE 2019 9th Int. Conf. Cybern. Intell. Syst. Robot. Autom. Mechatronics, CIS RAM 2019*, pp. 298–303, 2019.

[13] S. Zhang, H. Wang, W. Huang, and Z. You, "Plant diseased leaf segmentation and recognition by fusion of superpixel, K-means and PHOG," *Optik (Stuttg).*, vol. 157, pp. 866–872, 2018.

[14] Y. Shen, T. Ai, W. Li, M. Yang, and Y. Feng, "A polygon aggregation method with global feature preservation using superpixel segmentation," *Comput. Environ. Urban Syst.*, vol. 75, no. January, pp. 117–131, 2019.

[15] S. Lauguico *et al.*, "A Fuzzy Logic-Based Stock Market Trading Algorithm Using Bollinger Bands," *2019 IEEE 11th Int. Conf. Humanoid, Nanotechnology, Inf. Technol. Commun. Control. Environ. Manag. HNICEM 2019*, pp. 2–7, 2019.

[16] C. Lopez, S. Tucker, T. Salameh, and C. Tucker, "An unsupervised machine learning method for discovering patient clusters based on genetic signatures," *J. Biomed. Inform.*, vol. 85, no. June, pp. 30–39, 2018.

[17] L. Al Attar, M. Al-Oudat, B. Safia, and B. A. Ghani, "Transfer factor of 90Sr and 137Cs to lettuce and winter wheat at different growth stage applications," *J. Environ. Radioact.*, vol. 150, pp. 104–110, 2015.

[18] A. Narayanan, M. P. Rajasekaran, Y. Zhang, V. Govindaraj, and A. Thiyagarajan, "Multi-channeled MR brain image segmentation: A novel double optimization approach combined with clustering technique for tumor identification and tissue segmentation," *Biocybern. Biomed. Eng.*, vol. 39, no. 2, pp. 350–381, 2019.

[19] R. S. Concepcion, F. R. G. Cruz, F. A. A. Uy, J. M. E. Baltazar, J. N. Carpio, and K. G. Tolentino, "Triaxial MEMS digital accelerometer and temperature sensor calibration techniques for structural health monitoring of reinforced concrete bridge laboratory test platform," *HNICEM 2017 - 9th Int. Conf. Humanoid, Nanotechnology, Inf. Technol. Commun. Control. Environ. Manag.*, vol. 2018-Janua, pp. 1–6, 2017.

[20] Z. Alasvand, M. Naderan, and G. Akbarizadeh, "Superpixel-based feature learning for joint sparse representation of hyperspectral images," *3rd Int. Conf. Pattern Anal. Image Anal. IPRIA 2017*, no. Ipria, pp. 156–159, 2017.

[21] P. Sellars, A. I. Aviles-Rivero, N. Papadakis, D. Coomes, A. Faul, and C. B. Schonlieb, "Semi-Supervised Learning with Graphs: Covariance Based Superpixels for Hyperspectral Image Classification," *Int. Geosci. Remote Sens. Symp.*, pp. 592–595, 2019.

[22] K. B. Shobana, "3odqwv &odvvlilfdwlrq 8vlqj 0dfklqh/hduqlqj $ojrulwkp," pp. 96–100, 2020.

[23] R. S. Concepcion and L. C. Ilagan, "Application of Hybrid Soft Computing for Classification of Reinforced Concrete Bridge Structural Health Based on Thermal-Vibration Intelligent System Parameters," *Proc. - 2019 IEEE 15th Int. Colloq. Signal Process. its Appl. CSPA 2019*, no. March, pp. 207–212, 2019.