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Abstract*— Strawberry quality has been a crucial factor when it comes to consumer satisfaction. Having quality and cost-efficient strawberries would increase consumer satisfaction while increasing sales from the merchants' perspective. As such, being able to classify strawberries into the desirable and undesirable categories would aid small businesses and consumers in determining whether the strawberries sold and bought are desirable based on key indicators such as shape and color. To address that, this study was conducted with the use of convolutional neural networks. The strawberry datasets used are a combination of a pre-classified dataset from another study and a dataset of images photographed solely for the purpose of this study. The images are classified as desirable and undesirable wherein 350 images of each set are used for training, 200 images for validation, and 100 images for testing. The generated CNN model is simulated using epochs=15 and batch size=8. The resulting CNN model has a training accuracy=98.41%, a validation accuracy=92.75%, and a testing accuracy=100% which makes the model efficient in classifying strawberries into the desirable and undesirable categories.

Keywords—artificial intelligence, convolutional neural network, food quality, object classification

I. INTRODUCTION

Strawberries are one of the most delicate berries. Typically, most whole uncut strawberries degrade in quality in just 1-2 days if they are not stored in a refrigerator or freezer. Like most fruits, the quality of strawberries is a very important factor for their desirability. However, some supermarkets and groceries tend to ignore some minor deficiencies by displaying and selling them to get more profit from consumers. This practice can be considered both an ethical and health issue because of the quality of food being sold to consumers [1].

With that, this study aims to provide producers, merchants, and consumers with a tool that allows them to determine the quality of the strawberries. This can be done using deep learning neural networks [2] used in conjunction with image processing techniques [3]. Neural networks work by emulating the inner workings of the human brain. In this way the machine can be trained to learn the way a human learns. On the other hand, image processing techniques can be utilized to detect and classify certain features. This study focuses on only two classifications – desirable and undesirable – in detecting strawberry quality. This will allow producers, consumers, and merchants to easily identify desirable strawberries while maximizing profits. Similarly, consumers will also be able to choose the best quality strawberries that would lessen health risks for consumption.

II. RELATED LITERATURE

A. *Strawberry Features*

Freshness serves as one of the key indicators in determining whether a fruit or crop is desirable or not [4] [5]. It is important to ascertain the quality of strawberries, especially in their post-harvest life. Certain key features, including pigment, indicate whether a strawberry is still desirable or not [6]. These features, and in turn desirability, may be affected by diseases contracted by the strawberries. These diseases do not only affect the individual strawberry, but also other strawberries within its proximity. Some of these diseases include leaf blight, gray mold, and powdery mildew. Several diseases cause a loss of seedlings, which means that the fruits do not reproduce as much, while others expedite the rotting process of the strawberry [7].

An idea presented by Mahmud, Zaman, Esau, Chang, Price, and Prithiviraj [8] provides a solution to this problem as they were able to create a system to detect these diseases on a larger scale. Building on this, Ge, Xiong, and J [9] were able to further expand on this idea and implement a machine vision system that could not only detect the appearance of certain diseases on the strawberries but also detect whether the said strawberry is pickable or unpickable. This type of classification can then be extended to determining whether a strawberry is desirable or undesirable.

B. *Image Processing Techniques*

As mentioned, the quality and marketability of strawberries heavily rely on their physical appearances, specifically their color and shape. However, it is evident that objectivity is an issue when the fruit is manually inspected [10]. Thus, image processing is gaining popularity in the detection of strawberry quality pre- and post-harvest. Eaton, Bush, and Gaw [11] presentes a technique wherein the saturation channel of the HSV color space in conjunction with the CIELAB color space were used to analyze the colors of strawberries in each punnet on a fast-paced production line in real time. At the same time, color analysis was used to differentiate underripe from overripe punnets. Meanwhile, Indrabayu, Arifin, and Areni [12] took another approach as they focused on individual strawberry quality. Real-time videos were used to detect individual strawberry ripeness with three classifications (unripe, partially ripe, ripe) wherein unripe and partially ripe were considered undesirable. It was found that a reduced image size from 1920x1080 to 1280x720 pixels resulted in faster execution and less memory usage. The image was then processed through a series of object detection stages starting with RGB to HSV conversion, then image masking, blob detection, and image cropping. The image was processed, then continued to feature extraction and labelling. Afterwards, the processed image was saved as a CSV field to be used for classification later. While the studies mentioned both utilized RGB and HSV color spaces, it was found that these features are not reliable enough when it comes to detecting damages on strawberries. In fact, out of the seven image features used in the experiment [13], the SURF feature showed the best performance as input data for the SVM classifier. SURF key points were able to effectively identify damaged parts of the strawberry. Local features, namely ORB and SIFT, also yielded favorable results, while color features such as HSV, RGB, and RGB histogram exhibits poor performance. Furthermore, the HOG feature was seen with the worst accuracy. Despite the great results from SURF, the extracted key points from a sample image seemed to cause an issue. As SURF key points were extracted, the remaining key points were omitted. This poses an issue for further machine learning classification as important information from the image is missing. Moreover, Yamamoto et al. [14] demonstrated the use of color distribution entropy (CDE) with normalized strawberry images for visual observation and suggests that strawberry classification can be further improved when shape analysis is also employed.

C. Convolutional Neural Networks (CNN)

Incorporating a deep learning neural network would increase the efficiency and efficacy in detecting undesirable features such as diseases [15]. Fitter [16] posits that among three analysis techniques, namely Local Binary Pattern (LBP), Convolutional Neural Networks (CNN), and Histogram of Oriented Gradients (HOG), the best and most effective by far is CNN. This technique was able to generate a model with an accuracy of 88% whilst being able to extract data from a small image (600x800).

Neural networks composed of a series of layers are called convolutional neural networks. These layers are composed of convolutional (CONV) layers, pooling (POOL) layers, an activation layer, and a fully connected layer. The CONV layers convert the input image into a matrix to be resized. Once this is achieved, batch normalization is applied to the matrix, making the matrix a normalized matrix. The normalized matrix is then passed onto the POOL layer for feature extraction. Once the features have been extracted, a fully connected layer learns from the data gathered to make predictions, while the activation layer gives the output classification [17].

Classification has been a modern problem particularly in the field of machine learning. However, certain algorithms were created using learning algorithms [18] as references. This allowed the advent of several different kinds of classification algorithms, one of which is the use of CNN [19]. CNN is a form of neural networking that paved the way for image analysis. CNN is capable of image processing and classification due to two operations it can handle – CONV and POOL. The convolution operation can convert the image into data, while pooling extracts features based on the data [20]. Certain augmentations and add-ons may be utilized alongside CNN to increase the performance of the algorithm. These augmentations, called accelerators, are based on FPGA, GPU, and ASIC designs. FGPA has been garnering the attention of researchers who utilize CNN due to its energy efficient performance, fast prototyping, and reconfigurability [19]. In the study by Thakur et al. [21], CNN serves as a method for classifying the strawberries in terms of its ripeness. CNN was utilized due to its inexpensive nature compared to other methods. For the CNN to be effective in classifying the strawberries, certain features such as surface color, size, and shape must be extracted from the images to create an accurate model. These features, particularly the surface color of the strawberry, is a key indicator of its ripeness. Since the CNN algorithm can extract these features automatically, this algorithm is the most apt for this application. Multiple CONV layers, POOL layers, and fully connected layers make up a different form of CNNs called the deep convolutional neural networks [22]. Where CNNs can just extract certain features and make predictions from these features, the deep convolutional neural networks provide better accuracy in prediction since it is now composed of more convolutional layers and pooling layers [23].

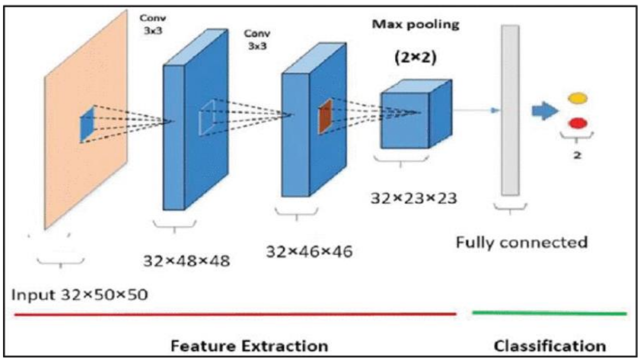

Fig. 1. Structure of CNN. [24]

III. METHODOLOGY

A. Dataset

The availability and accessibility of datasets pertaining to fruits and other consumables are not widespread at all. This has caused certain issues for the study since datasets are limited. A dataset [25] that already classified strawberries based on whether it is desirable, or undesirable is available. However, the data set is too small, less than 500 images for each classification, which means that additional images were necessary to further strengthen the dataset. With that, strawberries had been photographed in different angles and categorized accordingly for the sole purpose of this study. As such, there are a total of 1300 images in this study's dataset. 650 images are classified as desirable while the other 650 images as undesirable. The dataset is further divided into training, validation, and testing sets. For each category, 350 images are used for model training, 200 for model validation, and 100 for model testing. This would ensure that the model is trained and validated well enough before testing is carried out. Testing is necessary to ensure the model's performance is acceptable.

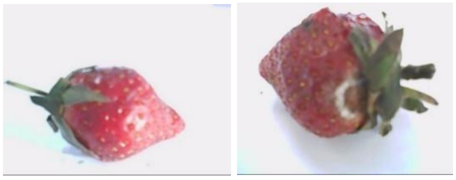

Fig. 2. Sample strawberry images from Mahendra.
(a) Desirable. (b) Undesirable. [25]

Fig. 3. Sample strawberry images taken by the researchers.
(a) Desirable. (b) Undesirable.

B. *Discussion of Methods*

Due to the nature of its algorithm, the use of CNN requires the least amount of intervention, especially when preparing the data for processing. CNN is also one of the algorithms that allows for rescaling in terms of data, making CNN one of the most flexible algorithms when it comes to image processing and classification. The images for training were passed through a 3-layer CNN. The CNN was trained using the Sigmoid function since the study deals with a binary classification problem. The model training is simulated using epochs=15 and batch size=8. After completion of the training simulation, the model was asked to classify 200 images, wherein 100 images had been manually classified as desirable while the remaining 100 images as undesirable. The resulting predictions were then manually cross checked with the actual classification and the testing accuracy was computed.

C. *Performance Metrics*

The performance metric and evaluation for this study would be the accuracy with which the program can correctly identify whether the strawberry in question is desirable or undesirable. This was done using the testing dataset wherein the correct and false predictions were manually recorded. The accuracy formula for the study can be mathematically expressed by:

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

where TP=true positive or the no. of correct predictions for desirable strawberries, TN=true negative or the no. of correct predictions for undesirable strawberries, FP=false positive is the no. of incorrect predictions for desirable strawberries, and FN=false negative or the no. of incorrect predictions for undesirable strawberries.

The model accuracy has been evaluated as acceptable (above or equal to 80% accuracy) or unacceptable (below 80% accuracy).

IV. Results

The trained model, which underwent 15 epochs with a batch size of 8, was found to have a training accuracy of 98.41%, which is above and beyond the acceptable threshold of 80%. Following this, when the model was tested with a new set of images, the model was able to correctly predict the classification of each image perfectly which led to a testing accuracy of 100%. Table II describes the confusion matrix in the testing stage wherein all 200 images had been accurately classified into 100 desirable strawberries and 100 undesirable strawberries.

TABLE I. Accuracy Results

Batch Size	**15 Epochs**		
	Training	***Validation***	***Testing***
8	98.41%	92.75%	100%

TABLE II. Confusion Matrix for Testing

		Actual Value	
		Desirable	***Undesirable***
Predicted Value	***Desirable***	100	0
	Undesirable	0	100

V. Conclusion

It can be concluded that this model trained through 15 epochs with a batch size of 8 is sufficient in creating a model that accurately classifies strawberries into the desirable and undesirable categories. As such, this model can be utilized in identifying whether a certain strawberry is desirable or undesirable. In future studies, it is recommended to integrate this model into a mobile app to allow the consumers and stores to be able to classify strawberries in real-time. At the same time, other image classification algorithms may be utilized such as the YOLO and Faster R-CNN algorithms.

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References

[1] F. Giampieri, S. Tulipanin, J. M. Alvarez-Suarez, J. L. Quiles, B. Mezzetti, and M. Battino, “The strawberry: Composition, nutritional quality, and impact on human health,” *Nutrition*, vol. 28, no. 1, pp. 9–19, 2012.

[2] M. E. Mital et al., "Transfer Learning Approach for the Classification of Conidial Fungi (Genus Aspergillus) Thru Pre-trained Deep Learning Models," 2020 IEEE REGION 10 CONFERENCE (TENCON), 2020, pp. 1069-1074, doi: 10.1109/TENCON50793.2020.9293803

[3] X. A. -r. P. Calangian et al., "Vision-based Canopy Area Measurements," 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology,Communication and Control, Environment and Management (HNICEM), 2018, pp. 1-4, doi: 10.1109/HNICEM.2018.8666251.

[4] J. Ni, J. Gao, L. Deng and Z. Han, "Monitoring the Change Process of Banana Freshness by GoogLeNet," in *IEEE Access*, vol. 8, pp. 228369-228376, 2020, doi: 10.1109/ACCESS.2020.3045394.

[5] C. L. C. Bual, R. D. Cunanan, R. A. R. Bedruz, R. K. C. Billones and R. R. P. Vicerra, "Microcontroller-based Irrigation System for Experimental Design of Mung Bean Sprouts Cultivation," 2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), 2019, pp. 1-6, doi: 10.1109/HNICEM48295.2019.9072801.

[6] R. E. Schouten and O. van Kooten, “KEEPING QUALITY OF STRAWBERRY BATCHES,” *Acta Horticulturae*, no. 566, pp. 329–335, 2001.

[7] J.-R. Xiao, P.-C. Chung, H.-Y. Wu, Q.-H. Phan, J.-L. A. Yeh, and M. T.-K. Hou, “Detection of Strawberry Diseases Using a Convolutional Neural Network,” *Plants*, vol. 10, no. 1, p. 31, 2020.

[8] M. S. Mahmud, Q. U. Zaman, T. J. Esau, Y. K. Chang, G. W. Price, and B. Prithiviraj, “Real-Time Detection of Strawberry Powdery Mildew Disease Using a Mobile Machine Vision System,” *Agronomy*, vol. 10, no. 7, p. 1027, 2020.

[9] Y. Ge, Y. Xiong and P. J. From, "Classification of pickable and unpickable strawberries under farm conditions," *2020 IEEE 16th International Conference on Automation Science and Engineering (CASE)*, Hong Kong, Hong Kong, pp. 961-966, doi: 10.1109/CASE48305.2020.9217022, 2020.

[10] S. Puttemans, Y. Vanbrabant, L. Tits and T. Goedemé, "Automated visual fruit detection for harvest estimation and robotic harvesting," *2016 Sixth International Conference on Image Processing Theory, Tools and Applications (IPTA)*, Oulu, pp. 1-6, 2016, doi: 10.1109/IPTA.2016.7820996.

[11] G. Eaton, A. Busch, R. Bartels and Y. Gao, "Colour Analysis of Strawberries on a Real Time Production Line," *2018 Digital Image Computing: Techniques and Applications (DICTA)*, Canberra, Australia, pp. 1-7, 2018, doi: 10.1109/DICTA.2018.8615779.

[12] I. Indrabayu, N. Arifin and I. S. Areni, "Strawberry Ripeness Classification System Based On Skin Tone Color using Multi-Class Support Vector Machine," *2019 International Conference on Information and Communications Technology (ICOIACT)*, Yogyakarta, Indonesia, pp. 191-195, 2019, doi: 10.1109/ICOIACT46704.2019.8938457.

[13] O. Mahendra, H. F. Pardede, R. Sustika and R. B. Suryo Kusumo, "Comparison of Features for Strawberry Grading Classification with Novel Dataset," *2018 International Conference on Computer, Control, Informatics and its Applications (IC3INA)*, Tangerang, Indonesia, pp. 7-12, 2018, doi: 10.1109/IC3INA.2018.8629534.

[14] K. Yamamoto, Y. Kimura, T. Togami, A. Hashimoto, T. Kameoka and Y. Yoshioka, "Color image database construction for the strawberry breeding," *Proceedings of SICE Annual Conference 2010*, Taipei, pp. 2451-2454, 2010.

[15] J. C. V. Puno, R. K. D. Billones, A. A. Bandala, E. P. Dadios, E. J. Calilune and A. C. Joaquin, "Quality Assessment of Mangoes using Convolutional Neural Network," 2019 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM), 2019, pp. 491-495, doi: 10.1109/CIS-RAM47153.2019.9095789.

[16] Y. Fitter, "Strawberry Detection Under Various Harvestation Stages", *Faculty of California Polytechnic State University*, 2019. Available: https://digitalcommons.calpoly.edu/cgi/viewcontent.cgi?article=3369&context=theses.

[17] W. Zhu, Y. Ma, Y. Zhou, M. Benton, and J. Romagnoli, “Deep Learning Based Soft Sensor and Its Application on a Pyrolysis Reactor for Compositions Predictions of Gas Phase Components,” *13th International Symposium on Process Systems Engineering (PSE 2018)*, pp. 2245–2250, 2018.

[18] R. K. C. Billones, E. J. Calilung, E. P. Dadios and N. Santiago, "Image-Based Macroscopic Classification of Aspergillus Fungi Species Using Convolutional Neural Networks," 2020 IEEE 12th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), 2020, pp. 1-4, doi: 10.1109/HNICEM51456.2020.9400079.

[19] P. Samudre, P. Shende, and V. Jaiswal, “Optimizing Performance of Convolutional Neural Network Using Computing Technique,” *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, 2019.

[20] H. I. Bulbul and Unsal Ö, “Comparison of Classification Techniques used in Machine Learning as Applied on Vocational Guidance Data,” 2011 10th International Conference on Machine Learning and Applications and Workshops, 2011.

[21] R. Thakur, G. Suryawanshi, H. Patel, and J. Sangoi, “An Innovative Approach For Fruit Ripeness Classification,” 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), 2020.

[22] M. Torres-Velazquez, W.-J. Chen, X. Li, and A. B. McMillan, “Application and Construction of Deep Learning Networks in Medical Imaging,” IEEE Transactions on Radiation and Plasma Medical Sciences, pp. 1–1, 2020.

[23] N. Dwivedi, D. K. Singh, and D. S. Kushwaha, “Weapon Classification using Deep Convolutional Neural Network,” *2019 IEEE Conference on Information and Communication Technology*, 2019.

[24] W. S. Ahmed and A. amir Karim, “The Impact of Filter Size and Number of Filters on Classification Accuracy in CNN,” *2020 International Conference on Computer Science and Software Engineering (CSASE)*, 2020.

[25] O. Mahendra, *Strawberry Dataset (Good and Damaged)*, 2018. Accessed on: January 14, 2021. [Online]. Available: https://github.com/okamahendra123/dataset_strawberry.