Real-Time Vegetable Detector with Freshness Detector and Nutritional Value Display

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Abstract: The Philippines is primarily an agricultural country, and a lot of Filipinos live in the provinces and support themselves through agricultural work. Thus, as the population grows, agricultural technologies must become more advanced to accommodate the food production needs as well as address the concerns on food waste, specifically in the storage and evaluation of fresh produce. Advanced methods such as computer vision and machine learning can be implemented to tackle the issues related to the produce's freshness and its corresponding nutrients. The developed real-time vegetable detection system in this study aims to combat food waste through better educating consumers and reducing reliance on aesthetic standards in produce selection. The system was built on Python and OpenCV, and it can determine the freshness of three particular vegetables, potato, carrot, and cabbage, and also displays nutritional information. Furthermore, the system used convolutional neural networks (CNNs), particularly MiniVGGnet. In turn, farmers can utilize the system for efficient sorting and quality assessment while consumers gain access to detailed nutritional insights. This increased efficiency on the user's end enables more sustainable food consumption. Furthermore, the study demonstrates the application of CNNs in food technology. The research exhibits the potential of integrating artificial intelligence in the real-world challenges of agriculture and food supply.

Key Words: vegetable detection; freshness detection; computer vision; machine learning; convolutional neural networks (CNNs)

1. INTRODUCTION

As most of the world continues to industrialize and rapidly develop, food has simultaneously become more accessible and harder to deal with. With the improvement of agricultural machinery and related processes, more and more food can be produced in smaller areas than ever before. This has led to concerns with regard to the processing, storage, and transportation of these food products. The byproduct of any inefficiencies in those stages is waste, which has been a growing problem in recent years as more and more food is being thrown away. According to the World Food Programme (2020) of the United Nations, around one-fifth of all food produced globally becomes wasted. Of the estimated $1 trillion US dollars lost annually due to food waste, it is estimated that upwards of 30% is due to fruit and vegetable waste specifically (Jeonsuu et al., 2020). This can be attributed to many factors, such as the inherent losses of agricultural machinery, discarded products due to pests and diseases, and even the aesthetic standards that the produce is subjected to in marketplaces (Hingston & Noseworthy, 2020). While some of the factors involved are due to natural occurrences and mechanical inefficiencies, the perception of aesthetics may be changed through the use of information technology.

Computer vision technologies have continuously improved over the past decades, with improving algorithms and increasing processing power, making them better than ever before. While there are many areas where computer vision is being used to improve upon existing workflows, one of the areas it has had the most success in is the food industry. A review paper by Kakani et al. (2020) detailed the various areas in the food industry in which computer vision could play a large part in the near future, such as harvesting, quality control, logistics, and others. This statement was further fueled by the growing role that the "AI boom" is playing in the development of computer vision technologies. The improvement in AI and machine learning models is making computer vision more accessible and more reliable, further increasing the reach it could have.

With this in mind, this paper details the development of a vegetable detection system that would also be able to detect the freshness of said vegetable and display its nutritional content. Since aesthetics and misinformation play a role in how produce is selected in grocery stores and in other marketplaces, a tool that makes accurate information more accessible immediately could help reduce food waste for these reasons. Proving the viability of such a tool could help consumers make better decisions in the future and open the way for the development of a mainstream application. Using computer vision to create such a system will allow it to perform said detection and information displays in real-time, making it more intuitive for consumer use should it ever reach that stage. The system was mainly created using Python code and the OpenCV library, with the machine-learning aspects being done with the requisite libraries. Through this paper, the students hope to introduce another method for determining whether or not a vegetable is close to rotting to minimize food waste.

2. METHODOLOGY

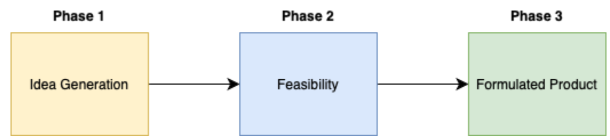

Fig. 1. Retrieved from De Alca et al. (2024). A Modified Framework based on Aramouni and Deschenes (2017), Process of Product Development.

The framework used to develop the system was from De Alca et al.'s (2024) paper, wherein the researchers modified the "Process of Product Development" framework taken from Aramouni and Deschenes (2017). There are three phases, namely: Idea Generation, Feasibility, and Formulated Product. In the first phase, the group conceptualized possible agriculture-related systems as the Philippines relies heavily on that industry. After that, the researchers checked if the conceptualized idea is possible to create by identifying what software tools are needed, and if it can be done in a simple setup using only a webcam. Once that's done, the group developed the system through the use of the identified software tools and a webcam.

2.1 Idea Generation

The real-time vegetable detection system was initially conceptualized in response to the pressing concern of food waste, particularly in the context of fresh produce. Especially in a country such as the Philippines, where agriculture plays a significant role in both the economy and daily life, inefficiencies in food storage and consumer purchasing behaviors aggravate the amount of waste. Consumers tend to rely on visual or aesthetic standards when selecting vegetables. This contributes to the disposal of perishable goods that may still be edible, including those that may only seem in poor condition. Given this problem, the project from its early stages explored ways to provide a more objective and accessible means of assessing freshness and nutritional value. Additionally, the system encourages a shift toward sustainable food consumption.

Transforming the mechanism from concept to function likewise involved research on existing integration in digital food processing and computer vision technologies. A major focus was the use of convolutional neural networks (CNNs), which have proven highly effective in image-based classification tasks, making them a viable choice for analyzing vegetable freshness. Such an option, as a result, has led to the utilization of OpenCV and Python in the project. Innovation of a nutritional value display was likewise equipped, allowing users to make more informed decisions beyond a mere freshness assessment.

2.2 Feasibility

The feasibility assessment focused on determining whether the concept of a system capable of identifying vegetable freshness and providing nutritional details could be realistically achieved with the available tools and resources. Python was used as the development environment due to its extensive support for machine learning and image processing tasks. In particular, libraries such as OpenCV and TensorFlow/Keras provided the functionalities for image classification, video frame analysis, and user interface development. This allowed for the development of a system capable of processing webcam input and performing real-time classification.

Another aspect of the feasibility study involved evaluating the availability and quality of image datasets for the selected vegetables, carrot, potato, and cabbage, across both fresh and spoiled conditions. Public datasets were acquired and preprocessed to meet the requirements of the MiniVGGNet architecture. Model training and validation confirmed that acceptable classification accuracy could be achieved using this architecture.

Furthermore, the system's ability to perform live classification and present relevant nutritional information was tested using a standard webcam setup. Frame-by-frame processing was achieved at a stable rate, and outputs were displayed in a clear and accessible format.

2.3 Formulated Product

The finished product of this study is a real-time vegetable detection system with a freshness and nutritional values display that is developed in the Python programming language to leverage its capabilities in computer vision tasks using OpenCV. It is comprised of two components, which are the convolutional neural network (CNN) and the display module that displays the results of the live webcam feed.

The system was made of the pre-processed dataset, the CNN architecture, and the webcam display module. An image dataset of the fresh and rotten carrots, potatoes, and cabbages was pre-processed by resizing to 32x32 pixels and normalizing pixel values to scale between 0 and 1. The pre-processed images were passed onto a CNN architecture, MiniVGGNet, to be more specific, and were optimized using a Stochastic Gradient Descent (SGD) optimizer using an exponential decay learning rate schedule and early stopping to prevent overfitting. This process is further illustrated in Fig. 2, which shows the flowchart of the system.

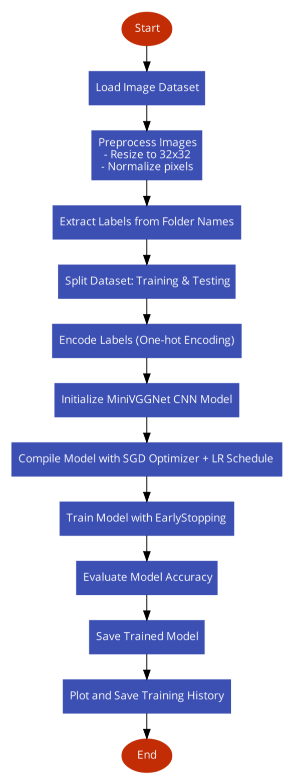

Fig. 2. Flowchart of the Real-Time Vegetable Detector Model Training Method

As shown in Fig. 3, the flowchart explains how the system displays the real-time detection through a live webcam feed. In this system, the Python application allows the trained model to be displayed through a live webcam feed, where each individual frame captured by the webcam is trained for classification. The prediction shows the vegetable, as well as its confidence score and the corresponding nutritional values. If the detected item is not recognized, none of the nutritional values are displayed. This encapsulates how the system classifies and detects the vegetables, carrots, potatoes, and cabbages using a live webcam feed.

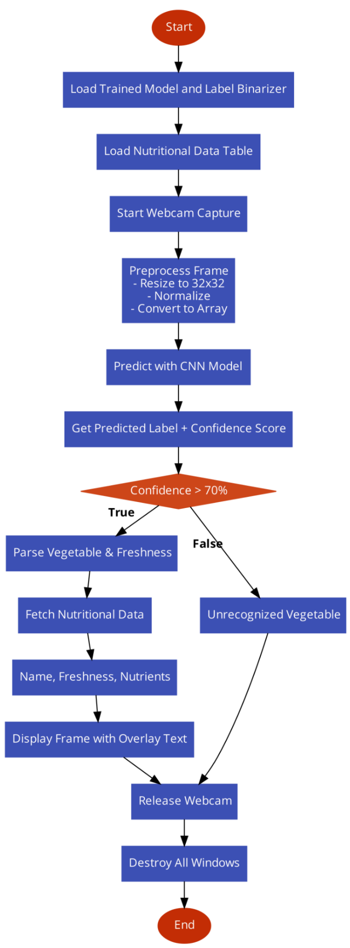

Fig. 3. Flowchart of the Real-Time Vegetable Detector System

3. RESULTS AND DISCUSSION

Computer vision systems provide rapid, consistent, and objective assessment, which is why they are used in the agriculture industry. For the created system, in order to identify which vegetable is being shown in the camera, the researchers used MiniVGGNet. The aforementioned architecture in neural networks is commonly used for object classification, and since it is the smaller version of VGGNet, it is easier to train, making it suitable if there are limitations in system resources.

Table 1. Model Performance after 40 epochs

Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
0.9786	0.0524	0.9371	0.1964

Table 1 shows the final result of the model. After 40 epochs with 46 batches, the final training accuracy is 97.86%, whereas the validation accuracy is 93.71%. This indicates that MiniVGGNet is suitable for the vegetable classification task, as the high training accuracy means that the model was able to learn the training data well, while the high validation accuracy shows an overall good generalization of the model. Thus, the results suggest that the developed system has the potential to effectively contribute to the automation and efficiency of the agriculture sector.

Fig. 4. Detected Fresh Cabbage

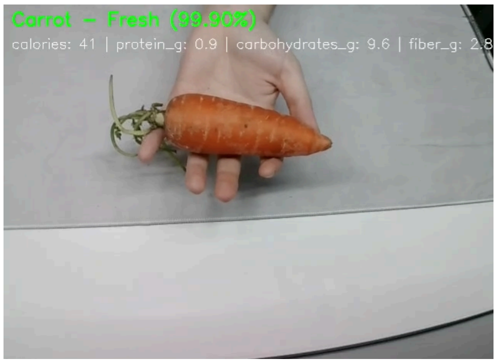

Fig. 5. Detected Fresh Carrot

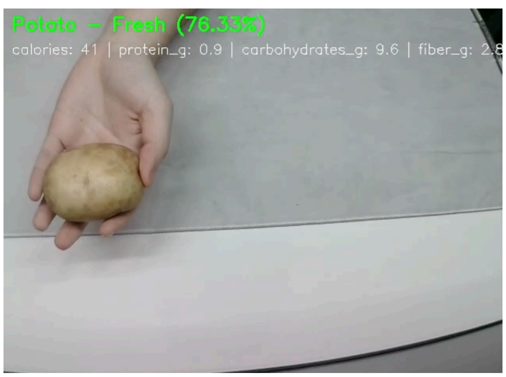

Fig. 6. Detected Fresh Potato

Fig. 7. Detected Rotten Carrot

As shown above, the created system was able to successfully produce confirmation with regard to a vegetable's identity and its freshness. Figures 4 to 6 show the model accurately detecting fresh variants of cabbage, carrots, and potatoes, showing that the trained CNN can distinguish vegetable types under proper lighting and positioning. These successful detections were made using a live webcam feed, supporting the real-time capability of the program, which is vital for user interactivity. However, even though the detection is functional, the authors noted that variations in camera angle and vegetable orientation led to reduced accuracy levels. This inconsistency implies that the system's current training may be somewhat sensitive to changes in the input conditions. Thus, while the current results are promising, further training on more diverse data is essential for more robust performance.

Fig. 8. Undetected Vegetable

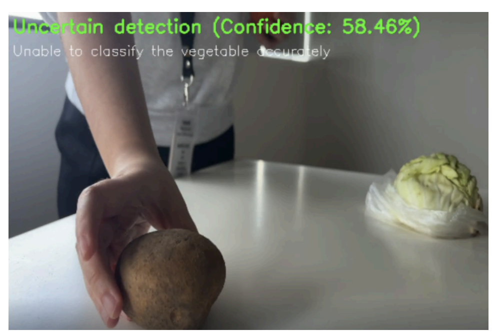

Fig. 9. Uncertain Vegetable Detection

Fig. 10. Uncertain Multiple Vegetable Detection

The example shown in Figure 8 introduces a limitation of the system by presenting a case where a vegetable is not properly identified. This "uncertain detection" label appears when the confidence score of the classification model falls below a predetermined threshold, which helps prevent mislabeling unknown or misoriented items. Such a mechanism is a safety net that prevents misinformation, particularly in a consumer-oriented application. As seen in the previously mentioned figure, the system does have difficulty identifying vegetables when they aren't at the center of the image. While this could be easily remedied by moving the subject to the center, improving upon its performance in these cases will likely help in real-world applications. Situations where a vegetable is dirtied up with soil, such as in Figure 9, also led to uncertain detections. A more varied training set with similarly dirtied examples and off-center images would likely aid future attempts to improve upon this model.

Another limitation of the system is its current inability to identify multiple vegetables in a single image (Figure 10). This may have been due to its use of an object detection algorithm and a lack of training on images with many subjects. Future researchers should try to look into using other algorithms or training using images with multiple vegetables if they would like to continue developing this system.

While there was success with testing for the detection of rotten vegetables (Figure 7), it was an area in which the system struggled at times. This could restrict the current system's ability to distinguish freshness levels reliably and could affect consumer trust in practical applications. Real-world data with varying degrees of freshness should also be looked into to validate the freshness detection mechanism's accuracy. Future iterations of the project should include field testing with naturally decaying produce to better ensure reliable detection under real-world conditions.

4. CONCLUSIONS

The presented system mainly aimed to demonstrate the application of image processing techniques and convolutional neural networks to perform the examination of the characteristics of vegetables. Furthermore, the researchers aimed to do this by making use of CNN to first recognize what vegetable is being shown, followed by determining its freshness state, and then displaying the nutritional facts of said vegetable. By doing this, the researchers were able to demonstrate a successful program that is capable of distinguishing between three vegetables: potato, carrot, and cabbage, as well as whether they are fresh or rotten. The real-time functionality of the system, together with the nutritional display, provides a solution for identifying vegetables and their conditions, hence, broadening the application of computer vision in agriculture, specifically food quality assessments.

Although the researchers were able to meet their objectives for the system, they identified and proposed several recommendations to improve the program in future implementations. Firstly, it is recommended that future works use more diverse datasets to improve accuracy. Such datasets can use sources from different environments with busier backgrounds, such as farmlands, plantations, grocery stores, or markets. This would contribute to the model being more trained in diverse conditions as well as vegetable appearance. Secondly, to improve user experience, the system would benefit from additional real-time feedback mechanisms, apart from the already employed feedback in the program. Auditory cues, such as a beep for fresh produce and a warning tone for rotten produce, would be valuable to those who receive information better via auditory signals. This would also equip the system to be more inclusive and accommodate a wider audience.

5. ACKNOWLEDGMENTS

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