

IMAGE PROCESSING TECHNIQUES FOR QUALITY EVALUATION OF FOOD

Abstract

The modern food industry places a premium on quality because it is the foundation for success in the current market's fierce competition. It is vital to enhance quality control procedures in order to meet consumers' rising awareness, sophistication, and expectations. When used in conjunction with effective image processing techniques, machine vision effective tool which can give helpful data for the quality of goods and the impact of the processing regime.

Keywords: Image Processing, X-Ray, Hyperspectral Imaging, Food Quality, Thermal Imaging.

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I. INTRODUCTION

Food quality is a degree of excellence of food includes factors such as appearance, taste, and nutritional quality. Sensory and objective evaluation methods are used in food industry in order to routinely monitor food quality and ensure that the foods being produced are acceptable to the consumer. Researchers have recently created different non-contact methods for evaluating food and beverage goods, which overcome the majority of the shortcomings of conventional approaches like human inspection. These techniques work by automatically identifying different visual aspects that may connect with qualities relating to sensory, chemical, and physical properties. Processing digital photos using a digital computer is referred to as a form of digital image processing. The food industry is among the top ten industries which using image processing techniques, for the objective and non-destructive evaluation of several products (Valous and Sun, 2012).

Image processing can be used as th method for enhancing the raw images that sensors and cameras capture. Compared to destructive approaches, it is a non-destructive process that is also relatively quick and affordable (Aulakh and Banga, 2012). For image processing of any image we have to collect the images by using image acquisition. Image acquisition contains light source, sensor or camera, black background for absorption of lights and computer system.

II. STEPS IN IMAGE PROCESSING

- 1. Image Acquisition:** Image acquisition is the action of capturing an image from some source. It is crucial to image processing because if the images are not captured accurately, even with various enhancement techniques present, the image processing algorithms may not be very effective (Joseph, 2018).
- 2. Image Enhancement:** The process of improving digital images makes them more suitable for display or additional picture analysis. The primary goal of the image enhancement system is to create techniques that are quick, effectively handling noise, and perform precise segmentation.
- 3. Image Restoration:** Restoring or recovering a picture which has been destroyed by degradation processes is attempted. It is the process of restoring a deteriorated image by reducing noise or blur to enhance the image's appearance. With the use of previous understanding of the noise or disturbance which leads to the image degradation, the image might be restored.
- 4. Wavelets and Compression:** The basis for describing images at different resolution levels is wavelets. Wavelet offers tools for decoding and creating signals and visual data. to denoise and compress data, and to recognize events like anomalies, switch points, and transients. To disassemble signals and images into their component elements and examine data at various time and frequency resolutions, and multiscale techniques such as wavelet analysis can be utilized. To train machine and deep learning models, wavelet technique is used to reduce dimensionality and extract distinguishing characteristics from signals and images (Sonka *et al.*, 2008).

5. **Image Segmentation:** The process of division of input picture into sections which are homogenous with regard to a certain image quality, such as intensity, colour, or texture is called as image segmentation. It may employ thresholding, edge detection, area identification, statistical classification, or a combination of these methods. Typically, the segmentation process results in a set of categorized elements (Valous and Sun, 2012).
6. **Representation and Description:** The output of a segmentation phase follows by representation and description. This output is frequently raw pixel data and depicts the area's boundaries or all of its points.
7. **Recognition:** The act of giving a label to an item depending on its descriptors is known as recognition. The goal of object identification is to teach a computer to recognize a certain object under a variety of lighting, background, and perspective conditions.

III. IMAGING TECHNIQUES

Different imaging techniques which are non-destructive can be used for determination of quality and defect detection in food produce and products such as X-Ray, computed tomography, hyperspectral, fluorescence, magnetic resonance, structured illumination reflectance, thermal imaging and machine vision (Rajarithnam and Ramteke, 2011).

1. **X-Ray Imaging:** In 1895, Wilhelm Conrad Rontgen, a German physicist, made the discovery of X-rays. He received first physics Nobel Prize for discovering X-Rays, often known as Rontgen rays. However, X-rays were first used to inspect food and agricultural products in the 1920s. As an electromagnetic radiation, X-rays have shorter wavelengths and more penetrating strength than visible light. It has a wavelength between 0.01 and 10 nm and energies between 100 eV and 100 KeV. Fast travelling electrons from a hot cathode collide with a heavy metal target to produce X-rays. An evacuated tube with a filament-like cathode and a metal target known as an anode make up a standard X-ray tube. The usage of gas-type X-ray sources with both positive and negative charge electrodes has been replaced by the use of filament-type cathodes that are commonly made of tungsten. The tungsten filament should be heated to a minimum of 2,200°C in to emit electrons. The cathode, which is kept at a strong negative potential, emits electrons that are drawn to the anode, which is kept at ground potential in a vacuum. Through a significant voltage, the accelerated electrons strike the target and emit X-rays (Karunakaran and Jayas, 2014).

Tube voltage and current has the impact on the quality of picture for each type of material and it will vary depending on the product properties such as thickness, density, and X-ray absorption qualities of different fruits vary (Jiang *et al.* 2008).

The potential of X-ray technology in the food business to identify internal flaws and contamination of the products has been determined by many researchers. It's one of the benefit is ability to detect metallic and nonmetallic impurities in food products, including metals, bone, glass, stone, plastics, and rubber (Schatzki *et al.* 1996). Because processed meals have more or less consistent thickness and metallic and nonmetallic impurities have different densities from food ingredients, X-ray inspection systems are particularly appealing to the food industry. Fruit, vegetable, nut, and grain infestations are

complicated since they may not be externally obvious and are difficult to physically detect. Insect eggs start to form during the flowering stage and do most of their growing inside the fruit's seed. The fruits could eventually suffer increasing harm as a result of the infestation.

Table 1: Applications of X-Ray Imaging

Product	Application	Voltage (kV)	Current (μ A)	Accuracy (%)	References
Wheat	Detection of sprouted wheat	13.5	185	87	Neethirajan <i>et al.</i> , 2007
	kerne Fungal infection detection	13.6	184	82	Narvankar <i>et al.</i> , 2009
Banana	Microstructure of banana slices	60	167		Leonard <i>et al.</i> , 2008
Apple Peach Tomato Guava	Automatic defect detection system	65-75	125	100 100 93.9 100	Chuang <i>et al.</i> , 2011
Salmon fish	Bone detection	40	21 mA	99	Mery <i>et al.</i> , 2011

2. **Computed Tomography Imaging Technique:** Computed Tomography technique introduced in 1970 by Godfrey Hounsfield and Allan Cornack. They got Noble prize for discovery of CT scan technique. After commencing the CT scan in the control room and through the X-ray tube, samples are introduced into the CT scan crate to capture the image. On the sample, X-rays were made. The light colours of the pears were absorbed by the crystals in the CT scan, and some of the energy was taken up by the sample while the remaining rays were rejected. They were then transformed into image codes using a light converter and sent to a room with computers to recreate images. According to Lim and Barigou (2004), 30-45 min were required to scan a 10 mm cube of cellular food products over 180° in 200 distinct steps of 0.9° . It has been discovered that employing X-ray beam projection, computed tomography may deliver comprehensive 3-dimensional information. It has been discovered that the 2-dimensional slices obtained from CT imaging exhibit higher contrast between the components of the corresponding slice. In contrast to transmission radiography, the generation of 2-D and 3-D slices takes longer.

Table 2: Applications of Computed Tomography Imaging

Products	Objective of Study	Current (mA)	Voltage (kV)	References
Sweet Potato	Development of Weevil larvae and subsequent damage in infested roots	230	120	Thai <i>et al.</i> , 1997
Apple	Quantification of pore space in apple tissue	156 (μ A)	63	Mendoza <i>et al.</i> , 2007

Wheat	Investigation of internal and structural features defects of wheat	96 (μ A)	100	Dogan, 2007
Pear	Pear bruise level determination due to external load	120	80	Azadbakht <i>et al.</i> , 2018
Apple	Water disorder	100	80	Herremans <i>et al.</i> , 2013

- 3. Hyperspectral Imaging:** Hyperspectral Imaging is based on conventional imaging and spectroscopy. It provides spectral and spatial information of the sample. It consisted of light source (illumination), wavelength dispersion device (spectrograph), and detector (camera), computer with corresponding software.

The object of surface absorbs the light from the source and then reflects it. Light have different wavelengths and different levels of bend-divergence propagation after passing through the front lens and entrance slit. When it finally converges at the collimation lens, light of various wavelengths splits into distinct bands. Finally, the imaging lens will present the spectrum signal to the detector. By using machine sweeping, a three-dimensional data cube rich in spectral and picture data is produced. Additionally, it's important to focus on highlighting the object and minimizing the background when selecting the light source. Meanwhile, the signals to noise ratio of the image must be increased to provide meaningful signal as much as possible while reducing noise interference. One of the most essential parts of the hyperspectral system is the imaging spectrometer, also known as a hyperspectral camera, which absorbs, processes, and transmits the target's reflection spectrum. The electronic control platform's primary job is to regulate the object's movement and keep it in line with the camera's sampling rate and time of exposure in order to avoid the problem of missed or repeated acquisition. By primarily controlling the functioning of pertinent equipment through parameters setting, data acquisition software effectively completes the data gathering task (Zhu *et al.*, 2020).

Table 3: Applications of Hyperspectral Imaging

Product	Application	Wavelength (nm)	References
Mangoes Soybean Pickling cucumbers	Insect Infestation	400 – 1000 400 – 1000 450 –740 740 –1000	Saranwong <i>et al.</i> , 2011 Huang <i>et al.</i> , 2013 Lu and Ariana 2013
Maize Kernel	Fungal Development	1900 and 2136	Williams <i>et al.</i> , 2012
Milk Powder	Melamine detection in milk powders	990-1700	Lim <i>et al.</i> , 2016
Blueberry	Internal browning	950-1650	Fan <i>et al.</i> , 2017
Cocoa Beans	Prediction of polyphenol content, fermentation index, and antioxidant activity	1000-2495	Caporaso <i>et al.</i> , 2018

- 4. Fluorescence Imaging:** The foundation of fluorescence imaging is the idea that when specific electromagnetic radiation or visible light excite organic molecules, they produce distinctive fluorescence. Many fruit tissues are rich in chlorophyll, which can emit fluorescence near the maxima of 685 nm and 730 nm. Chlorophyll will be lost when a fruit is crushed, which reduces the fluorescence excitation of the injured tissues relative to healthy tissues. The brightness of the images captured via fluorescence imaging are vary due to the diverse contents and are utilized to separate the injured tissues using some image processing techniques, such as threshold segment. Because it only use chlorophyll as an index to reflect the wounded tissues, fluorescence is only used to detect tissues that are rich in chlorophyll (Du *et al.*, 2020).

Table 4: Applications of Fluorescence Imaging

Product	Application	Wavelength (nm)	References
Grapes	Anthocyanin assessment in whole grape (<i>Vitis vinifera L.</i>) bunches	550 and 650	Agati et al., 2008
Mandarin Orange	Rotten mandarin orange detection, the extraction and identification of fluorescent substances contained in rotten parts of mandarin orange	360-375 and 530 - 550	Kondo et al., 2009
Tomato	Mature and immature green tomatoes differentiation	365	Fatchurrahman et al., 2020
Pickling Cucumbers	Chilling injury detection	675 and 750	Lu and Lu, 2021

- 5. Magnetic Resonance Imaging:** In magnetic resonance imaging, a powerful and consistent magnetic field is applied to the hydrogen nuclei, which are mostly found in water. As a result of the object tissues' varying levels of contrast in reaction to both a magnetic field and radio frequency signals, the image is created. It is based on the idea of nuclear magnetism, uses radio frequencies and applied magnetic fields to interact with the magnetic properties of nuclei to produce images. MRI can analyze molecular dynamics in tissues using a variety of contrast mechanisms by detecting different types of object properties according to magnetic properties, such as chemical shifts, proton density, relaxation duration, heteronuclei, and diffusion constants. To create two-dimensional and three-dimensional images of the object that show tissues with varied contrasts depending on the different physicochemical properties for bruise diagnosis and grading, it will be outfitted with magnetic gradient coils that can collect spatial data (Srivastava *et al.*, 2018)

Table 5: Applications of MRI

Product	Application	References
Mango	Internal quality assessment and monitoring of ripening	Joyce et al., 2002
Pears	Core breakdown	Lammertyn et al., 2003
Citrus	Internal quality assessment and monitoring of ripening	Galed et al., 2004

Pasta and Noodles	Evaluation of texture and structure during and after cooking	Lai and Hwang, 2004
Meat	Salt diffusion and water mobility in meat during brine curing	Hansen et al., 2008
Tomato and Pomegranate	Internal quality assessment and ripening monitoring	Musse et al., 2009 Khoshroo <i>et al.</i> , 2011

- 6. Structured-Illumination Reflectance Imaging:** A computer-controlled digital light projector will be utilized in a structure-illumination reflectance imaging (SIRI) system to project shifted in phase sinusoidal patterns onto a sample, and a camera used to record the reflectance image from the sample. A computer, a digital light projector with a radiometric power supply controller, and a back-illuminated electron-multiplying charge-coupled device camera with a fixed C-mount focal length lens make up the bulk of the system. For multispectral imaging, a liquid crystal tuneable filter (LCTF) is positioned in front of the lens, allowing any wavelength that falls in the spectral range of 650 to 1000 nm to be chosen. A linear polarizer is positioned in front the projector, which works with a liquid crystal adjustable filters to reduce specular reflectance. A fibre optic cable is utilized to route the lamp's output into the projector. It is run inside a small, dark room (Lu and Lu, 2019).

Table 6: Applications of Structural Illumination Reflectance Imaging System

Products	Applications	Wavelength (nm)	References
Apple	Subsurface Tissue Bruising	800-1000	Li et al., 2016
Apple	Detection of fresh bruises	600-1000	Lu et al., 2016
Peach	Detection of early decay	690-810	Sun et al., 2019

- 7. Thermal Imaging:** All materials emit infrared radiation and measures the infrared radiation emitted from the object rather than reflected infrared light thermal imaging is based on this principle. Different materials have different physicochemical properties and have different thermal diffusivity differences. The basic fundamental of thermal imaging has relied on the object that releases infrared radiation in the infrared wavelength region of 0.75 until 100 μm .

Thermal imaging devices operate in the short-wave to long-wave regions of the infrared spectrum. The vast majority of food business applications require the high sensitivity that the mid-wave infrared wavelength areas typically offer. The key variables that were impacted by the radiation's intensity were temperature and emissivity. It primarily consists of a computer, signal processor, and thermal camera with infrared sensors. The sample's infrared radiation was picked up by the infrared sensor, which transformed it into an electrical reaction before turning it into an image. The can be captured in a form a matrix of numerous colour levels that define a specific temperature, showing the temperature pattern of the sample. The infrared sensor works in such a way that the temperature rises when heated by the infrared radiation passing through the thermal imaging device. It does not need an illumination unit compared to the hyperspectral and multispectral imaging systems since it integrates a heating or cooling source in order to provide a thermal distribution. The selection of wavelength bands can

be determined according to various aspects whereas the criteria of image processing analysis rely on the proposed application of the system. The types of the camera mostly differ on its spectral wavelengths, temperature range and image size (Du *et al.*, 2020).

Table 7: Applications of Thermal Imaging

Products	Applications	Wavelength (nm)	References
Apple	Watercore detection	8000–13,000	Baranowski <i>et al.</i> , 2008
	Detection of early apple bruises	8000-14000	Baranowski <i>et al.</i> , 2009
Guava	Chilling injury	700–1000	Goncalves <i>et al.</i> , 2015
Grapes	Detection of volatile compounds released from decayed grapes	10,000- 11,000	Ding <i>et al.</i> , 2017
Mango	Maturity Grading	700-1000	Naik and Patel, 2017
Blueberry	Bruise detection	700-1000	Kuzy <i>et al.</i> , 2018
Tomato	Disease detection	700-1000	Zhu <i>et al.</i> , 2018

- 8. Machine Vision:** Machine vision is an engineering technology that combines mechanics, optical instrumentation, electromagnetic sensing, and digital image processing technology which is frequently utilized as a nondestructive method that uses image analysis in its functioning. At present, machine vision is frequently used to identify surface insect damage in agricultural products, but identifying interior flaws is more difficult.

Table 8: Applications of Machine Vision

Products	Applications	Accuracy (%)	References
Wheat	Classification	94	Zayas <i>et al.</i> , 1996
	Disease infection		Ruan <i>et al.</i> , 1997
Wheat, Barley, Oats, Rye	cereal grains classification	98, 97, 100 and 91, respectively	Majumdar <i>et al.</i> , 1997
Rice	Grading	91	Wan <i>et al.</i> , 2000
Strawberries	Sorting	98-100	Bato <i>et al.</i> , 2000
Sweet potato	Grading	84	Wooten <i>et al.</i> , 2000
Papaya	Shape characteristics analysis for papaya size classification	94	Riyadi <i>et al.</i> , 2007

IV. MERITS AND DEMERITS OF IMAGING TECHNIQUES

Imaging techniques have been significantly reintroduced in recent years by a number of researchers in a number of applications or real-world applications in the food sector. The timeliness and ease of usage in normal operations are the key advantages that

these approaches have over the conventional chemical and chromatographic methods. The usage of these technologies is nevertheless subject to a number of restrictions. In the food industry is still limited by problems relating to the availability of commercially viable and reliable instrumentation, the large amount of data generated during the analysis, the requirement for complex data analysis and algorithms, and the small number of samples in the majority of applications reported in the literature.

Table 9: Advantages and Limitations of Imaging Techniques

Methods	Advantages	Limitations
X –Ray Imaging	It can detect internal defects based on density difference and thickness of the sample	High cost Observed poor penetration in a product with high water content. Difficult to differentiate normal and infested tissues with similar densities.
Hyperspectral Imaging	Provides both spatial and spectral features for accurate segmentation	High cost
Magnetic Resonance Imaging	No harmful ionizing radiation High – resolution visual information of internal structure	High cost
Structured-illumination Reflectance Imaging	Enhance the detection resolution Depth-resolved detection by controlling spatial frequency	Less speed
Thermal Imaging	Portability and easy handling	Sensitive to environmental condition. It is costly to obtain high resolution images.
Machine Vision	Easy and Fast Consistent and cost effective Automated inspection of produce	Object identification being considerably more difficult in unstructured scenes. Need of artificial lighting for dark conditions.

V. CONCLUSION

The development of inexpensive image processing systems is particularly crucial for the assessment of food quality in order to meet the demand for cost-effective solutions. Heavy-duty real-time applications still struggle to handle the massive data streams due to processing speed. On the one hand, creating sufficiently precise and efficient image processing algorithms can speed up the processing rate to match the demands of contemporary production. The addition of image processing algorithms to specialized technology can cut down on the amount of time spent processing images. The techniques of image processing will become more and more crucial in determining the quality of food as a result of quick and inexpensive software and hardware solutions.

REFERENCES

- [1] Agati, G., Traversi, M. L. and Cerovic, Z. G., 2008, Chlorophyll fluorescence imaging for the noninvasive assessment of anthocyanins in whole grape (*Vitis vinifera* L.) bunches. *Photochemistry and Photobiology*, 84(6):1431-1434.
- [2] Aulakh, J. S. and Banga, V. K., 2012, Grading for rice grains by image processing. *International Journal of Engineering Research and Technology*, 1(4):222-240.
- [3] Azadbakht, M., Vahedi Torshizi, M. and Mahmoodi, M. J., 2019, The use of CT scan imaging technique to determine pear bruise level due to external loads. *Food science and nutrition*, 7(1):273-280.
- [4] Baranowski, P., Lipecki, J., Mazurek, W. and Walczak, R. T., 2008, Detection of watercore in 'Gloster' apples using thermography. *Postharvest biology and technology*, 47(3):358-366.
- [5] Baranowski, P., Mazurek, W., Witkowska-Walczak, B. and Sławinski, C., 2009, Detection of early apple bruises using pulsed-phase thermography. *Postharvest biology and technology*, 53(3):91-100.
- [6] Bato, P. M., Nagata M., Cao, Q. X., Hiyoshi, K. and Kitahara, T., 2000, Study on sorting system for strawberry using machine vision: development of sorting system with direction and judgement functions for strawberry (Akihime variety). *Journal of the Japanese Society of Agricultural Machinery*, 62(2):101–110.
- [7] Caporaso, N., Whitworth, M. B., Fowler, M. S. and Fisk, I. D., 2018, Hyperspectral imaging for non-destructive prediction of fermentation index, polyphenol content and antioxidant activity in single cocoa beans. *Food chemistry*, 258:343-351.
- [8] Chuang, C. L., Ouyang, C. S., Lin, T. T., Yang, M. M., Yang, E. C., Huang, T. W., Kuei, C. F., Luke, A. and Jiang, J. A., 2011, Automatic X-ray quarantine scanner and pest infestation detector for agricultural products. *Computers and electronics in agriculture*, 77(1):41-59.
- [9] Diels, E., van Dael, M., Keresztes, J., Vanmaercke, S., Verboven, P., Nicolai, B., Saeys, W., Ramon, H. and Smeets, B., 2017, Assessment of bruise volumes in apples using X-ray computed tomography. *Postharvest Biology and Technology*, 128:24-32.
- [10] Ding, L., Dong, D., Jiao, L. and Zheng, W., 2017, Potential using of infrared thermal imaging to detect volatile compounds released from decayed grapes. *Public Library of Science*, 12(6):1-11.
- [11] Dogan, H., 2007, Nondestructive imaging of agricultural products using X-ray microtomography. *Microscopy and Microanalysis*, 13(2):1316-1317.
- [12] Fan, S., Li, C., Huang, W. and Chen, L., 2017, Detection of blueberry internal bruising over time using NIR hyperspectral reflectance imaging with optimum wavelengths. *Postharvest Biology and Technology*, 134:55-66.
- [13] Fan, S., Li, J., Zhang, Y., Tian, X., Wang, Q., He, X., Zhang, C. and Huang, W., 2020, Online detection of defective apples using computer vision system combined with deep learning methods. *Journal of Food Engineering*, 286:110102.
- [14] Fatchurrahman, D., Amodio, M. L., Chiara, M. L. V., Chaudhry, M. M. A. and Colelli, G., 2020, Early discrimination of mature and immature-green tomatoes (*Solanum lycopersicum* L.) using fluorescence imaging method. *Postharvest Biology and Technology*, 169:111287.
- [15] Galed, G., Fernandez-Valle M. E., Martinez, A. and Heras, A., 2004, Application of MRI to monitor the process of ripening and decay in citrus treated with chitosan solutions. *Magnetic Resonance Imaging*, 22(1):127–137.
- [16] Gonçalves, B. J., Oliveira Giarola, T. M., Pereira, D. F., Boas, E., V. and Resende, J. V., 2016, Using infrared thermography to evaluate the injuries of cold-stored guava. *Journal of food science and technology*, 53(2):1063-1070.
- [17] Herremans, E., Verboven, P., Bongaers, E., Estrade, P., Verlinden, B. E., Wevers, M., Hertog, M. L. and Nicolai, B. M., 2013, Characterisation of 'Braeburn' browning disorder by means of X-ray micro-CT. *Postharvest Biology and Technology*, 75:114-124.
- [18] Huang, P. X., Yao, Z. X., Hui, S. U., Sun, K. and Xing, H. Y., 2012, Research progress in nondestructive inspection of food by means of hyperspectral imaging. *Science and Technology of Food Industry*, 35:412-417.
- [19] Joseph, S., 2018, Image processing techniques and its applications: an overview. *International Research Journal of Engineering and Technology*, 4(3):2395-4396.
- [20] Joyce, D. C., Hockings, P. D., Mazucco, R. A. and Shorter A., J., 2002, Nuclear magnetic resonance imaging of the ripening of 'Kensington Pride' mango fruit. *Plant Biology*, 29(7):873–879.
- [21] Khoshroo, A., Keyhani, A., Zoroofi, R.A., Rafiee, S., Zamani, Z. and Alsharif, M.R., 2009. Classification of pomegranate fruit using texture analysis of MR images. *Agricultural Engineering International CIGR Journal*, 11:1182.

- [22] Kondo, N., Kuramoto, M., Shimizu, H., Ogawa, Y., Kurita, M., Nishizu, T., Chong, V., K. and Yamamoto, K., 2009, Identification of fluorescent substance in mandarin orange skin for machine vision system to detect rotten citrus fruits. *Engineering in agriculture, Environment and Food*, 2(2):54-59.
- [23] Kuzy, J., Jiang, Y. and Li, C., 2018, Blueberry bruise detection by pulsed thermographic imaging. *Postharvest Biology and Technology*, 136:166-177.
- [24] Lammertyn, J., Dresselaers T., Van Hecke, P., Jancsok, P., Wevers M. and Nicolai B.,M, 2000. MRI and X-ray CT study of spatial distribution of core breakdown in 'conference' pears. *Magnetic Resonance Imaging*, 21(7):805–815.
- [25] Leonard, A., Blacher, S., Nimmol, C. and Devahastin, S., 2008. Effect of far-infrared radiation assisted drying on microstructure of banana slices: An illustrative use of X-ray microtomography in microstructural evaluation of a food product. *Journal of Food Engineering*, 85(1):154-162.
- [26] Lim, J., Kim, G., Mo, C., Kim, M. S., Chao, K., Qin, J. and Cho, B. K., 2016, Detection of melamine in milk powders using near-infrared hyperspectral imaging combined with regression coefficient of partial least square regression model. *Talanta*, 151:183–191.
- [27] Lu, Y. and Lu, R., 2019, Structured-illumination reflectance imaging for the detection of defects in fruit: Analysis of resolution, contrast and depth-resolving features. *Biosystems engineering*, 180:1-15.
- [28] Lu, Y., Lu, R. and Li, R., 2016, Structured-illumination reflectance imaging as a new modality for food quality detection. *Agricultural Engineering Conference*, pp. 1-7.
- [29] Majumdar, S., 1997. Classification of cereal grains using machine vision. *American Society of Agricultural Engineers*, 43(6): 1669-1675.
- [30] Mendoza, F., Verboven, P., Mebatsion, H. K., Kerckhofs, G., Wevers, M. and Nicolai, B., 2007, Three-dimensional pore space quantification of apple tissue using X-ray computed microtomography. *Planta*, 226(3): 559-570.
- [31] Mery, D., Lillo, I., Loebel, H., Riffo, V., Soto, A., Cipriano, A. and Aguilera, J. M., 2011, Automated fish bone detection using X-ray imaging. *Journal of Food Engineering*, 105(3): 485-492.
- [32] Musse, M., De Guio, F., Quellec, S., Cambert, M., Challos, S. and Davenel, A., 2010, Quantification of microporosity in fruit by MRI at various magnetic fields: comparison with X-ray microtomography. *Magnetic Resonance Imaging*, 28(10):1525–1534.
- [33] Naik, S. and Patel, B., 2017, Thermal imaging with fuzzy classifier for maturity and size based non-destructive mango (*Mangifera Indica L.*) grading. *International Conference on Emerging Trends and Innovation in ICT*, pp: 15-20.
- [34] Narvankar, D. S., Singh, C. B., Jayas, D. S. and White, N. D. G., 2009, Assessment of soft X-ray imaging for detection of fungal infection in wheat. *Biosystems Engineering*, 103(1):49-56.
- [35] Rajarathnam, S. and Ramteke, R. S., 2011, Advances in preservation and processing technologies of fruits and vegetables. *New India Publishing Agency*, 37-72.
- [36] Riyadi, S., Rahni, A. A., Mustafa, M. M. and Hussain, A., 2007, Shape characteristics analysis for papaya size classification. *Student Conference on Research and Development*, pp.1-5.
- [37] Ruan, R., Ning, S., Ning, A., Jones, R. and Chen, P. L., 1997, Estimation of scabby wheat incident rate using machine vision and neural network. *ASAE Annual International Meeting Technical Papers*, pp. 49085-9659.
- [38] Sonka, M., Hlavac, V. and Boyle, R., 2014, Image processing, analysis, and machine vision. *Cengage Learning*.
- [39] Srivastava, R.K., Talluri, S., Beebi, S.K. and Kumar, B.R., 2018. Magnetic resonance imaging for quality evaluation of fruits: a review. *Food Analytical Methods*, 11(10):2943-2960.
- [40] Stangierski, J., Weiss, D. and Kaczmarek, A., 2019. Multiple regression models and Artificial Neural Network (ANN) as prediction tools of changes in overall quality during the storage of spreadable processed Gouda cheese. *European Food Research and Technology*, 245(11):.2539-2547.
- [41] Sun, Y., Lu, R., Lu, Y., Tu, K. and Pan, L., 2019, Detection of early decay in peaches by structured-illumination reflectance imaging. *Postharvest Biology and Technology*, 151:68-78.
- [42] Thai, C. N., Tollner, E. W., Morita, K. and Kays, S. J., 1997, X-ray characterization of sweet potato weevil larvae development and subsequent damage in infested roots. *Proceedings Sensors for nondestructive testing: Measuring quality of Fresh Fruits and Vegetables-Florida*, pp.361-368.
- [43] Valous, N. A., and Sun, D. W., 2012, Image processing techniques for computer vision in the food and beverage industries. *Computer vision technology in the food and beverage industries*, pp. 97-129.
- [44] Wan, Y. N., Lin, C. M. and Chiou, J. F., 2000, Adaptive classification method for an automatic grain quality inspection system using machine vision and neural network. *American Society of Agricultural Engineers*, pp. 49085–9659.

- [45] Williams, P. J., Geladi, P., Britz, T. J. and Manley, M., 2012, Investigation of fungal development in maize kernels using NIR hyperspectral imaging and multivariate data analysis. *Journal of Cereal Science*, 55(3):272-278.
- [46] Wooten, J. R., White, J. G., Thomasson, J. A. and Thompson, P. G., 2000. Yield and quality monitor for sweetpotato with machine vision. *American Society of Agricultural Engineers*, pp.1-18.
- [47] Zayas, I. Y., Martin, C. R., Steele, J. L. and Katsevich, A., 1996, Wheat classification using image analysis and crush-force parameters. *Transactions of the American Society of Agricultural Engineers*, 39(6):2199-2204.
- [48] Zhu, M., Huang, D., Hu, X. J., Tong, W. H., Han, B. L., Tian, J. P. and Luo, H. B., 2020, Application of hyperspectral technology in detection of agricultural products and food: A Review. *Food Science & Nutrition*, 8(10):5206-5214.
- [49] Zhu, S., Zhou, L., Zhang, C., Bao, Y., Wu, B., Chu, H., Yu, Y., He, Y. and Feng, L., 2019, Identification of soybean varieties using hyperspectral imaging coupled with convolutional neural network. *Sensors*, 19(19):4065.
- [50] Zhu, W., Chen, H., Ciechanowska, I. and Spaner, D., 2018, Application of infrared thermal imaging for the rapid diagnosis of crop disease. *International Federation of Automatic Control*, 51(17):424-430.