Current Research in Food Science 9 (2024) 100802

Contents lists available at ScienceDirect

Current Research in Food Science

journal homepage: www.sciencedirect.com/journal/current-research-in-food-science

Dual imaging technique for a real-time inspection system of foreign object detection in fresh-cut vegetables

Hary Kurniawan [a,d], Muhammad Akbar Andi Arief [a], Santosh Lohumi [b], Moon S. Kim [c], Insuck Baek [c], Byoung-Kwan Cho [a,b,*]

[a] Department of Smart Agriculture Systems, College of Agricultural and Life Science, Chungnam National University, 99 Daehak-ro, Yuseong-gu, Daejeon, 34134, South Korea
[b] Department of Biosystems Machinery Engineering, College of Agricultural and Life Science, Chungnam National University, 99 Daehak-ro, Yuseong-gu, Daejeon, 34134, South Korea
[c] Environmental Microbial and Food Safety Laboratory, Agricultural Research Service, United States, Department of Agriculture, Beltsville, MD, 20705, USA
[d] Department of Agricultural Engineering, Faculty of Food Technology and Agroindustry, University of Mataram, West Nusa Tenggara, 83126, Indonesia

ARTICLE INFO

Keywords:
Fresh-cut vegetables
Foreign materials
Color imaging
Fluorescence imaging

ABSTRACT

Fresh-cut vegetables are a food product susceptible to contamination by foreign materials (FMs). To detect a range of potential FMs in fresh-cut vegetables, a dual imaging technique (fluorescence and color imaging) with a simple and effective image processing algorithm in a user-friendly software interface was developed for a real-time inspection system. The inspection system consisted of feeding and sensing units, including two cameras positioned in parallel, illuminations (white LED and UV light), and a conveyor unit. A camera equipped with a long-pass filter was used to collect fluorescence images. Another camera collected color images of fresh-cut vegetables and FMs. The feeding unit fed FMs mixed with fresh-cut vegetables onto a conveyor belt. Two cameras synchronized programmatically in the software interface simultaneously collected fluorescence and color image samples based on the region of interest as they moved through the conveyor belt. Using simple image processing algorithms, FMs could be detected and depicted in two different image windows. The results demonstrated that the dual imaging technique can effectively detect potential FMs in two types of fresh-cut vegetables (cabbage and green onion), as indicated by the combined fluorescence and color imaging accuracy. The test results showed that the real-time inspection system could detect FMs measuring 0.5 mm in fresh-cut vegetables. The results showed that the combined detection accuracy of FMs in the cabbage (95.77%) sample was superior to that of green onion samples (87.89%). Therefore, the inspection system was more effective at detecting FMs in cabbage samples than in green onion samples.

1. Introduction

Fresh-cut fruits and vegetables are among the most popular commodities worldwide because they are fresh, convenient, uniform in size, and require minimal preparation. They are also recognized as a powerful source of nutrients vital to human nourishment, such as vitamins, dietary fiber, and minerals (Allende and Artés, 2003; Castro-Ibáñez et al., 2017; Che et al., 2022; Mo et al., 2017; Olaimat and Holley, 2012; Tunny et al., 2022; Yousuf et al., 2018) Fresh-cut fruits and vegetables refer to fresh fruits or vegetables that have been slightly physically modified by slicing, cutting, peeling, or trimming into small serving-size portions and ready to eat or cook (Ma et al., 2017; Zhang et al., 2022). Pradas-Baena et al. (2015) and (Raffo and Paoletti, 2022) have reported the main steps in fresh-cut vegetable processing.

Initially, the fresh-cut industry was established to supply hotels, restaurants, and catering services. However, due to the growing need for fresh fruit and vegetables for consumption and technological advancements, this industry has become popular and developed rapidly in the last decade (Kim, 2008; Tunny et al., 2022). By increasing the popularity of fresh, healthy, convenient, and additive-free prepared products consumed globally, they have developed into a major, rapidly expanding food segment of interest to growers, processors, retailers, and

* Corresponding author. Department of Smart Agriculture Systems, College of Agricultural and Life Science, Chungnam National University, 99 Daehak-ro, Yuseong-gu, Daejeon, 34134, South Korea.
E-mail address: chobk@cnu.ac.kr (B.-K. Cho).

https://doi.org/10.1016/j.crfs.2024.100802
Received 10 April 2024; Received in revised form 25 June 2024; Accepted 3 July 2024
Available online 4 July 2024

consumers (Castro-Ibáñez et al., 2017; Lamikanra, 2002; Pradas-Baena et al., 2015). Consequently, the fresh-cut industry has become an essential segment of the agriculture industry with multi-billion dollar sales (Castro-Ibáñez et al., 2017; Fouayzi et al., 2006; Rico et al., 2007; Yu et al., 2022).

However, the presence of foreign materials (FMs) in food is one of the major concerns in the food industry (Mathew, 2021; Trafialek et al., 2016). An FM is a technical term that refers to any extraneous object visible to the naked eye, not intended to be present in food, and causing illness or complications to a person during consumption. This term can also be defined as anything that the consumer perceives as alien to the food (Marsh and Angold, 2004; Mohd Khairi et al., 2018; Trafialek et al., 2016). According to the U.S. Food and Drug Administration, hard or sharp foreign objects measuring between 7 mm and 25 mm are generally considered hazardous and may cause injuries (Djekic et al., 2017). FM can be accidently present at any stage of the production process and carry destructive microbes, creating a more prominent (Aladjadjiyan, 2005; Jia et al., 2024; Mathew, 2021). The FM sources mainly can be classified as intrinsic and extrinsic. Intrinsic types refer to unintended foreign material typically found in raw food, such as bones, stems, or seed pits. Extrinsic types refer to FMs that are materials not expected to be found in food, such as stones, insects, or fragments of plastic, metal, or glass (Edwards and Stringer, 2007; Mohd Khairi et al., 2018; Payne et al., 2023). These FMs can disgust and injure the consumer, whether breaking a tooth, injuring the tongue, or falling into the larynx (Golian et al., 2018; Mittal, 2009). However, the range of contaminants is very diverse and depends on the specific product (Trafialek et al., 2016). According to Edwards and Stringer (2007), FMs are the highest single source of customer complaints received by many food manufacturers, retailers, and enforcement authorities. Plastic, metal, glass, insects, wood, and stone are the types of foreign objects associated with several contamination incidents in the food industry. Further, the most common foreign materials of concern, their hazards, and their common sources have been well-reviewed and presented in Payne et al. (2023) and Edwards and Stringer (2007).

Among several food products, fresh-cut vegetables are most susceptible to physical contamination before, during harvest, and post-harvest operations such as transport, storage, and retail distribution. Some are common contaminants in fresh-cut vegetables, including plastics (Edwards and Stringer, 2007), insects (Caparros Megido et al., 2014), stones (Choi et al., 2019), and wood pieces (Gil et al., 2009). The presence of these contaminants downgrade the quality and can result in significant economic losses for producers and retailers (Lohumi et al., 2021; Lu and Lu, 2017). An average of 500 product recalls are initiated annually in Europe, with the second most significant cause being FM contamination (20%). The main products of concern are fruits and vegetables (14%) (RSA Insurance, 2016). In 2021 and 2022, the Rapid Alert System for Food and Feed (RASFF) Window received notifications about FM contaminants and recall of products in fruits and vegetables. Plastic and insects were found in frozen bell pepper strips from Turkey and organic brown lentils, respectively, a piece of glass in canned peas, and a freeze-dried organic fruit mixture from Germany. Pointed stones and several agglomerates of soil, plant parts, sand, or rock were detected in pinto beans from Iran. Insects were reported in pickled tomatoes from Poland and glass fragments in fruit spreads from Denmark (www.webgate.ec.europa.eu). Therefore, it is imperative for the fresh-cut vegetable industry to implement a proper inspection system to ensure product safety, thereby guaranteeing consumer satisfaction and health. Additionally, such measures are essential for compliance with stringent food safety regulations (Jha and Matsuoka, 2000; Tang et al., 2022; Zhu et al., 2021).

To address the challenge of identifying FMs in different food products, a wide range of techniques has been utilized. According to (Lee et al., 2012), these techniques include thermal imaging, terahertz imaging, microwave imaging, ultrasonic imaging, metal detectors, X-ray inspection, and color imaging (optical detectors). These techniques have been applied to a diverse range of samples. However, these techniques are only suitable for certain FMs, and their effectiveness differs based on the specific properties of the samples, such as density, color, water content, and sensitivity to temperature variations. The advantages and limitations of these techniques for detecting foreign objects in food have been thoroughly examined and detailed in the study by (Mohd Khairi et al., 2018; Tang et al., 2022). Meanwhile, despite the critical issue of recurrent FM contamination in fresh-cut vegetables, no study has been performed to investigate the performance of the systems mentioned earlier for fresh-cut vegetables. Of the techniques mentioned above, only metal detection, X-ray inspection, and color imaging are the predominant methods used in the commercial sector; while terahertz imaging, in particular, is still in its infancy as a food inspection technique (Lohumi et al., 2021; Mohd Khairi et al., 2018). Metal detectors are commonly utilized in food processing facilities, such as fresh-cut lettuce processing, as a final line of defense to detect foreign objects. However, metal detectors can only detect metal objects and cannot effectively identify metals with low conductivity, such as stainless steel. It is essential to understand that this system cannot be viewed as a total elimination device for foreign objects; contamination is possible to get past this system (Hurst, 2002; Payne et al., 2023). Similarly, sophisticated X-ray inspection instruments are unsuitable for detecting objects with the same density as water, such as paper and plastic. Also, X-rays sometimes cannot keep up with the manufacturing speed, and the allowable energy of the X-ray source is limited, which precludes using X-ray detectors on thicker products (H. Chen et al., 2020; Payne et al., 2023). Furthermore, color camera-based machine vision methods may struggle to identify opaque foreign objects (such as plastic) or those with a similar color to the conveyor background or fresh-cut vegetables. Terahertz imaging has limitations including expensive, low spatial resolution, significant attenuation in water media, and difficulty to use in the production line (Mohd Khairi et al., 2018; Tang et al., 2022). Furthermore, color camera-based machine vision methods may struggle to identify opaque foreign objects (such as plastic) or those with a similar color to the conveyor background or fresh-cut vegetables (Lee et al., 2012; Mohd Khairi et al., 2018).

Recently, (Mustafic et al., 2014) introduced a novel approach to detecting and differentiating cotton foreign objects using fluorescence imaging. Blue and UV LED-induced fluorescence were investigated to identify botanical and non-botanical foreign objects in cotton. (Zhou and Ding, 2010a) addressed the challenge of detecting cotton lint trash, particularly differentiating between colored and white trash types within the ultraviolet–visible (UV–Vis) spectral range. The study introduced an efficient method for trash detection using imaging techniques that alternate between white light and UV light to minimize spectral interference from white light in fluorescence imaging. These previously mentioned studies showed that foreign bodies with fluorescence properties could be distinguished through fluorescence imaging. Since commercial plastics currently widely used contain additives with significant fluorescence emission, such as optical brighteners, most plastics will show significant signs of fluorescence when irradiated with UV-A light (365 nm). In addition, leafy greens naturally show distinct chlorophyll peaks in the red or far-red regions of the electromagnetic spectrum when irradiated with UV-A light (Arenas et al., 2016; Everard et al., 2014; Payne et al., 2023) These considerations can help distinguish such contaminants from freshly cut vegetables. Considering the unique advantages of fluorescence imaging, fluorescence imaging systems can detect contaminants in fresh-cut vegetables.

Meanwhile, using long-pass filters in color cameras to capture fluorescence imaging has been a subject of interest in various scientific studies. The long-pass filter is an optical filter that allows longer wavelengths associated with fluorescence emissions to pass through while blocking shorter excitation wavelengths. By selectively transmitting the long wavelength emission signal and blocking excitation light, the long-pass filter enhances the contrast and visibility of fluorescence signals emitted by foreign objects against a background

(Yamazaki et al., 2012; Wei et al., 2013) developed a hand-held fluorescence imaging device that incorporates a long-pass thin-film interference filter to reject scattered excitation light, enabling the visualization of single nanoparticles and viruses. Crowther (2022) discussed using Quaser filters for ultraviolet fluorescence photography, similar to long-pass filters. Bueno et al. (2014) emphasized the importance of dichroic mirrors and filters in color cameras to acquire fluorescence images effectively. Chen et al. (2014) proposed a single-camera imaging system capable of capturing both near-infrared fluorescence and color images, demonstrating the practical application of filter systems in fluorescence-guided surgery. These studies underscore the significance of filter technologies, including long-pass filters, in enhancing color cameras' capability for fluorescence imaging applications.

Integrating a long-pass filter is crucial to enhance fluorescence signal detection in foreign object detection with a color camera. The filter allows the transmission of longer wavelengths associated with fluorescence emissions while blocking shorter excitation wavelengths, thereby improving the contrast and visibility of signals emitted by foreign objects against a background. Incorporating a long-pass filter into a color camera system offers various advantages, such as isolating fluorescence signals from excitation light, reducing background noise, and enhancing the signal-to-noise ratio. This selective filtering process is crucial for improving the sensitivity and specificity of foreign object detection, particularly for the fluorescence of foreign objects (Wei et al., 2013). By optimizing the spectral characteristics of the filter, the color camera setup can be tailored to target specific fluorescence wavelengths associated with the foreign objects under investigation (Wei et al., 2013). Thus, incorporating a long-pass filter into a color camera system for fluorescence imaging significantly aids foreign object detection by selectively capturing fluorescence signals and minimizing background interference.

Based on the above ideas, we proposed an alternative approach using fluorescence imaging to detect FMs in fresh-cut vegetable processing. Capturing fluorescence images using a camera equipped with a long-pass filter and color images is a new approach in this study for designing a foreign material detection system, especially for fresh-cut vegetables. Therefore, this work aimed to develop a real-time inspection system to detect FMs using dual imaging techniques (color and fluorescence images) in fresh-cut vegetable processing. To achieve this, a camera equipped with a long-pass filter was used to collect fluorescence images of fresh-cut vegetables and fluorescence FMs. A color camera was also installed to collect color images of fresh-cut vegetables and non-fluorescence FMs, which can be overlooked in fluorescence imaging. Image processing algorithms were developed and incorporated into a custom-built software interface. Finally, the system's FM detection performance was investigated by synchronizing the sensing units with conveyor belt movement.

The rest of the paper is organized as follows. Section 2 introduces the materials and methods, including sample preparation, software interface design, real-time inspection system design, image acquisition, and analysis. Section 3 describes the experimental and analysis results. Finally, Section 4 describes the conclusions and prospects of this paper.

2. Materials and methods

This section provides a detailed description of the experimental setup and procedures for the study. It includes information on vegetable samples and foreign materials, software interface design, a real-time inspection system, image acquisition, and analysis.

2.1. Sample preparation

Two different types of fresh-cut vegetables (cabbage and green onion) purchased fresh from the local market in Daejeon, Republic of Korea, were used in this study and cut into small pieces. These vegetables were selected for their versatility and diverse coloration. As Lohumi et al. (2021) reported, cabbages exhibited a color range from light green to near white. By contrast, green onions showed a broader spectrum of shades, including light green and dark green, and transitioned from yellowish-white to white. Moreover, these vegetables exhibited unique fluorescence responses, leading to variations in both fluorescence intensity and color based on their color differences.

Additionally, the study introduced different types of FMs, both fluorescence and non-fluorescence, of diverse shapes and sizes. This selection was based on a comprehensive review of literature identifying common contaminants in fresh vegetables, including plastics (Edwards and Stringer, 2007), insects (Caparros Megido et al., 2014), stones (Choi et al., 2019), and wood pieces (Gil et al., 2009). Other potential FMs typically encountered in the food processing environment were also considered, as illustrated in Fig. 1.

2.2. Software interface design

To develop a simple and user-friendly software interface for synchronizing the camera and conveyor unit, LabVIEW was used as a graphical programming language because it provides tools for instrumental control, data acquisition, data processing and analysis, and various display modes. The software interface developed using LabVIEW was installed on Microsoft Windows with a vision development and acquisition software module (v2017, National Instruments, Austin, TX, USA). A software development kit (SDK) provided by the camera manufacturer was modified to operate the camera for imaging and control conveyor units.

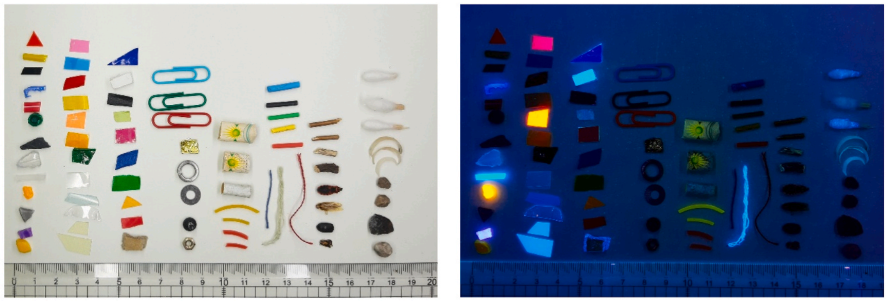
2.3. Real-time inspection system

In this study, we developed an inspection system that simultaneously applies fluorescence and color imaging to detect foreign objects in fresh-cut vegetables, as shown in Fig. 2. The system consisted of two main elements: feeding and sensing units, including cameras, illumination, and a conveyor unit. The feeding unit designed to feed fresh-cut vegetables to the conveyor had dimensions of 318 x 60 × 116 cm. The unit comprised three trays with identical lengths but varying widths from top to bottom at 30 cm, 35 cm, and 40 cm, respectively. The vibration of each tray was adjusted by the control panel, which had voltage and frequency settings.

The sensing unit consisted of two-color cameras with a 5-megapixel CMOS USB 3.0 camera (MV-CA050-20UC, Hikvision, USA) featuring an 8 mm focal length C-mount lens and a 1:1.4 aperture ratio. The first camera captured color images under a white LED light source, while the second camera captured fluorescence images under UV light conditions. UV light is intended to provide the best possible excitation light for the fluorescence foreign material (Zhou and Ding, 2010b). The second camera also had a 415 nm long-pass filter (LP415, Midwest Optical Systems Inc., USA). A long-pass filter was placed in front of the camera to avoid overlapping with the fluorescence excitation of the sample being observed (Mustafic et al., 2014). Both cameras were positioned parallel at 35 cm apart and perpendicular to the conveyor at 35 cm above the conveyor belt. The first camera was positioned 20 cm away from the LED light, with a spacing of 15 cm between the adjacent LED lights. The second camera was placed 20 cm from the UV light and maintained a 15 cm distance between each adjacent UV light. Both cameras were housed within a dark chamber to negate external light interference and separated by a 5 mm thick dark board. It ensured that illumination from the white LED, used for color imaging, did not affect the fluorescence imaging produced by UV-A lighting and vice versa.

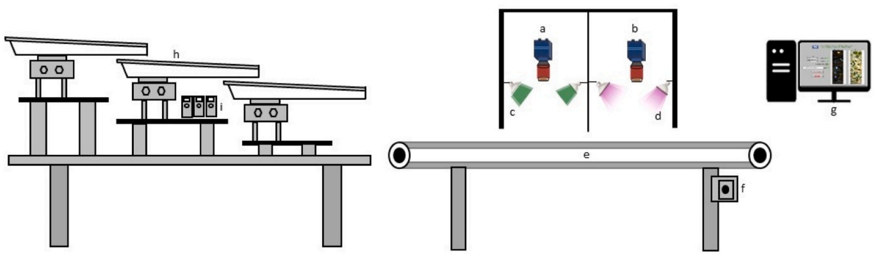
2.4. Image acquisition and analysis

In this work, three test sets were prepared for each type of fresh-cut vegetable. In test set 1, each type of fresh-cut vegetable was mixed solely with non-fluorescence FMs. In test set 2, only fluorescence FMs were



(a) Hard plastic; (b) Soft plastic (film); (c) Paper; (d) Metal; (e) Cigarette butt; (f) Rubber; (g) Cable; (h) Thread; (i) Wood; (j) Insect; (k) Cotton bud; (l) Nail; (m) Stone

Fig. 1. Photograph of the different types of fluorescence and non-fluorescence foreign materials.
(a) Hard plastic; (b) Soft plastic (film); (c) Paper; (d) Metal; (e) Cigarette butt; (f) Rubber; (g) Cable; (h) Thread; (i) Wood; (j) Insect; (k) Cotton bud; (l) Nail; (m) Stone.



(a) Camera 1, (b) Camera 2, (c) White LED light, (d) UV light, (e) Conveyor, (f) Motor control, (g) Computer unit, (h) Feeding unit, and (i) Control panel.

Fig. 2. Schematics of a real-time inspection system for foreign material detection.
(a) Camera 1, (b) Camera 2, (c) White LED light, (d) UV light, (e) Conveyor, (f) Motor control, (g) Computer unit, (h) Feeding unit, and (i) Control panel.

mixed with each fresh-cut vegetable. The remaining test sets were used as validation sets, comprising mixes of non-fluorescence and fluorescence FMs with each fresh-cut vegetable.

Color and fluorescence images of FMs mixed with fresh-cut vegetables were collected for each test set. Fig. 3(a) shows the software user interface for programmatically controlling two cameras and a conveyor belt to simultaneously collect color and fluorescence images. The color image was first collected by arranging the sample on a conveyor unit illuminated by a white light source, followed by collecting the fluorescence image irradiated by UV light, as shown in Fig. 3(b). Both images' field of view (FOV) was 6 x 30 cm. The areas captured in the color image by the first camera and the fluorescence image by the second camera were identical. This method detected fluorescence foreign objects not visible in the color image. Both fluorescence and color images were then saved in *.tiff* format.

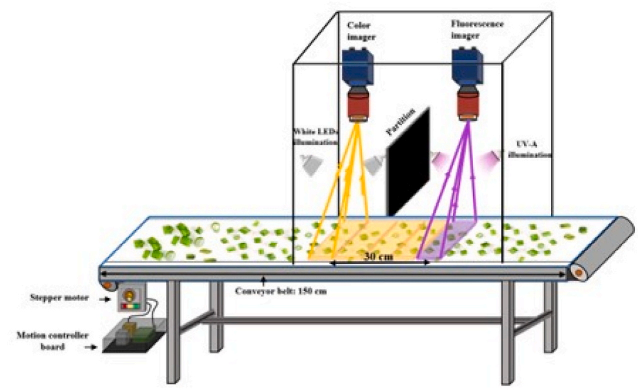
An image processing algorithm applying simple thresholding was developed for fluorescence and color image analysis. Thresholding involves dividing the image into several regions based on pixel intensity levels, distinguishing between foreground and background (Eesa and Talib, 2021). Color images were converted to grayscale images to identify dark-colored objects. Also, the color images were extracted into its color channels (red, green, and blue). The grayscale image then subtracted the intensity of each channel to identify red-yellow, green, and blue-colored objects, respectively. The foreign material of each of these colors was then identified by applying the optimal threshold value to the reduced image as expressed by equation (1) (Cañero-Nieto et al., 2019). The selection of this threshold value was based on minimizing the number of false negative and false positive pixels generated. Also, the image was converted to grayscale for fluorescence images, and each channel was extracted. Each channel was then analyzed using the appropriate threshold to identify red-yellow, green, and dark objects. Image summation was then applied between the red channel and the grayscale image to identify dark objects before applying the threshold. The image processing flowchart for fluorescence and color image analysis is shown in Fig. 4.

$$h(x,y)\begin{cases} = 1 & f(x,y) \geq \mathit{Threshold} \\ = 0 & f(x,y) < \mathit{Threshold} \end{cases} \tag{1}$$

The FM detection algorithm was first applied to test sets 1 and 2. Test set 1, which included only non-fluorescence FMs, was used to determine an optimal threshold value for differentiating FMs from fresh-cut vegetables and the conveyor belt background. Furthermore, the threshold value for detecting fluorescence FMs was selected based on test set 2. An optimal threshold value in each case (test sets 1 and 2) was determined by considering the lowest number of resulting false-negative and false-positive pixels. Thus, based on the selected threshold, all FMs mixed with fresh-cut vegetables would be classified correctly with minimal misclassification. Furthermore, the determined threshold values were applied to the processed images of the remaining test sets for each fresh-cut vegetable.

Furthermore, The developed fluorescence and color image processing algorithms were then incorporated into the LabVIEW-based software interface to deploy the developed real-time inspection system. The performance of the developed foreign material detection system was

(a)



(b)

Fig. 3. Image acquisition: (a) software interface for collecting color and fluorescence images: Cabbage (left), Green onion (right); (b) capturing a field of view of 6 × 30 cm on color and fluorescence images. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

evaluated by customizing it to operate in a production line environment.

3. Results and discussion

3.1. Dual imaging-based classification for foreign materials detection

In this study, a simple yet effective algorithm was developed to construct a detection system for FMs in fresh-cut vegetables. The algorithm was evaluated separately for color and fluorescence images, both non-fluorescence and fluorescence FMs. For non-fluorescence types, the evaluation results facilitated the identification of an ideal threshold value to differentiate between FMs and fresh-cut vegetables and the conveyor belt background. Conversely, the threshold value for fluorescence FM detection was determined by examining fluorescence types. In each scenario, optimal threshold values were determined to reduce false negatives and false positives. As a result, applying these selected threshold values ensured the accurate categorization of FMs mixed with fresh-cut vegetables, significantly reducing misclassification. These established threshold values were then applied to analyzed images of the different FM test sets in each sample category, as shown in Fig. 5.

Fig. 5(a) and (b) show that the algorithm could reliably identify specific types of foreign material under two different lighting conditions in the cabbage and green onion samples, respectively. Although the color imaging method was not optimal for FM detection, it was still reliable due to the color discrimination power of color cameras, which depended heavily on the color difference between samples and foreign objects. As shown in the cabbage and green onion color images (left (a) and left (b)), colored FMs were successfully detected in cabbage and green onion samples, respectively. For color image processing, the algorithm is straightforward. The grayscale image of the RGB image was initially created, and the red, green, and blue channels were eliminated. Each subtracted image was then subjected to threshold settings to identify the small FMs of the corresponding colors. Each case's optimal threshold value was established by considering the fewest number of false-positive and false-negative pixels that resulted. However, detecting FMs with color similarities with vegetables and conveyor backgrounds from fresh vegetable samples, such as transparent plastic, green plastic, paper, nail pieces, cotton buds, cloth, and nylon, was impossible. These results indicate that it is challenging for color image processing algorithms to distinguish them from vegetables.

Meanwhile, fluorescence imaging is advantageous for detecting FMs that cannot be detected by color imaging alone. Fluorescence imaging allows the identification of unique features for each FM and fresh-cut vegetable, regardless of their chromatic appearance. It works by exploiting the fluorescence properties of an object, that is, the ability of some substances to absorb light at a specific wavelength and then re-emitting light at longer wavelengths. As irradiated with UV light at a specific wavelength (excitation), the material with fluorescence properties will absorb this light, emit it at a different wavelength (emission), and then capture it with a camera. These emission patterns can then be detected and analyzed to identify the presence of FMs. Fluorescence imaging will produce a high contrast between FMs and samples, facilitating detection even when visual differences are minimal (Hwang et al., 2021; Karoui and Blecker, 2011). In this study, the reliability of fluorescence images provides an advantage in detecting FMs that cannot be identified by color images alone. The reliability of fluorescence imaging has also been reported by Mustafic et al. (2014) in classifying various types of foreign objects, such as cotton contaminants, which are difficult to distinguish by conventional methods. The results of the developed algorithm for FM detection based on fluorescence images for cabbage and green onion samples are shown on the right (a) and right (b) of Fig. 5. It can be seen that the fluorescence FMs are in high contrast with vegetables. It should be noted that all FMs, including transparent plastics, films, paper, threads, and cotton buds, were successfully detected in both samples. Thus, this dual imaging technique can be powerful for detecting FMs that would have been missed if only one type of imaging was used.

Validation test sets consisting of non-fluorescence and fluorescence FMs for each FM type were used to validate further the developed algorithm for FM detection in fresh-cut vegetables. Tables 1 and 2 present the accuracy of FM detection in cabbage and green onion samples by comparing color images and fluorescence images, which show varying results depending on the type of FM. In both tables, almost all FMs provided unsatisfactory detection accuracy if only one type of imaging was relied upon. For example, in plastic, color, and fluorescence images, only 59.38% and 65.63% were accurate in the cabbage sample, respectively. In green onion, the accuracy rates were 42.11% and 82.46% for color and fluorescence images, respectively.

Experimental results highlight the importance of using a combined detection approach to improve accuracy. Table 1 shows that FMs such as wood, stone, metal, thread, and cable had an overall detection accuracy below 95%, with wood exhibiting the lowest accuracy. Conversely, other types of FMs achieved a total detection accuracy of 100%, for instance, plastic, film, and insects, when the detection methods from both types of images were combined. Meanwhile, in Table 2, almost all FM types provided satisfactory combined accuracy, with threads at 93%, films at 98%, and other FMs reaching 100% accuracy. However, only metal, wood, stone, and insects were significantly detected in color images with unsatisfactory accuracy. They were not identified in fluorescence images, indicating that these materials do not exhibit fluorescence. This discrepancy could be due to their color characteristics, which are similar to natural color variations in green onions. Green onion samples typically display a color spectrum from yellowish-white to dark green in color images. Distinguishing unfamiliar objects from

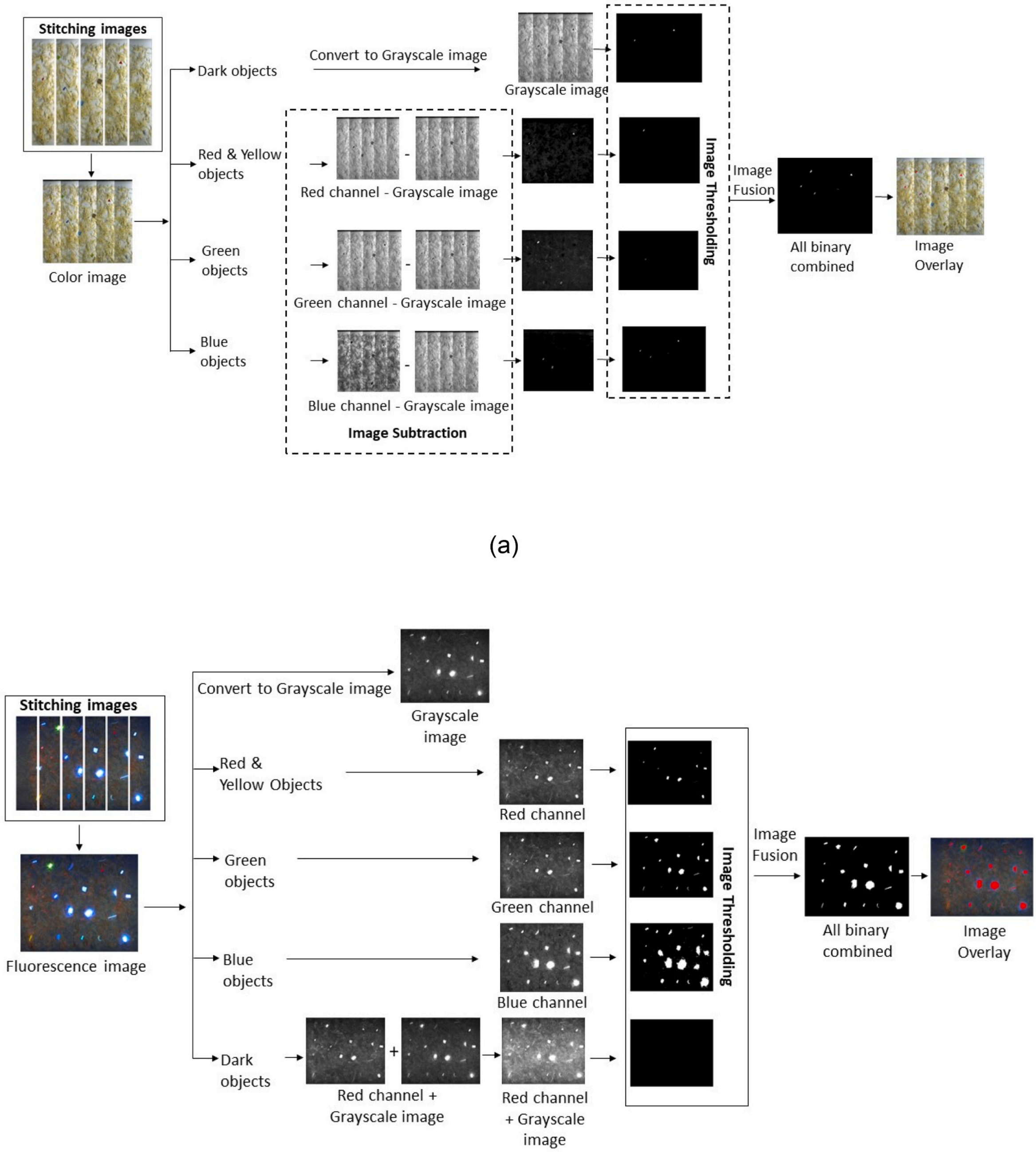


Fig. 4. Image processing flowchart for (a) color and (b) fluorescence image analysis. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

the product's wide range of colors can be challenging if they share the same color tone. In particular, metal, wood, stone, and insects can have darker colors that mix with green onions dark green color, leading to lower detection rates. Color-based detection algorithms could only identify the contrast between green onions and foreign objects; when the colors were not different enough, the algorithm failed to identify them as anomalies.

These findings indicate that detection methods' effectiveness varies greatly depending on FM type. Since not all FMs have the same reflective or fluorescence characteristics, the detection technique's effectiveness depends on the specific optical properties of each FM type. Combining color images with fluorescence images significantly improved overall detection accuracy, as evidenced by the high percentage of combined accuracy for most FMs. However, for some FMs, one method may be superior to another.

3.2. Real-time foreign material detection

A user-friendly software interface was developed, and previously developed fluorescence and color image processing algorithms were incorporated into LabVIEW-based software interfaces, as shown in Fig. 6 (a). The sample moved at a constant speed of 30 cm/s across the conveyor belt, which spanned a length of 150 cm. As they moved, the color camera first captured an image with a field of view (FOV) of 6 x 30 cm. Subsequently, a fluorescence camera captured a corresponding image with an identical FOV, ensuring precise overlap between the two imaging modalities. To achieve this congruence, the image data collection interval was meticulously set to 200 ms. In conjunction with the conveyor speed, this interval was critical for aligning the FOV of both color and fluorescence images, resulting in a seamless and synchronized dual imaging process. Therefore, the software interface

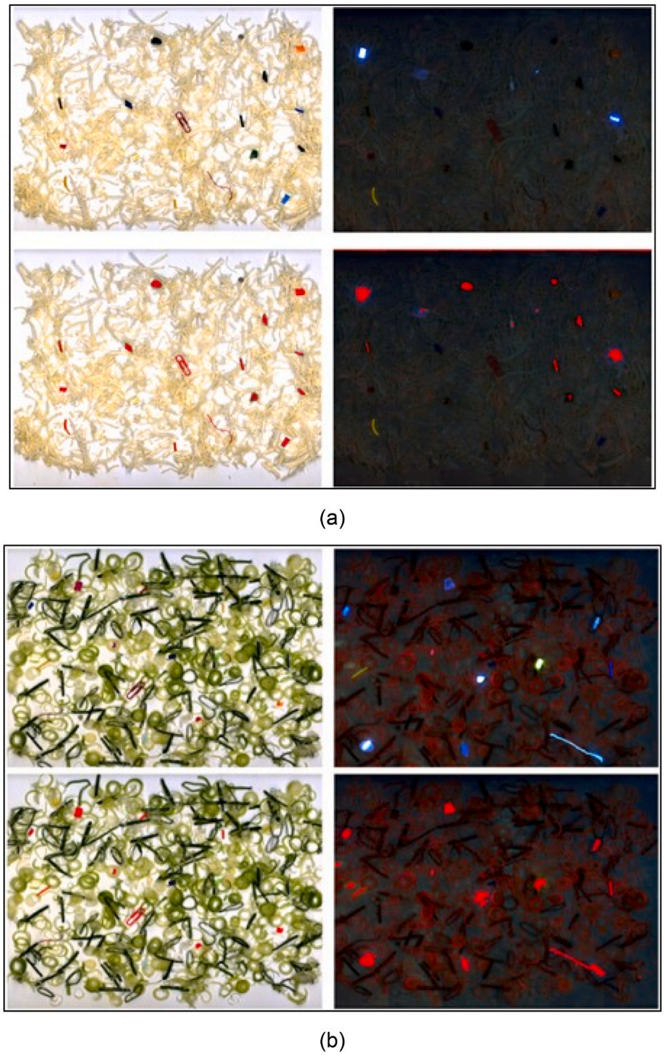


Fig. 5. Color and fluorescence images of foreign materials in two fresh-cut vegetables: (a) cabbage; and (b) green onion. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

focused on capturing images within the specified region of interest (FOV), displaying only the cropped image region (left for fluorescence and right for color imaging in Fig. 6(a)). The developed algorithm was applied to real-time FM detection of moving samples. A button to select the type of vegetable for image processing is provided on the user interface.

To evaluate the performance of the developed system for real-time FM detection in fresh-cut vegetables, each sample mixed with FMs was introduced to the conveyor via a feeding unit. The feeding unit minimized the risk of undetectable foreign materials caused by overlapping samples (Fig. 6(b)). As the sample was dropped on the moving conveyor surface, fluorescence and color images were simultaneously captured for image processing (Fig. 6(c)). Upon activating the image processing button, the system detected and displayed any foreign matter. The study found that most foreign materials were identifiable through fluorescence and color imaging.

Table 3 shows that most FMs were detected with 100% accuracy, such as plastics, films, insects, cigarette butts, cotton buds, nails, rubbers, and Styrofoam. Metal, paper, and thread generated a combined accuracy of about 90–96%. However, unsatisfactory combined accuracy was obtained by wood and stone. It should be noted that the algorithm developed in this inspection system successfully identifies small-sized foreign bodies, such as nylon (0.5 mm), with 100% accuracy. To better illustrate how the system can successfully identify these objects, it can be shown in the yellow bounding box in Fig. 6(a). It demonstrates that the uniqueness of fluorescence imaging can overcome the shortcomings of relying solely on color imaging. Furthermore, in Table 4, low combined accuracy was obtained by stone, insects, metal, wood, and plastic, which was less than 90%. Film, paper, and thread produced a combined accuracy of 90–96%, and the rest provided a combined accuracy of 100%.

It should be noted that cabbage typically presents a more uniform color range, primarily different shades of green, which can be more consistent and predictable. This uniformity allows the optical detection system to more easily contrast between the natural cabbage color and anomalies (foreign materials). In contrast, green onions exhibit a broader spectrum of colors ranging from yellowish-white to dark green. This variation can make it difficult for optical systems to differentiate between the plant's natural color variance and foreign materials, remarkably when the colors of FMs closely resemble parts of the green onion. Optical systems relying on color detection algorithms are also tuned to identify contrasts. Since cabbages have a more uniform color, the contrast between the cabbage and most foreign materials (such as metals, woods, stones, and insects) might be more pronounced, leading to better detection rates. On the other hand, the diverse coloration in green onions decreases the likelihood of strong contrast, thus reducing

Table 1
Evaluation of detection accuracy for individual foreign materials in cabbage sample.

Type of FMs	No. FMs	No. of FMs detected		Accuracy (%)		Total FMs detected (Color + Fluorescence image)	Combine Accuracy (%)
		Color image	Fluorescence image	Color image	Fluorescence image		
Plastic	64	38	42	59.38	65.63	64	100.00
Film	39	26	24	66.67	61.54	39	100.00
Insect	8	8	6	100.00	75.00	8	100.00
Stone	9	7	6	77.78	66.67	8	88.89
Wood	8	5	3	62.50	37.50	5	62.50
Metal	20	18	8	90.00	40.00	18	90.00
Paper	31	16	19	51.61	61.29	31	100.00
Thread	16	9	6	56.25	37.50	15	93.75
Cable	17	16	6	94.12	35.29	16	94.12
Rubber	3	3	2	100.00	66.67	3	100.00
Cigarette butt	5	2	3	40.00	60.00	5	100.00
Cotton bud	4	0	4	0.00	100.00	4	100.00
Nail	5	0	5	0.00	100.00	5	100.00

FMs: Foreign materials.

Table 2
Evaluation of detection accuracy for individual foreign materials in green onion sample.

Type of FMs	No. FMs	No. of FMs detected		Accuracy (%)		Total FMs detected (Color + Fluorescence Image)	Combine Accuracy (%)
		Color image	Fluorescence image	Color image	Fluorescence image		
Plastic	57	24	47	42.11	82.46	57	100.00
Film	50	33	25	66.00	50.00	49	98.00
Paper	46	21	40	45.65	86.96	46	100.00
Metal	11	8	0	72.73	0.00	7	63.64
Wood	5	2	0	40.00	0.00	2	40.00
Stone	5	1	0	20.00	0.00	1	20.00
Insect	4	2	0	50.00	0.00	2	50.00
Thread	15	6	8	40.00	53.33	14	93.33
Rubber	7	6	3	85.71	42.86	7	100.00
Cotton bud	7	0	7	0.00	100.00	7	100.00
Cigarette butt	6	3	6	50.00	100.00	6	100.00
Nail	7	0	7	0.00	100.00	7	100.00
Cable	6	4	2	66.67	33.33	6	100.00

FMs: Foreign materials.

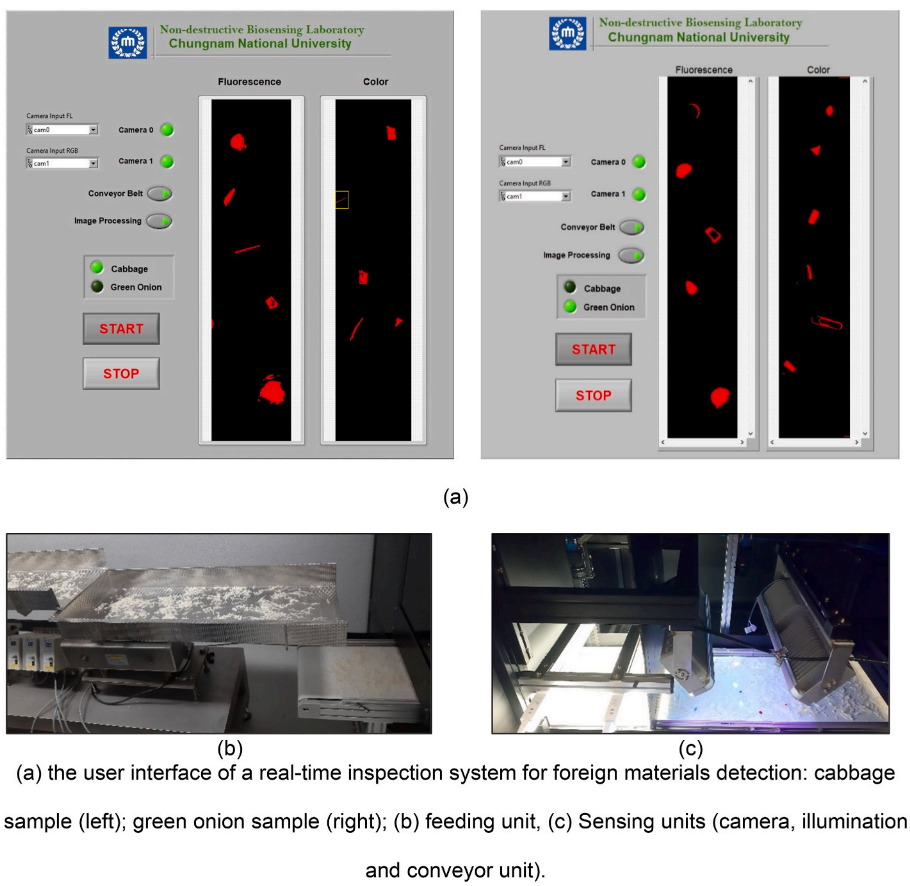


Fig. 6. Photograph of a real-time inspection system for foreign material detection using dual imaging techniques.
(a) the user interface of a real-time inspection system for foreign materials detection: cabbage sample (left); green onion sample (right); (b) feeding unit, (c) Sensing units (camera, illumination, and conveyor unit). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

the algorithm's effectiveness. Overall, the combined detection accuracy of cabbage (95.77%) samples was superior to green onion samples (87.89%). Hence, the developed inspection system was significantly more effective in detecting FMs in cabbage samples than in green onion samples.

The dual imaging-based inspection system developed in this study has improved the detection accuracy of various foreign objects potentially present in fresh-cut vegetables. The system can detect types of foreign objects that existing commercial inspection systems find difficult to detect. For example, metal detection is the most common and standardized technology that food manufacturers utilize to detect foreign materials. It can be used in all food industries and is commonly found in production facilities. These systems have very high sensitivity and performance in detecting various types of metals (Kilifarev, 2024; Righelato, 2018). However, plastics and foreign materials of biological origin, such as insects and wood pieces, are the most problematic foreign

Table 3
Performance of developed system in detection accuracy for individual foreign materials. in cabbage sample.

Type of FMs	No. FMs	No. of FMs detected		Total FMs detected (Color + Fluorescence image)	Combine Accuracy (%)
		Color image	Fluorescence image		
Plastic	24	10	17	24	100.00
Film	23	15	14	23	100.00
Insect	13	13	6	13	100.00
Wood	10	7	3	7	70.00
Stone	12	9	6	10	83.33
Metal	14	13	0	13	92.86
Paper	25	13	17	24	96.00
Cable	17	17	7	17	100.00
Thread	17	10	6	16	94.12
Cigarette butt	7	2	4	7	100.00
Cotton bud	7	0	7	7	100.00
Nail	8	0	8	8	100.00
Rubber	4	3	1	4	100.00
Styrofoam	3	0	3	3	100.00
Nylon	5	0	5	5	100.00

Table 4
Performance of developed system in detection accuracy for individual foreign materials in green onion sample.

Type of FMs	No. FMs	No. of FMs detected		Total FMs detected (Color + Fluorescence image)	Combine Accuracy (%)
		Color image	Fluorescence image		
Plastic	54	27	30	46	85.19
Film	25	17	11	23	92.00
Paper	27	13	19	26	96.30
Insect	7	4	0	4	57.14
Stone	8	4	0	4	50.00
Wood	6	5	0	5	83.33
Metal	10	7	0	7	70.00
Thread	18	4	13	17	94.44
Cable	12	10	3	12	100.00
Nail	4	0	4	4	100.00
Cotton bud	4	0	4	4	100.00
Nylon	4	0	4	4	100.00
Cigarette butt	5	1	5	5	100.00
Styrofoam	2	0	2	2	100.00
Rubber	4	4	4	4	100.00

materials to detect in food (Payne et al., 2023; Righelato, 2018). Meanwhile, X-ray systems are less sensitive to low-density FMs such as paper, wood chips, plastic, insects, thread, and cartilage (Einarsdóttir et al., 2016). The results of a study conducted by (Voss et al., 2021) on the effectiveness of using X-ray, CT and MR in detecting wood, plastic and glass showed that X-ray had the lowest detection rate (61.8%) compared to MR (97.1%) and CT (86%). Additionally, the results of a study conducted by (Kwon et al., 2008) in the classification of foreign bodies (stainless steel ball, stainless steel wire, Teflon ball, aluminum ball, rubber ball, glass ball, ceramic ball) showed a detection rate above 98% without false positives. However, the detection rate is low for small diameters (0.3–5 mm) and low-density materials such as Teflon (2.18 g/cm3) and rubber (1.30 g/cm3). Therefore, additional techniques are indispensable as a layer of defense that must be applied to achieve a higher level of safety and minimize the risk of contamination to ensure product safety and quality.

Nonetheless, FMs such as non-fluorescence transparent plastics posed a challenge to the developed system, as they could not be detected in either color or fluorescence images. This discrepancy is due to their nature of emitting or refracting light without significant change, which causes them to blend into the background, especially if they are color-matched. Fresh vegetables' similar reflectivity and refractive index also contribute to detection difficulty. Dark green foreign objects such as insects, stones, wood, and metals were poorly detected for the green onion sample. Due to color similarity, light brown pieces of wood and white stones were not detected for cabbage. Therefore, as a continuation of this research, we will focus on different approaches and more advanced algorithms such as deep learning approaches to identify FMs with a broader scope.

4. Conclusion

To detect various potential FMs in fresh-cut vegetables, a real-time inspection system was developed using a dual imaging technique (color and fluorescence imaging) with a simple and effective image processing algorithm in a user-friendly software interface. The system consisted of a feeding unit that feeds and avoids overlapping FMs and fresh-cut vegetables, a sensing unit with two cameras positioned in parallel, and a conveyor unit. All hardware, including two color cameras and a conveyor belt, was synchronized programmatically to simultaneously collect color and fluorescence image samples as they passed through the moving conveyor belt. Combining fluorescence and color imaging to detect foreign material in fresh-cut vegetables demonstrated improvements in detection accuracy. The combined accuracy of cabbage and green onion samples was higher than that obtained by a single imaging technique. The testing results also showed that the real-time inspection system could detect foreign material in fresh-cut vegetables up to a size of 0.5 mm. The combined detection accuracy of FMs in cabbage samples was superior to that of green onion samples. In the green onion sample, FMs such as metal, wood, stones, and insects were not identified in the fluorescence image and were only significantly detected in the color image with unsatisfactory accuracy. Therefore, the developed inspection system was more effective at detecting FMs in cabbage samples than in green onion samples.

The developed inspection system was focused on enhancing the accuracy and reliability of detecting foreign objects in fresh-cut vegetables using dual imaging techniques. The system could serve as an additional layer in the production line of fresh-cut vegetables. It addresses the shortcomings of existing commercial inspection systems and can significantly reduce the risk of food contamination. However, the system still faces challenges, particularly in detecting foreign objects similar in color to the conveyor background, such as non-fluorescence transparent plastic. Moving forward, We will explore using more sophisticated image processing algorithms, including machine learning and deep learning, to improve the system's detection capabilities.

CRediT authorship contribution statement

Hary Kurniawan: Conceptualization, Methodology, Investigation, Formal analysis, Data curation, Writing – original draft. **Muhammad Akbar Andi Arief:** Formal analysis, Data curation. **Santosh Lohumi:** Conceptualization, Methodology, Investigation, Formal analysis, Software. **Moon S. Kim:** Conceptualization, Methodology. **Insuck Baek:** Conceptualization, Methodology. **Byoung-Kwan Cho:** Conceptualization, Methodology, Formal analysis, Data curation, Validation, Writing – review & editing, Funding acquisition, Supervision, All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This study was supported by Chungnam National University, South Korea.

References

Aladjadjiyan, A., 2005. Physical hazards in the Agri-food chain. In: Luning, P.A., Devlieghere, F., Verhe, R. (Eds.), Safety in the Agri-Food Chain. Wageningen Academic Publishers. https://doi.org/10.3920/978-90-76998-77-0.

Allende, A., Artés, F., 2003. UV-C radiation as a novel technique for keeping quality of fresh processed "Lollo Rosso" lettuce. Food Res. Int. 36 (7), 739–746. https://doi.org/10.1016/S0963-9969(03)00054-1.

Arenas, A., Beltrán, F.R., Alcázar, V., Orden, M.U., de La Martínez-Urreaga, J., de la Orden, M.U., Martínez Urreaga, J., 2016. Fluorescence Labeling of Polymers for Automatic identification in mixed plastic waste streams. Thermal and photochemical stability. Proc. Cyprus 1–17.

Bueno, G., Déniz, O., Fernández-Carrobles, M.D.M., Vállez, N., Salido, J., 2014. An automated system for whole microscopic image acquisition and analysis. Microsc. Res. Tech. 77 (9), 697–713. https://doi.org/10.1002/jemt.22391.

Cañero-Nieto, J.M., Solano-Martos, J.F., Martín-Fernández, F., 2019. A comparative study of image processing thresholding algorithms on residual oxide scale detection in stainless steel production lines. Procedia Manuf. 41, 216–223. https://doi.org/10.1016/j.promfg.2019.07.049.

Caparros Megido, R., Sablon, L., Geuens, M., Brostaux, Y., Alabi, T., Blecker, C., Drugmand, D., Haubruge, É., Francis, F., 2014. Edible insects acceptance by Belgian consumers: promising attitude for entomophagy development. J. Sensory Stud. 29 (1), 14–20. https://doi.org/10.1111/joss.12077.

Castro-Ibáñez, I., Gil, M.I., Allende, A., 2017. Ready-to-eat vegetables: current problems and potential solutions to reduce microbial risk in the production chain. LWT - Food Sci. Technol. (Lebensmittel-Wissenschaft -Technol.) 85, 284–292. https://doi.org/10.1016/j.lwt.2016.11.073.

Che, J., Chen, K., Song, J., Tu, Y., Reymick, O.O., Chen, X., Tao, N., 2022. Fabrication of γ-cyclodextrin-Based metal-organic frameworks as a carrier of cinnamaldehyde and its application in fresh-cut cantaloupes. Curr. Res. Food Sci. 5 (October), 2114–2124. https://doi.org/10.1016/j.crfs.2022.10.025.

Chen, H., Liou, B.K., Dai, F.J., Chuang, P.T., Chen, C.S., 2020. Study on the risks of metal detection in food solid seasoning powder and liquid sauce to meet the core concepts of ISO 22000:2018 based on the Taiwanese experience. Food Control 111. https://doi.org/10.1016/j.foodcont.2019.107071.

Chen, Z., Zhu, N., Pacheco, S., Wang, X., Liang, R., 2014. Single camera imaging system for color and near-infrared fluorescence image guided surgery. Biomed. Opt Express 5 (8), 2791. https://doi.org/10.1364/BOE.5.002791.

Choi, J., Lee, S.I., Rackerby, B., Moppert, I., McGorrin, R., Ha, S.-D., Park, S.H., 2019. Potential contamination sources on fresh produce associated with food safety. Journal of Food Hygiene and Safety 34 (1), 1–12. https://doi.org/10.13103/JFHS.2019.34.1.1.

Crowther, J., 2022. Ultraviolet fluorescence photography—choosing the correct filters for imaging. Journal of Imaging 8 (6), 162. https://doi.org/10.3390/jimaging8060162.

Djekic, I., Jankovic, D., Rajkovic, A., 2017. Analysis of foreign bodies present in European food using data from Rapid Alert System for Food and Feed (RASFF). Food Control 79, 143–149. https://doi.org/10.1016/j.foodcont.2017.03.047.

Edwards, M.C., Stringer, M.F., 2007. Observations on patterns in foreign material investigations. Food Control 18 (7), 773–782. https://doi.org/10.1016/j.foodcont.2006.01.007.

Eesa, A.M., Talib, H.R., 2021. Comparison of the methods of image slicing after initial image processing using the statistical confidence limits technique. Annals of Pure and Applied Mathematics 24 (1), 53–64. https://doi.org/10.22457/apam.v24n1a06838.

Einarsdóttir, H., Emerson, M.J., Clemmensen, L.H., Scherer, K., Willer, K., Bech, M., Larsen, R., Ersbøll, B.K., Pfeiffer, F., 2016. Novelty detection of foreign objects in food using multi-modal X-ray imaging. Food Control 67, 39–47. https://doi.org/10.1016/j.foodcont.2016.02.023.

Everard, C.D., Kim, M.S., Lee, H., 2014. A comparison of hyperspectral reflectance and fluorescence imaging techniques for detection of contaminants on spinach leaves. J. Food Eng. 143, 139–145. https://doi.org/10.1016/j.jfoodeng.2014.06.042.

Fouayzi, H., Caswell, J.A., Hooker, N.H., 2006. Motivations of fresh-cut produce firms to implement quality management systems. Rev. Agric. Econ. 28 (1), 132–146. https://doi.org/10.1111/j.1467-9353.2006.00277.x.

Gil, M.I., Selma, M.V., López-Gálvez, F., Allende, A., 2009. Fresh-cut product sanitation and wash water disinfection: problems and solutions. Int. J. Food Microbiol. 134 (1–2), 37–45. https://doi.org/10.1016/j.ijfoodmicro.2009.05.021.

Golian, J., Nagyová, Ľ., Andocsová, A., Zajác, P., Palkovič, J., 2018. Food safety from consumer perspective: health safety. Slovak Journal of Food Sciences 12 (1), 313–322. https://doi.org/10.5219/917.

Hurst, W.C., 2002. Safety aspects of fresh-cut fruits and vegetables. In: Fresh-cut Fruits and Vegetables: Scince, Technology and Market. CRC Press LLC, pp. 54–99.

Hwang, C., Mo, C., Seo, Y., Lim, J., Baek, I., Kim, M.S., 2021. Development of fluorescence imaging technique to detect fresh-cut food organic residue on processing equipment surface. Appl. Sci. 11 (1), 458. https://doi.org/10.3390/app11010458.

Jha, S.N., Matsuoka, T., 2000. Non-destructive techniques for quality evaluation of intact fruits and vegetables. Food Sci. Technol. Res. 6 (4), 248–251. https://doi.org/10.3136/fstr.6.248.

Jia, K., Qin, X., Bu, X., Zhu, H., Liu, Y., Wang, X., Li, Z., Dong, Q., 2024. Prevalence, antibiotic resistance and molecular characterization of Staphylococcus aureus in ready-to-eat fruits and vegetables in Shanghai, China. Curr. Res. Food Sci. 8 (December 2023), 100669 https://doi.org/10.1016/j.crfs.2023.100669.

Karoui, R., Blecker, C., 2011. Fluorescence spectroscopy measurement for quality assessment of food systems—a review. Food Bioprocess Technol. 4 (3), 364–386. https://doi.org/10.1007/s11947-010-0370-0.

Kilifarev, H., 2024. Development of a monitoring device for metal fragments in food products – hardware. BIO Web of Conferences 102, 03009. https://doi.org/10.1051/bioconf/202410203009.

Kim, J.G., 2008. Quality maintenance and food safety of fresh-cut produce in Korea. Asian Australas. J. Plant Sci. Biotechnol. 1 (February), 1–6. http://www.globalsciencebooks.info/Online/GSBOnline/images/0812/AAJPSB_2(1&2)/AAJPSB_2(1)1-6o.pdf.

Kwon, J.-S., Lee, J.-M., Kim, W.-Y., 2008. Real-time detection of foreign objects using X-ray imaging for dry food manufacturing line. In: 2008 IEEE International Symposium on Consumer Electronics, pp. 1–4. https://doi.org/10.1109/ISCE.2008.4559552.

Lamikanra, O., 2002. Fresh-Cut Fruits and Vegetables: Science, Technology, and Market, first ed. CRC Press, pp. 1–469. https://doi.org/10.1201/9781420031874.

Lee, Y.-K., Choi, S.-W., Han, S.-T., Woo, D.-H., Chun, H.-S., 2012. Detection of foreign bodies in foods using continuous wave terahertz imaging. J. Food Protect. 75 (1), 179–183. https://doi.org/10.4315/0362-028X.JFP-11-181.

Lohumi, S., Cho, B.-K., Hong, S., 2021. LCTF-based multispectral fluorescence imaging: system development and potential for real-time foreign object detection in fresh-cut vegetable processing. Comput. Electron. Agric. 180 (November 2020), 105912 https://doi.org/10.1016/j.compag.2020.105912.

Lu, Y., Lu, R., 2017. Non-destructive defect detection of apples by spectroscopic and imaging technologies: a review. Transactions of the ASABE 60 (5), 1765–1790. https://doi.org/10.13031/trans.12431.

Ma, L., Zhang, M., Bhandari, B., Gao, Z., 2017. Recent developments in novel shelf life extension technologies of fresh-cut fruits and vegetables. Trends Food Sci. Technol. 64, 23–38. https://doi.org/10.1016/j.tifs.2017.03.005.

Marsh, R.A., Angold, R.E., 2004. Identifying potential sources of foreign bodies in the supply chain. In: Detecting Foreign Bodies in Food. Woodhead Publishing Ltd. https://doi.org/10.1533/9781855738393.1.3.

Mathew, A., 2021. Citation: Mathew A (2021) how food gets contaminated-types of food contamination. J Food Nutr Popul Health 5 (7), 65. https://www.imedpub.com/food-nutrition-and-population-health/.

Mittal, G.S., 2009. Online detection of foreign bodies in packaged foods using ultrasound. New Food 2009 (3). https://www.newfoodmagazine.com/article/275/online-detection-of-foreign-bodies-in-packaged-foods-using-ultrasound/.

Mo, C., Kim, G., Kim, M.S., Lim, J., Lee, K., Lee, W.H., Cho, B.K., 2017. On-line fresh-cut lettuce quality measurement system using hyperspectral imaging. Biosyst. Eng. 156, 38–50. https://doi.org/10.1016/j.biosystemseng.2017.01.005.

Mohd Khairi, M.T., Ibrahim, S., Md Yunus, M.A., Faramarzi, M., 2018. Noninvasive techniques for detection of foreign bodies in food: a review. J. Food Process. Eng. 41 (6) https://doi.org/10.1111/jfpe.12808.

Mustafic, A., Li, C., Haidekker, M., 2014. Blue and UV LED-induced fluorescence in cotton foreign matter. J. Biol. Eng. 8 (1), 29. https://doi.org/10.1186/1754-1611-8-29.

Olaimat, A.N., Holley, R.A., 2012. Factors influencing the microbial safety of fresh produce: a review. Food Microbiol. 32 (1), 1–19. https://doi.org/10.1016/j.fm.2012.04.016.

Payne, K., O'Bryan, C.A., Marcy, J.A., Crandall, P.G., 2023. Detection and prevention of foreign material in food: a review. Heliyon 9 (9), e19574. https://doi.org/10.1016/j.heliyon.2023.e19574.

Pradas-Baena, I., Moreno-Rojas, J.M., Luque de Castro, M.D., 2015. Effect of processing on active compounds in fresh-cut vegetables. In: Processing and Impact on Active Components in Food. Elsevier, pp. 3–10. https://doi.org/10.1016/B978-0-12-404699-3.00001-9.

Raffo, A., Paoletti, F., 2022. Fresh-cut vegetables processing: environmental sustainability and food safety issues in a comprehensive perspective. Front. Sustain. Food Syst. 5 (January) https://doi.org/10.3389/fsufs.2021.681459.

Rico, D., Martín-Diana, A.B., Barat, J.M., Barry-Ryan, C., 2007. Extending and measuring the quality of fresh-cut fruit and vegetables: a review. Trends Food Sci. Technol. 18 (7), 373–386. https://doi.org/10.1016/j.tifs.2007.03.011.

Righelato, R., 2018. Rapid and on-line instrumentation for food quality assurance. Issue 1. In: Tothill, I.E. (Ed.), Analytical Biochemistry, vol. 11. Woodhead Publishing Limited. http://link.springer.com/10.1007/978-3-319-59379-1/0A. https://doi.org/10.1016/B978-0-12-420070-8.00002-7%0A. https://doi.org/10.1016/j.ab.2015.03.024/0A. https://doi.org/10.1080/07352689.2018.1441103%0A. http://www.chile.bmw-motorrad.cl/sync/showroom/lam/es/.

RSA Insurance, 2016. Contamination insurance experts in food & drink. https://www.rsainsurance.co.uk/media/zkwjlmch/rsa-contamination-and-product-recall.pdf.

Tang, T., Zhang, M., Mujumdar, A.S., 2022. Intelligent detection for fresh-cut fruit and vegetable processing: imaging technology. Compr. Rev. Food Sci. Food Saf. 21 (6), 5171–5198. https://doi.org/10.1111/1541-4337.13039.

Trafialek, J., Kaczmarek, S., Kolanowski, W., 2016. The risk analysis of metallic foreign bodies in food products. J. Food Qual. 39 (4), 398–407. https://doi.org/10.1111/jfq.12193.

Tunny, S.S., Amanah, H.Z., Faqeerzada, M.A., Wakholi, C., Kim, M.S., Baek, I., Cho, B.K., 2022. Multispectral wavebands selection for the detection of potential foreign materials in fresh-cut vegetables. Sensors 22 (5), 1–16. https://doi.org/10.3390/s22051775.

Voss, J.O., Doll, C., Raguse, J.D., Beck-Broichsitter, B., Walter-Rittel, T., Kahn, J., Böning, G., Maier, C., Thieme, N., 2021. Detectability of foreign body materials using X-ray, computed tomography and magnetic resonance imaging: a phantom study. Eur. J. Radiol. 135 (December 2020) https://doi.org/10.1016/j.ejrad.2020.109505.

Wei, Q., Qi, H., Luo, W., Tseng, D., Ki, S.J., Wan, Z., Göröcs, Z., Bentolila, L.A., Wu, T.-T., Sun, R., Ozcan, A., 2013. Fluorescent imaging of single nanoparticles and viruses on a smart phone. ACS Nano 7 (10), 9147–9155. https://doi.org/10.1021/nn4037706.

Yamazaki, M., Krishnadasan, S., DeMello, A.J., DeMello, J.C., 2012. Non-emissive plastic colour filters for fluorescence detection. Lab Chip 12 (21), 4313. https://doi.org/10.1039/c2lc40718c.

Yousuf, O., Titikshya, S., Singh, A., 2018. Fresh-cut fruits and vegetables: scope in developing countries and approaches to improve quality and safety 6 (3), 2226–2229. https://www.researchgate.net/publication/326092027.

Yu, H., Lin, Z., Lin, M.S., Neal, J.A., Sirsat, S.A., 2022. Consumers' knowledge and handling practices associated with fresh-cut produce in the United States. Foods 11 (14), 1–15. https://doi.org/10.3390/foods11142167.

Zhang, X., Meng, W., Chen, Y., Peng, Y., 2022. Browning inhibition of plant extracts on fresh-cut fruits and vegetables—a review. J. Food Process. Preserv. 46 (5) https://doi.org/10.1111/jfpp.16532.

Zhou, F., Ding, T., 2010a. Detection of cotton lint trash within the ultraviolet—visible spectral range. Appl. Spectrosc. 64 (8), 936–941. https://doi.org/10.1366/000370210792081091.

Zhou, F., Ding, T., 2010b. White trash detection of cotton lint with ultraviolet-induced fluorescence imaging method. Sixth International Symposium on Precision Engineering Measurements and Instrumentation 7544, 75443T. https://doi.org/10.1117/12.885504.

Zhu, L., Spachos, P., Pensini, E., Plataniotis, K.N., 2021. Deep learning and machine vision for food processing: a survey. Curr. Res. Food Sci. 4 (December 2020), 233–249. https://doi.org/10.1016/j.crfs.2021.03.009.