

# A robust 4.0 dual-classifier for determining the internal condition of watermelons using YOLOv4-tiny and sensory

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## ABSTRACT

This study presents a robust internet of things (IoT) based approach to solve the challenge of sorting fruit (watermelons) either as a raw material or final product in fruit manufacturing lines. A real-time objection detection technique called you only look once (YOLO) was used in the features detection, extraction, and matching of watermelons. The hardware framework of the system was developed on an Arduino microprocessor which integrates the sensors and camera into the system. The accuracy of the developed classifier is about 88% with a loss of 0.3, with images captured automatically saved on a designated folder which makes the detection and classification of upcoming products in the production line more accurate. The classified watermelons were further categorized into two possible states of ripe or rotten condition with an accuracy rate of 85%-90% with the tested data. These data were sent to the cloud via the Wi-Fi module and can be accessed using the Things Speak website (which is an application programming interface (API) for data retrieval and storage via the internet). An easy download option was incorporated into the system to obtain data from predictions and the cloud to a designated comma separated values (CSV) file locally for documentation and reference.

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## 1. INTRODUCTION

Fruits are essential composite of human nutrition as recommended by the World Health Organization (WHO) which specified 400g of fruits and vegetables (FVs) in a day [1]. In an ideal situation, the steps for converting FVs harvested from the farm to either raw materials or finished products are cleaning, sorting, processing, mixing, liquefaction and distillation, filling and capping, packaging, storage, and preservation for its application as raw materials used by [2]-[6] in the production of fruit juice and syrup, canned fruit, and alcoholic beverages [7].

The steps of converting these fruits to either finished products or raw materials vary but should contain one or more of the mentioned. Often, FVs arrive at the production plant with significant variation in the quality which can be categorized as unripe, ripe, and rotten conditions. These conditions can be attributed to the distance between the farm to plant, logistic miscalculation, and the capacity of the plant. These conditions affect the fruit's yield, quality of taste, nutrient factors, and profit margin of the business. The conventional approach of manual inspection used by the manufacturers in detecting, categorizing, and sorting fruits and vegetables has proven not to be reliable and effective because of the clear reason of human fatigue and error [8], [9]. Therefore, manufacturers must have a reliable mechanism that can detect, categorize, and

sort fruits and vegetables based on their conditions on arrival to ensure the best quality product. The advent of industry 4.0 has created a hybrid approach in overcoming such challenges and other arising ones for production industries thereby making production lines smarter, more flexible, and reducing production cost by exploration of the internet of things (IoT), artificial intelligence, embedded software systems, cloud computing, augmented reality, additive manufacturing, and big data and security [10]-[12].

A research work carried out by Bhargava Bansal [13] on four types of fruits (orange, apple, banana, and avocado) extracted the geometric features of the fruits using four classifiers; k-nearest neighbor (k-NN), support vector machine (SVM), sparse representative classifier (SRC), and artificial neural network (ANN) to develop the classifier model to predict fruit quality. The author indicated that SVM was rated the best with an accuracy of 98.48% for fruit detection and 95.72% for fruit quality. Blasco *et al.* [14] used Bayesian discriminant analysis (BDA) for the segmentation process, allowing fruits to be precisely identified from the background and detect spots on the fruit with an accuracy of 86%. Another study used the combination of SVM, feature extraction algorithm, and X-ray computer tomography effectively determine the internal conditions of pear fruits. The developed classifiers were able to differentiate defective in the internal quality of fruit quality with an accuracy of 90-95% [15]. In the work of Mumera *et al.* [16], hyperspectral imaging (visible and near Infrared) approach combined with a machine learning-based classifier (random forest and extreme gradient boost XGBoost), were used to identify both external and internal defects in 'Algerie' loquat fruit. The success rate of 97.5%, 96.7%, and 95.9% were obtained.

In addition, Saripa *et al.* [17] shows how the maturity of watermelon can be predicted using ultraviolet near-infrared spectroscopy. The research demonstrated how the internal quality parameters of watermelon such as soluble solids content (SSC), pH level, firmness, and moisture content of the fruits can be used to predict the maturity and quality of the watermelon. Using the SVM model, the maturity prediction accuracy of 85% for the watermelon was achieved. Zhang *et al.* [18] explored an acoustic technique of kernel principal component analysis (KPCA) combined with machine learning to classify watermelons into unripe, ripe, and over-ripe. A set of fundamental electrical signals were obtained by hitting a microphone on the watermelons (unripe, ripe, and overripe), these electrical signals are converted to discrete signals. KPCA was used to extract features and patterns from the converted signals, three classifier models were built using the extracted features. The classifiers were tested, and an accuracy of 92% prediction was achieved. Ding *et al.* [19] assessed the firmness of watermelon as a key parameter to determine the internal quality of the fruit. The authors used the acoustic vibration technique combined with Near-infrared spectroscopy (NIR) spectroscopy to determine the firmness of the watermelon with a prediction accuracy of about 0.841.

Furthermore, a study carried out by Xu *et al.* [20], discussed the relative relationship between the density of watermelon and hollow detection inside of the fruit. The study demonstrated with the use of Helmholtz resonance system, the volume system of watermelon can be obtained with the Helmholtz resonance, and hence, the density can be deduced. With an overall prediction percentage of 82.5%, it can be said that Helmholtz resonance showed great prospective for measuring the volume and internal quality of watermelon. Another work by Castro *et al.* [21], used machine learning techniques and color space models to develop a classifier for Cape gooseberry fruits. According to the author's results, the classification of Cape gooseberry fruits by their ripeness level is sensitive to both the classification technique and the color space used. The study of [22], discussed how the sweetness of watermelon can be classified, it proposed a quantitative approach by conducting a sensory test to classify sweetness criteria and proofed; very sweet (with °Brix > 10), sweet ( $7 \geq \text{°Brix} \leq 10$ ), and flat ( $\text{°Brix} < 7$ ) and used machine learning techniques to build a better classifier which predicts sweetness of watermelon than NIR spectroscopy. Mao *et al.* [23], developed an acoustic device that measures the firmness of watermelon after studying the effect of hitting ball and fruit tray on the spectrum. Firmness index of  $f^2m$  and acoustic parameters were recommended to correlate the firmness of watermelon. Finally, De-la-Torre *et al.* [24] explored the multi-features extraction ability of five algorithms on color space models to determine the ripeness of Cape gooseberry fruits. The results presented show that selection and combination of color channels allow classifiers to reach similar levels of accuracy.

This paper proposes a robust dual-classifier scheme microcontroller-based sensory system with machine learning (MCSS-ML), which is based on a MCSS and ML by exploring the flexibility of microcontroller in this case Arduino to integrate an IoT-based system that can be used to detect and classify watermelons (ripe, and unripe) using an IP-camera, humidity/temperature and gas sensors. Then, you only look once (YOLO) classification technique is used to develop a classifier model which identifies and classifies watermelon. Also, a method to improve the trained dataset is established by automatically adding watermelon successfully identified to the dataset. Datasets obtained by the system based on their conditions during testing were sent to the cloud for easy access, and the downloadable option of these datasets via a web-enabled device anywhere for easy reference is incorporated. The rest of this paper is structured as shown in: Section 2 describes the design flow and building block of the proposed dual classifier, while section 3 discusses the results obtained from the developed dual-classifier on the watermelon and the performance evaluation of the developed classifier at different specifications and time is presented with further analysis to

validate the proposed system, Also, a cloud-based database application created to save the datasets is discussed; and finally, section 4 concludes the paper.

## 2. METHODS

MCSS-ML proposes a scheme built on the Arduino UNO microcontroller to receive, compute and send out process watermelon in real-time. The materials and methods used in analyzing each fruit sample is herewith stated. This scheme is robust because it integrates a lot of the features of industry 4.0 into it.

### 2.1. Watermelon fruit samples

The samples were purchased from a major fruit market called Shasha market, Ado Ekiti, Nigeria, located at [7°33'03.4"N 5°13'08.6"E]. The sample of twenty watermelons was used with different degrees of ripeness measured until the watermelons were rotten to know the threshold of ethylene gas produced by watermelons. The degree of ethylene in/emitted by fruits has been used to classify the ripening stages of fruits, studies showed a direct proportion in the increase of ethylene content of fruits as they get more ripening [25]-[28]. Having said that, an experiment was carried out for four weeks on twenty watermelons to obtain the maximum threshold limit of temperature, humidity, and ethylene values needed to determine if a watermelon is ripe or rotten in a controlled environment. These values are now used as benchmarks to classify if a watermelon is ripe or rotten. Note that most of the watermelons were physically rotten by the fourth week. The results of the experiment are summarized in Table 1.

Table 1. Results of ripening stages' parameters of watermelons

Week	Average Humidity Obtained (%)	Average Temperature Obtained (°C)	Average Ethylene Emission (ppm)
1	65.54	33.29	1.96
2	69.16	32.14	4.086
3	69.53	30.86	10.68
4	70.79	31.00	33.00

The temperature and humidity values range from 30-33 °C and 65-71% respectively to produce a minimum ethylene emission of 1.96 ppm and a maximum ethylene emission of 33.00 ppm averaging across 20 watermelons for a month. As seen in the descriptive table, not all watermelons were fully bad, but began to go bad faster after the ethylene value range of 50-70 ppm was passed, which shows that watermelons begin to rotten faster when exposed to a large sum of ethylene from its self or other watermelons and hence the threshold parameters were identified. (\*\*This is not showing in the table and no appendix included)

### 2.2. MCSS-ML

#### 2.2.1. Hardware Unit

The hardware units of the system are described as shown in:

- Microcontroller (Arduino ATmega328P): Arduino is an open-source, high-performance, and highly flexible microcontroller that permits analog and digital inputs and outputs (I/O ports), SPI, and serial interfaces, analog-to-digital converter channel, memory units, timer, and system clock. The functionalities to be developed are programmed using the C++ language.
- IP-camera: An external HD camera of 108x720 resolution provides the input to the microcontroller which is placed about 35cm to the watermelon.
- Temperature/humidity sensor (DHT11): DHT11 output temperature and humidity sensor which generates digital signal already calibrated. The sensor includes an 8-bit microprocessor for serial data output of temperature and humidity values. Due to being calibrated, it makes it easy to connect to other microcontrollers. With an accuracy of  $\pm 1^\circ\text{C}$  and  $\pm 1\%$ , the sensor can measure temperature from  $0^\circ\text{C}$  to  $50^\circ\text{C}$  and humidity from 20% to 90% [29], [30].
- Gas sensor (MQ-3): This sensor is used for detecting ethanol, benzene gas, and ethylene, etc. The sensor is highly sensitive and can instantaneously obtain readings. The MQ-3 gas sensor's sensitive substance is tin (iv) oxide ( $\text{SnO}_2$ ), which has lower conductivity in fresh air [31]. The sensor is used to obtain ethylene gas emitted by the watermelons.
- WiFi Module (ESP8622): The ESP8266 is a low-budget WiFi microchip produced by Espressif Systems, which allows the microcontroller to communicate wirelessly to a wireless network with a full TCP/IP using Hayes-style commands [32]. The module has powerful onboard processing and storage abilities that allow it to be incorporated into the design of mobile devices, wearables, and IoT-based systems.

**2.2.2. Software unit**

Visual studio code (VSC) is the integrated development environment (IDE) used to develop the model in Python programming language which detects and classify watermelon using a trained YOLOv4-tiny algorithm. VSC has rich libraries for Python language which were used in the development of the classifier. Some of the important libraries used in the model are Open CV, NumPy, Pandas, CSV, OS, and JSON modules.

- Google Colab: Google Colab is a Python development environment that runs on the browser used to train the watermelons and is integrated with Google cloud for a robust database system to save the dataset to be trained. Thereby allowing the user to have access to a free designated GPU.
- ThingSpeak: is an open-source cloud-based database that allows real-time generated datasets to be cumulated, visualized, and analyzed from the cloud via an API. The generated data can be sent to ThingSpeak from devices and downloaded when needed from the cloud. Also, user-defined alerts can be set up as well [33]. In this case, watermelons being classified as either ripe or rotten will be saved to the cloud for easy access.

**2.3. Network/system architecture**

This YOLOv4-tiny which stands for “You Only Look Once version 4-tiny” is a lighter and compressed version of YOLOv4 deep learning algorithm developed using a backbone based on a convolutional neural network to increase the speed of real-time object detection on mobile devices, and the embedded system as applicable in this research work. YOLOv4-tiny uses CSPDarknet53-tiny network as the backbone network. The CSPDarknet53-tiny network uses CBLblock and CSPBlock for feature extraction and exploits the LeakyRelu function as an activation function for simple computation [34]-[38]. The LeakyRelu function is given as:

$$Y_i = \begin{cases} X_i, X_i \geq 0 \\ \frac{X_i}{a_i}, X_i < 0 \end{cases} \tag{1}$$

where  $a_i$  is a constant factor greater than 1.

The CBLblock covers the convolution operation, batch normalization, and activation function while CSPBlock splits the input feature map into two parts and concatenates the two parts in the cross-stage residual edge. Figure 1 shows the network structure of YOLOv4-tiny.

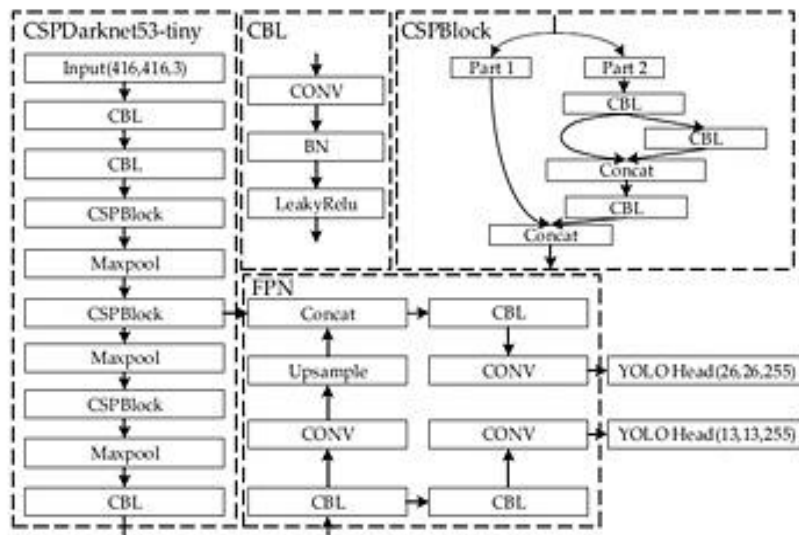


Figure 1. The system arrangement of YOLOv4-tiny

The YOLOv4-tiny model is typically pre-trained on imagenet classification, pre-trained such that the network's weights have been adapted to detect relevant features in an image, but it was retrained using a watermelon dataset containing 549 images and 549 text files containing the bounding box coordinates of each watermelon in the image to suit the aim of this research. The structure of this model consists of 21

convolutional layers, 2 maxpool layers, an output layer, and an input layer, which have different specifications of batch normalization, filters, size, stride, pad, and activation. The whole structure of the pre-trained model is seen in the config file. And a label file that holds the names of all objects the model is expected to recognize.

#### 2.4. Method

Training: The training was done using Google Colab with the Darknet YOLOv4 training environment installed. The watermelon dataset is linked up appropriately and a custom YOLOv4 training config file for Darknet is configured. The training of this custom model for the watermelon YOLOv4 object detector was run for 2,000 interactions with a run time of 2 hours and at an average of 0.5 seconds per iteration. Figures 2 and 3 show the model produce the best accuracy of 88.10%, an average loss of 0.30% which changes as the weight of the custom model is reloaded. With a learning rate of 0.000026 during these 2,000 iterations, the model runs 96,000 images respectively.

```
(next mAP calculation at 2000 iterations)
Last accuracy mAP@0.5 = 88.10 %, best = 88.10 %
1996: 0.273805, 0.294537 avg loss, 0.000026 rate, 0.540627 seconds, 95808 images, 0.015532 hours left
Loaded: 0.000042 seconds

(next mAP calculation at 2000 iterations)
Last accuracy mAP@0.5 = 88.10 %, best = 88.10 %
1997: 0.254799, 0.290564 avg loss, 0.000026 rate, 0.538806 seconds, 95856 images, 0.015382 hours left
Loaded: 0.000049 seconds

(next mAP calculation at 2000 iterations)
Last accuracy mAP@0.5 = 88.10 %, best = 88.10 %
1998: 0.269628, 0.288470 avg loss, 0.000026 rate, 0.513975 seconds, 95904 images, 0.015233 hours left
Loaded: 0.000052 seconds

(next mAP calculation at 2000 iterations)
Last accuracy mAP@0.5 = 88.10 %, best = 88.10 %
1999: 0.309421, 0.290565 avg loss, 0.000026 rate, 0.524612 seconds, 95952 images, 0.015084 hours left
Loaded: 0.000050 seconds

(next mAP calculation at 2000 iterations)
Last accuracy mAP@0.5 = 88.10 %, best = 88.10 %
2000: 0.392564, 0.300765 avg loss, 0.000026 rate, 0.511344 seconds, 96000 images, 0.014934 hours left

calculation mAP (mean average precision)...
108
detections_count = 543, unique_truth_count = 156
class_id = 0, name = watermelon, ap = 87.79% (TP = 132, FP = 47)

for conf_thresh = 0.25, precision = 0.74, recall = 0.85, F1-score = 0.79
for conf_thresh = 0.25, TP = 132, FP = 47, FN = 24, average IoU = 52.52 %

IoU threshold = 50 %, used Area-Under-Curve for each unique Recall
mean average precision (mAP@0.50) = 0.877936, or 87.79 %
Total Detection Time: 0 Seconds
```

Figure 2. Watermelon custom model showing the level of accuracy

The watermelon is placed 35 cm to the HD camera to detect and classify the object placed in front as a watermelon using the model that has been trained using YOLOv4-tiny. When a positive classification has been made, the new image is saved to the trained dataset to improve the level of accuracy. The number of watermelons identified by the classifier is sent to the ThingSpeak (cloud database) by the WiFi module and this data be downloaded in a CSV format.

Furthermore, after identification has been made of the watermelon, the two sensors drive into action by determining if the watermelon is ripe or rotten based on the threshold set. This is achieved with the use of conditional statements concatenate together to set the conditions discussed in Table 1 which determines if the watermelon is ripe or rotten based on the ethylene being emitted by the fruit. Also, the number of watermelons classified as either ripe or rotten are sent to the cloud and downloadable in CSV format. The MCSS-ML scheme is represented in the block diagram shown in Figure 4.

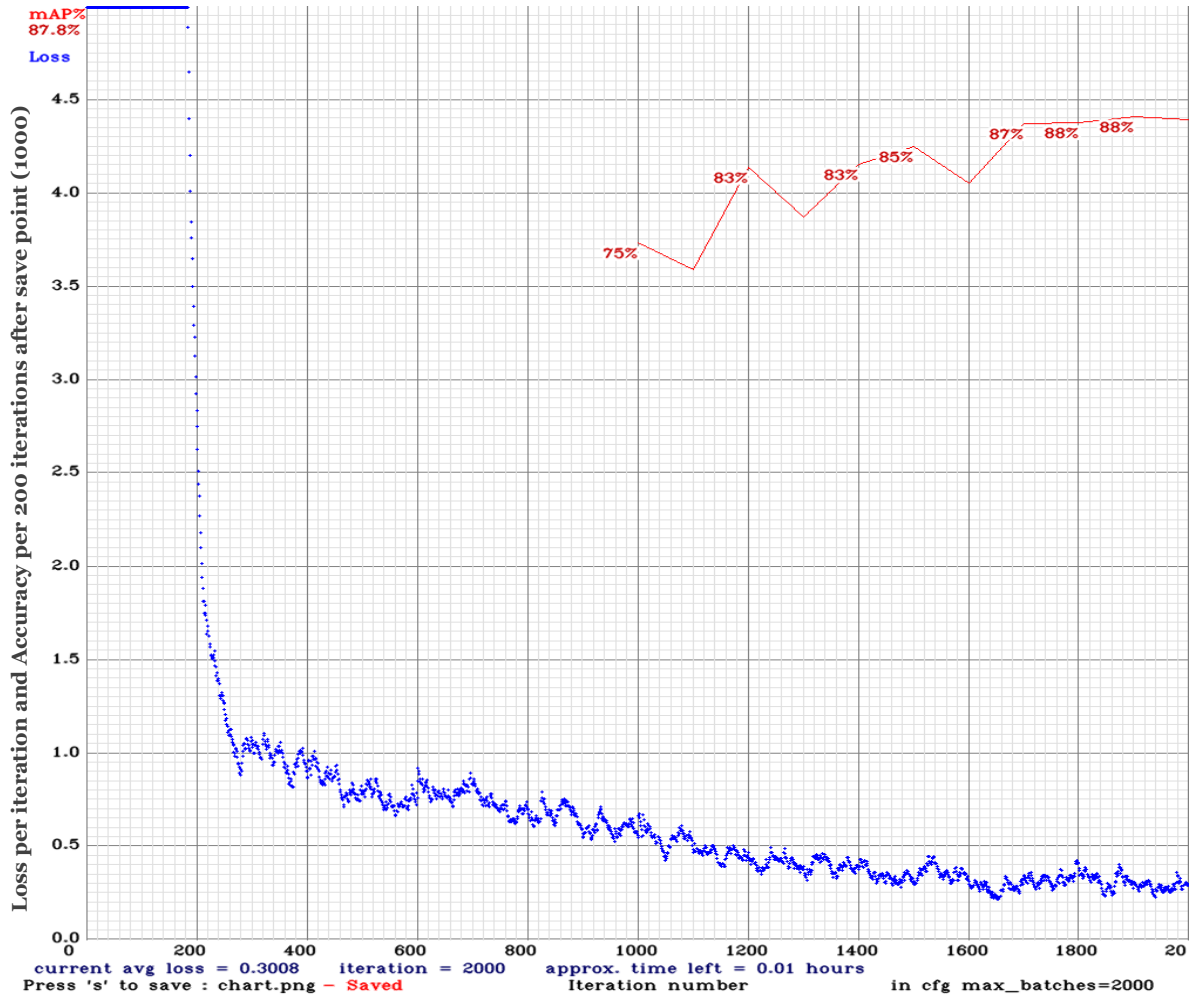


Figure 3. Graph showing the achieved accuracy and loss of training

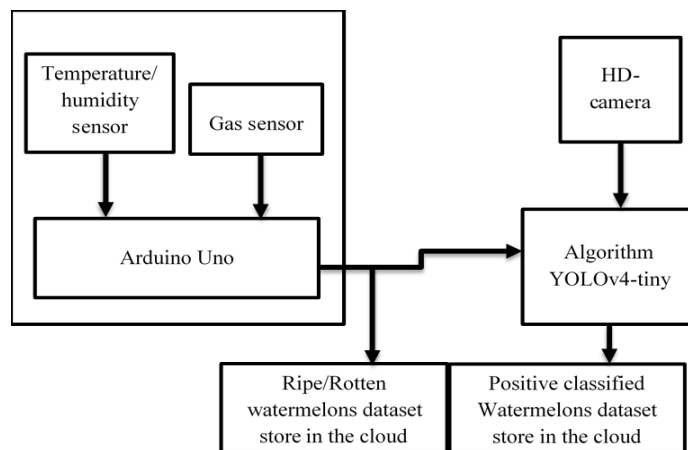


Figure 4. Block diagram of MCSS-ML scheme for detecting/classifying watermelon

**3. RESULTS AND DISCUSSION**

MCSS-ML was tested in a controlled environment as the values used to build the system were obtained in a controlled environment. Figure 5 shows that the system makes a detection while visualizing the Detected watermelon within a bounding box, which shows the name/label of the object detected. Consistently, the accuracy of the object detected as watermelon when MCSS-ML was validated with

watermelon is between 0.9-1.0. Additionally, MCSS-ML determines if the watermelon detected is ripe or rotten based on the ethylene reading obtained from the sensors. Figure 6 shows the systematic classification of watermelon based on ethylene readings obtained by the sensors on the microcontroller.

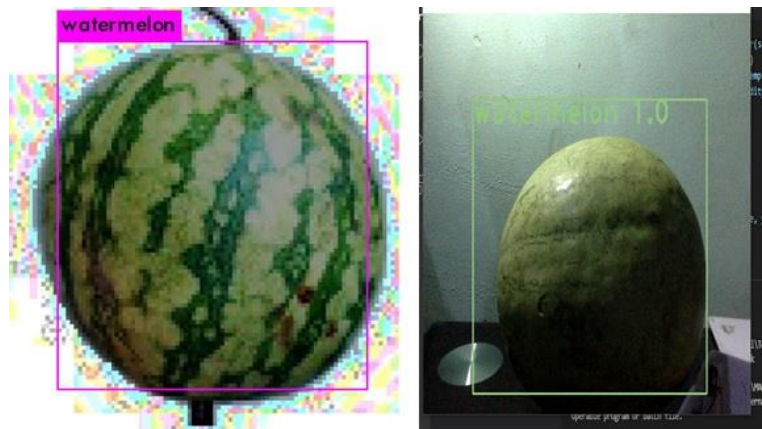


Figure 5. MCSS detecting and classifying watermelon with an accuracy of 1.0

```

realpy  data.csv X
documentation > data.csv
1 Name,Date,Time,Created Date,Temperature,Humidity,Ethylene Readings,Grade
2
3
4 watermelon0.jpg,07/01/2021, 19:16^02,2021-07-01T18:15:56Z,30.00,69.00,44,Grade: Ripe
5 watermelon1.jpg,07/01/2021, 19:16^06,2021-07-01T18:15:56Z,30.00,69.00,44,Grade: Ripe
6 watermelon2.jpg,07/01/2021, 19:16^10,2021-07-01T18:15:56Z,30.00,69.00,44,Grade: Ripe
7 watermelon3.jpg,07/01/2021, 19:16^14,2021-07-01T18:15:56Z,30.00,69.00,44,Grade: Ripe
8 watermelon4.jpg,07/01/2021, 19:16^18,2021-07-01T18:15:56Z,30.00,69.00,44,Grade: Ripe

data.csv X
documentation > data.csv
1 Name,Date,Time,Created Date,Temperature,Humidity,Ethylene Readings,Grade
2
3
4 watermelon0.jpg,07/10/2021, 13:53^41,2021-07-03T12:18:12Z,27.00,71.00,92,Grade: Rotten
5 watermelon1.jpg,07/10/2021, 13:53^47,2021-07-03T12:18:12Z,27.00,71.00,92,Grade: Rotten
6 watermelon2.jpg,07/10/2021, 13:53^52,2021-07-03T12:18:12Z,27.00,71.00,92,Grade: Rotten
7 watermelon3.jpg,07/10/2021, 13:53^59,2021-07-03T12:18:12Z,27.00,71.00,92,Grade: Rotten

```

Figure 6. MCSS classifying ripe and rotten watermelons

The dataset obtained based on the number of watermelons classified as either ripe or rotten was successfully sent to the ThingSpeak database using the WiFi module of the system and downloadable in a CSV format for easy referencing. Figure 7 shows the template of the CSV file downloadable from ThingSpeak. Also, the real-time values of the ethylene, temperature and humidity readings of the environment are taken and sent to the cloud for monitoring. This allows the system to be robust and creates a means to view the performance of the system in real-time. Figure 8 shows a real-time graphical display of the ethylene, temperature, and humidity readings obtained and sent to ThingSpeak.

	A	B	C	D	E	F	G	H
1	Name	Date	Time	Created Date	Temperature	Humidity	Ethylene	Grade
2	watermelon0.	7/10/2021	13:53"41	2021-07-03T12	27	86	44	Grade:Ripe
3	watermelon1.	7/10/2021	13:53"47	2021-07-03T12	27	86	44	Grade:Ripe
4	watermelon2.	7/10/2021	13:53"52	2021-07-03T12	27	86	44	Grade:Ripe
5	watermelon3.	7/10/2021	13:53"59	2021-07-03T12	27	86	44	Grade:Ripe

Figure 7. CSV template of the downloaded file from ThingSpeak

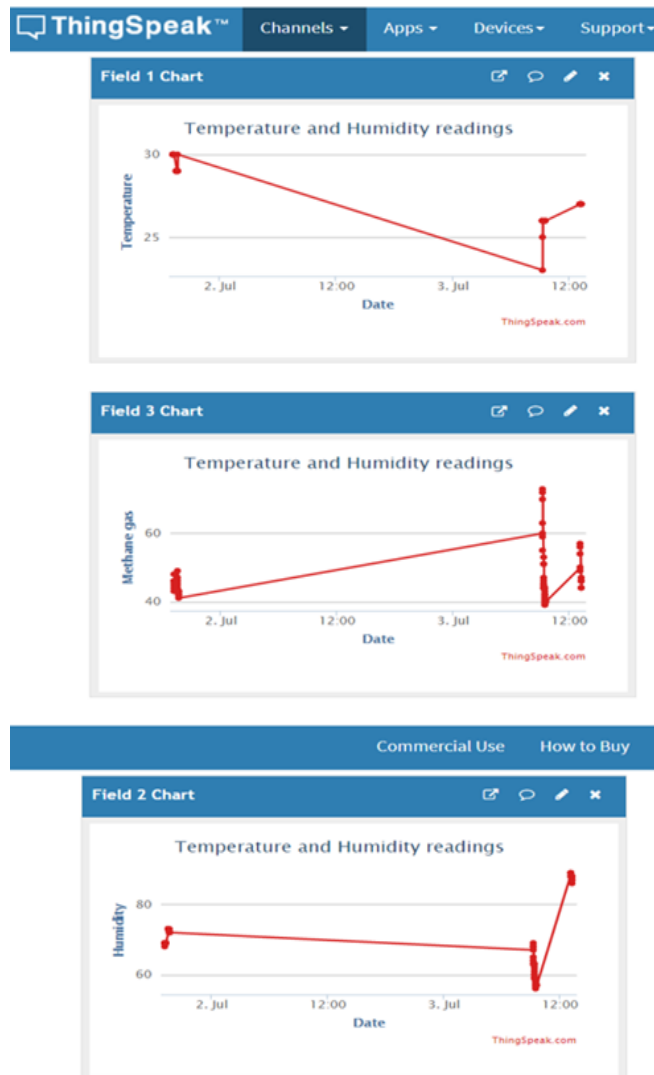


Figure 8. Real-time graphical readings of the fruits' conditions on ThingSpeak.com

**4. CONCLUSION**

A robust MCSS dual-classifier that uses real-time images and sensors as an input to detect and classify watermelon has been designed and implemented. The system was able to accurately detect watermelon with an accuracy of about 88.10% and a loss of 0.3. Also, a classification model was integrated into the system to determine if a watermelon is ripe or rotten, which was achieved to about 85-90%



prediction accuracy with the tested data. Furthermore, a cloud-based database is used to save data obtained from the monitoring system as well as recover data from it by the algorithm. This data recovered is then saved in a designated CSV file locally for easy access, documentation, and future reference. The developed dual-classifier can be deployed on a conveyor in a manufacturing line for maximal performance with a robotic hand that can sort these watermelons based on the information received from MCSS. Finally, the development and integration of a robotic hand into the system that can perform an accurate sorting of watermelons based on the classifier (ripe/rotten) is the next futuristic phase for the developed system.




## REFERENCES

- [1] R. Jayawardena, D. T. Jeyakumar, M. Gamage, P. Sooriyaarachchi, and A. P. Hills, "Fruit and vegetable consumption among South Asians: A systematic review and meta-analysis," *Diabetes and Metabolic Syndrome: Clinical Research and Reviews*, vol. 14, no. 6, pp. 1791–1800, Nov. 2020, doi: 10.1016/j.dsx.2020.09.004.
- [2] R. Rahim and A. A. A. Raman, "Cleaner production implementation in a fruit juice production plant," *Journal of Cleaner Production*, vol. 101, pp. 215–221, Aug. 2015, doi: 10.1016/j.jclepro.2015.03.065.
- [3] M. A. Waheed, S. O. Jekayinfa, J. O. Ojadiran, and O. E. Imeokparia, "Energetic analysis of fruit juice processing operations in Nigeria," *Energy*, vol. 33, no. 1, pp. 35–45, Jan. 2008, doi: 10.1016/j.energy.2007.09.001.
- [4] N. B. Ackah, "Developing a verification program for sanitation and pasteurisation activities during pineapple juice production," *Food Science and Quality Management*, vol. 25, no. 2007, pp. 1–9, 2014.
- [5] R. Vinayakumar, M. Alazab, K. P. Soman, P. Poornachandran, A. Al-Nemrat, and S. Venkatraman, "Deep learning approach for intelligent intrusion detection system," *IEEE Access*, vol. 7, pp. 41525–41550, 2019, doi: 10.1109/ACCESS.2019.2895334.
- [6] C. Bhattacharjee, V. K. Saxena, and S. Dutta, "Fruit juice processing using membrane technology: A review," *Innovative Food Science and Emerging Technologies*, vol. 43, pp. 136–153, Oct. 2017, doi: 10.1016/j.ifset.2017.08.002.
- [7] WHO, "Food and Agriculture Organization of the United Nations. Fruits and vegetables for health: Report of a Joint FAO," 2005.
- [8] S. Yogitha and P. Sakthivel, "A distributed computer machine vision system for automated inspection and grading of fruits," in *Proceeding of the IEEE International Conference on Green Computing, Communication and Electrical Engineering, ICGCCEE 2014*, Mar. 2014, pp. 1–4, doi: 10.1109/ICGCEE.2014.6922281.
- [9] D. C. Slaughter, C. H. Crisosto, J. K. Hasey, and J. F. Thompson, "Comparison of Instrumental and Manual Inspection of Clingstone Peaches," *Applied Engineering in Agriculture*, vol. 22, no. 6, pp. 883–889, 2006, doi: 10.13031/2013.22242.
- [10] L. S. Dalenogare, G. B. Benitez, N. F. Ayala, and A. G. Frank, "The expected contribution of Industry 4.0 technologies for industrial performance," *International Journal of Production Economics*, vol. 204, pp. 383–394, Oct. 2018, doi: 10.1016/j.ijpe.2018.08.019.
- [11] A. G. Frank, L. S. Dalenogare, and N. F. Ayala, "Industry 4.0 technologies: Implementation patterns in manufacturing companies," *International Journal of Production Economics*, vol. 210, pp. 15–26, Apr. 2019, doi: 10.1016/j.ijpe.2019.01.004.
- [12] S. Vaidya, P. Ambad, and S. Bhosle, "Industry 4.0 - A Glimpse," *Procedia Manufacturing*, vol. 20, pp. 233–238, 2018, doi: 10.1016/j.promfg.2018.02.034.
- [13] A. Bhargava and A. Bansal, "Automatic detection and grading of multiple fruits by machine learning," *Food Analytical Methods*, vol. 13, no. 3, pp. 751–761, Mar. 2020, doi: 10.1007/s12161-019-01690-6.
- [14] J. Blasco, N. Aleixos, and E. Moltó, "Machine vision system for automatic quality grading of fruit," *Biosystems Engineering*, vol. 85, no. 4, pp. 415–423, Aug. 2003, doi: 10.1016/S1537-5110(03)00088-6.
- [15] T. V. D. Loooverbosch *et al.*, "Nondestructive internal quality inspection of pear fruit by X-ray CT using machine learning," *Food Control*, vol. 113, p. 107170, Jul. 2020, doi: 10.1016/j.foodcont.2020.107170.
- [16] S. Munera *et al.*, "Discrimination of common defects in loquat fruit cv. 'Algerie' using hyperspectral imaging and machine learning techniques," *Postharvest Biology and Technology*, vol. 171, p. 111356, Jan. 2021, doi: 10.1016/j.postharvbio.2020.111356.
- [17] S. Saripa, R. Binti, and M. Lazim, "Non-destructive assessment of the internal quality of watermelon using ultraviolet near-infrared spectroscopy," Msc., Universiti Putra Malaysia, 2018.
- [18] Y. Zhang, X. Deng, Z. Xu, and P. Yuan, "watermelon ripeness detection via extreme learning machine with kernel principal component analysis based on acoustic signals," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 33, no. 8, p. 1951002, Jul. 2019, doi: 10.1142/S0218001419510029.
- [19] C. Ding, D. Wang, Z. Feng, W. Li, and D. Cui, "Integration of vibration and optical techniques for watermelon firmness assessment," *Computers and Electronics in Agriculture*, vol. 187, p. 106307, Aug. 2021, doi: 10.1016/j.compag.2021.106307.
- [20] H. Xu, H. Chen, Y. Ying, and N. Kondo, "Fruit density as an indicator for watermelon hollow detection using helmholtz resonance," *Transactions of the ASABE*, vol. 57, no. 4, pp. 1163–1172, 2014, doi: 10.13031/trans.57.10560.
- [21] W. Castro, J. Oblitas, M. De-La-Torre, C. Cotrina, K. Bazan, and H. Avila-George, "Classification of Cape Gooseberry Fruit According to its Level of Ripeness Using Machine Learning Techniques and Different Color Spaces," *IEEE Access*, vol. 7, pp. 27389–27400, 2019, doi: 10.1109/ACCESS.2019.2898223.
- [22] A. Zeb *et al.*, "Is this melon sweet? A quantitative classification for near-infrared spectroscopy," *Infrared Physics and Technology*, vol. 114, p. 103645, May 2021, doi: 10.1016/j.infrared.2021.103645.
- [23] J. Mao, Y. Yu, X. Rao, and J. Wang, "Firmness prediction and modeling by optimizing acoustic device for watermelons," *Journal of Food Engineering*, vol. 168, pp. 1–6, Jan. 2016, doi: 10.1016/j.jfoodeng.2015.07.009.
- [24] M. De-la-Torre *et al.*, "Multivariate analysis and machine learning for ripeness classification of cape gooseberry fruits," *Processes*, vol. 7, no. 12, p. 928, Dec. 2019, doi: 10.3390/PR7120928.
- [25] J. H. Oetiker and S. F. Yang, "The role of ethylene in fruit ripening," *Acta Horticulturae*, no. 398, pp. 167–178, Mar. 1995, doi: 10.17660/actahortic.1995.398.17.
- [26] J. B. Golding, D. Shearer, S. G. Wyllie, and W. B. McGlasson, "Application of 1-MCP and propylene to identify ethylene-dependent ripening processes in mature banana fruit," *Postharvest Biology and Technology*, vol. 14, no. 1, pp. 87–98, Sep. 1998, doi: 10.1016/S0925-5214(98)00032-5.
- [27] V. Ziosi *et al.*, "A new index based on vis spectroscopy to characterize the progression of ripening in peach fruit," *Postharvest Biology and Technology*, vol. 49, no. 3, pp. 319–329, Sep. 2008, doi: 10.1016/j.postharvbio.2008.01.017.




- [28] M. Zhou *et al.*, “Comparative dynamics of ethylene production and expression of the ACS and ACO genes in normal-ripening and non-ripening watermelon fruits,” *Acta Physiologiae Plantarum*, vol. 38, no. 9, p. 228, Sep. 2016, doi: 10.1007/s11738-016-2248-x.
- [29] Y. Zhou, Q. Zhou, Q. Kong, and W. Cai, “Wireless temperature & humidity monitor and control system,” in *2012 2nd International Conference on Consumer Electronics, Communications and Networks, CECNet 2012 - Proceedings*, Apr. 2012, pp. 2246–2250, doi: 10.1109/CECNet.2012.6201725.
- [30] Y. Wang and Z. Chi, “System of wireless temperature and humidity monitoring based on Arduino Uno platform,” in *Proceedings - 2016 6th International Conference on Instrumentation and Measurement, Computer, Communication and Control, IMCCC 2016*, Jul. 2016, pp. 770–773, doi: 10.1109/IMCCC.2016.89.
- [31] S. Al-Youif, M. A. M. Ali, and M. N. Mohammed, “Alcohol detection for car locking system,” in *ISCAIE 2018 - 2018 IEEE Symposium on Computer Applications and Industrial Electronics*, Apr. 2018, pp. 230–233, doi: 10.1109/ISCAIE.2018.8405475.
- [32] P. Rai and M. Rehman, “ESP32 based smart surveillance system,” in *2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*, 2019, pp. 1–3.
- [33] V. Viegas, J. M. D. Pereira, P. M. Girão, and O. Postolache, “Study of latencies in ThingSpeak,” *Study of latencies in ThingSpeak*, no. 1, pp. 342–348, 2021.
- [34] M. Kulshreshtha, S. S. Chandra, P. Randhawa, G. Tsaramiris, A. Khadidos, and A. O. Khadidos, “Oater: Outdoor autonomous trash-collecting robot design using yolov4-tiny,” *Electronics (Switzerland)*, vol. 10, no. 18, p. 2292, Sep. 2021, doi: 10.3390/electronics10182292.
- [35] Z. Jiang, L. Zhao, S. Li, and Y. Jia, “Real-time object detection method based on improved YOLOv4-tiny,” *Computer Vision and Pattern Recognition*, Nov. 2020, [Online]. Available: <http://arxiv.org/abs/2011.04244>.
- [36] X. Hou, J. Ma, and S. Zang, “Airborne infrared aircraft target detection algorithm based on YOLOv4-Tiny,” *Journal of Physics: Conference Series*, vol. 1865, no. 4, p. 042007, Apr. 2021, doi: 10.1088/1742-6596/1865/4/042007.
- [37] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “YOLOv4: optimal speed and accuracy of object detection,” *arXiv:2004.10934*, 2020, [Online]. Available: <http://arxiv.org/abs/2004.10934>.
- [38] H. Wu, C. Du, Z. Ji, M. Gao, and Z. He, “Sort-ym: An algorithm of multi-object tracking with yolov4-tiny and motion prediction,” *Electronics (Switzerland)*, vol. 10, no. 18, p. 2319, Sep. 2021, doi: 10.3390/electronics10182319.

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