**IMAGE PROCESSING TECHNIQUES FOR QUALITY EVALUATION OF FOOD**

**Dahihande Pranali Bharatkumar1, Dr. Sharanagouda Hiregoudar2, Dr. Udaykumar Nidoni3, Dr. Pramod Katti4**

**1Ph.D. Research Scholar, Department of Processing and Food Engineering, College of Agricultural Engineering, University of Agricultural Sciences, Raichur, Karnataka.**

**E-mail-pranalidahihande96@gmail.com**

**2 Professor and Head, Department of Processing and Food Engineering, College of Agricultural Engineering, University of Agricultural Sciences, Raichur, Karnataka.**

**3 Head of the University, College of Agricultural Engineering, University of Agricultural Sciences, Raichur, Karnataka.**

**4 Professor, Department of Agricultural Entomology, University of Agricultural Sciences, Raichur, Karnataka.**

**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. Machine vision is a tried-and-true technology that can provide useful information on product quality and the effects of the processing regime when combined with efficient image processing methods.

***Keywords:*** *Image processing, X-ray, hyperspectral imaging, food quality, thermal imaging*

1. **INTRODUCTION**

Food quality can be defined as degree of excellence of food includes factors such as taste, appearance, and nutritional quality. Sensory and objective evaluationmethods are used in food industry in order to routinely monitor food quality and to ensure that the foods being produced are acceptable to the consumer. In recent years, researchers have developed several non-contact methods for the assessment of food and beverage products, overcoming most of the drawbacks of traditional methods such as human inspection. These methods are based on the automatic detection of various image features, which may correlate with attributes related to sensorial, chemical and physical properties. The field of digital image processing refers to processing digital images by means of a digital computer. The food industry ranks among the top ten industries using image processing techniques, which have been proven successful for the objective and non-destructive evaluation of several (Valous and Sun, 2012).

Image processing is a technique to enhance raw images received from cameras/sensors. The image processing is a non destructive method, it is very fast and cheap process compared to the destructive methods (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.

1. **STEPS IN IMAGE PROCESSING**
2. **Image Acquisition**

Image acquisition is the action of retrieving an image from some source. Image acquisition plays a important role in image processing, since if the images are not acquired properly the various image processing techniques may not be much effective, even with the presence of various enhancement techniques (Joseph, 2018).

1. **Image Enhancement**

 The process of improving digital images makes them more suited 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.

1. **Image Restoration**

Image restoration attempts to reconstruct or recover an image that has been degraded by degradation phenomenon. The process of recovering degraded or corrupted image by removing the noise or blur, to improve the appearance of the image is called image restoration. The degraded image is the convolution of the original image, degraded function, and additive noise. Restoration of the image is done with the help of prior knowledge of the noise or the disturbance that causes the degradation in the image.

1. **Wavelets and Compression**

Wavelets are the foundation for representing images in various degrees of resolution. Wavelet provides functions for analyzing and synthesizing signals and images. To detect events like anomalies, change points, and transients, and denoise and compress data. Wavelet analysis and other multiscale methods can be used to break down signals and images into their component parts and analyse data at multiple time and frequency resolutions. Wavelet techniques can be used to reduce dimensionality and extract discriminating features from signals and images to train machine and deep learning models (Sonka *et al*., 2008).

1. **Image Segmentation**

 Image segmentation is defined as an partitioning of an input image into regions, each of which is considered to be homogeneous with respect to some image property of interest for example intensity, colour or texture. It may make use of statistical classification, thresholding, edge detection, region detection, or any combination of these techniques. Usually a set of classified elements is obtained as the output of the segmentation step (Valous and Sun, 2012).

1. **Representation and Description**

 The output of a segmentation step, which is often raw pixel data and represents either the region's boundaries or all of its points, is followed by representation and description.

1. **Recognition**

Recognition is the process that assigns a label to an object based on its descriptors.Object recognition deals with training the computer to identify a particular object from various perspectives, in various lighting conditions, and with various backgrounds.

1. **IMAGING TECHNIQUES**

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

1. **X-Ray Imaging**

Wilhelm Conrad Rontgen, a German physicist, made the discovery of X-rays in 1895. He received the 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. X-rays are produced when fast moving electrons from a hot cathode impinge on a heavy metal target. A typical X-ray tube consists of a filament-type cathode and a metal target called an anode in an evacuated tube. The usage of filament-type cathodes, which are typically constructed of tungsten, has replaced the use of gas-type X-ray tubes with negative and positive charge electrodes. To emit electrons, the tungsten filament needs to be heated to a minimum of 2,200°C. 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).

The quality of the X-ray image for different kinds of fruits depends greatly on the selection of proper tube voltage and current because of the variable thickness, density and X-ray absorption characteristics of different fruits (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. The technology's advantage is that it can identify metallic and nonmetallic impurities in food products, including metals, bone, glass, stone, plastics, and rubber (Schatzki *et al*. 1996). The metallic and nonmetallic contaminants have different densities than food materials and processed foods have more or less uniform thickness these characteristics make X-ray inspection system very attractive in the food industries. Insect infestations and internal defects in fruits, vegetables, nuts and grains are complex as infestations may not be visible outside and cannot be easily identified manually. The insect eggs develop from the flowering stage and mostly develop inside the fruit’s seed. The infestation may later on lead to progressive damage to the fruits.

**Table 1: Applications of X-Ray Imaging**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Product** | **Application**  | **Voltage (kV)**  | **Current****(μA)**  | **Accuracy****(%)**  | **References**  |
| Wheat | Detection of sprouted wheat kerneFungal infection detection (*Aspergillus niger, A. glaucus* group, and *Penicillium spp*.) | 13.513.6 | 185184 | 8782 | Neethirajan *et al.,* 2007Narvankar *et al.,* 2009 |
| Banana  | Microstructure of banana slices  | 60  | 167  |  | Leonard *et al.,* 2008  |
| ApplePeach TomatoGuava  | Automatic defect detection system  | 65-75 | 125  | 10010093.9100  | Chuang *et al.,* 2011  |
| Salmon fish  | Bone detection  | 40  | 21 mA  | 99  | Mery *et al.,* 2011  |

1. **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 perform the imaging. 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. Lim and Barigou (2004) observed that to scan a 10 mm cube of cellular food products over 180° in 200 discrete steps of 0.9° , it took about 30–45 min. Computed tomography has been found to provide detailed 3-dimensional information using X-ray beam projection. The 2-dimensional slices extracted from CT imaging have been found to show better contrast among the constituents of the respective slice. However, it takes more time to generate 2-D and 3-D slices compared to transmission radiography.

 **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 et al., 1997  |
| Apple  | Pore space quantification of apple tissue  | 156 (μA)  | 63  | Mendoza et al., 2007  |
| Wheat  |  Investigation of internal and structural features defects of wheat  | 96 (μA)  | 100  | Dogan, 2007  |
| Pear  | Determination of pear bruise level due to external load  | 120  | 80  | Azadbakht *et al*.,2018 |
| Apple  | Water disorder  | 100  | 80  | Herremans *et al*., 2013  |

1. **Hyperspectral Imaging**

Hyperspectral Imaging is based on spectroscopy and conventional imaging. It provides both spectral and spatial information of the sample. It consists of Light source (illumination), wavelength dispersion device (spectrograph), and detector (camera), computer with corresponding software.

The surface of the object absorbs the light from the source and then reflects it. Light of different wavelengths will have 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. The three-dimension data cube rich in image and spectral information are obtained by machine sweeping. Moreover, when choosing the light source, we should pay attention to highlight the object and weaken the background. Meanwhile, to present useful signal as much as possible, the signal to noise ratio of the image should be improved, thus reduce noise interference. Imaging spectrometer is also called hyperspectral camera, which absorb, process, and transmit the reflection spectrum of target, is one of the most core part of the whole hyperspectral system. The main function of the electronic control platform is to control the moving speed of the object and make it consistent with the sampling frequency and exposure time of the camera, thus prevent the phenomenon of missing or repeated acquisition. Data acquisition software mainly controls the operation of relevant equipment through parameter setting, thus efficiently completing the data acquisition work (Zhu *et al*., 2020).

**Table 3: Applications of Hyperspectral Imaging**

|  |  |  |  |
| --- | --- | --- | --- |
| **Product** | **Application** | **Wavelength (nm)** | **References** |
| MangoesSoybeanPickling cucumbers  | Insect Infestation  | 400 – 1000400 – 1000450 –740740 –1000 | Saranwong *et al*., 2011 Huang *et al.,* 2013 Lu and Ariana 2013 |
| Maize Kernel  | Fungal Development  | 1900 and 2136  | Williams *et al.,* 2012  |
| Milk Powder  | Detection of melamine in milk powders  | 990-1700  | Lim *et al*., 2016  |
| Blueberry  | Internal browning  | 950-1650  | Fan *et al.,* 2017  |
| Cocoa Beans  | Prediction of fermentation index, polyphenol content and antioxidant activity  | 1000-2495  | Caporaso *et al*., 2018  |

1. **Fluorescence Imaging**

 Fluorescence imaging is based on the principle that organic materials emit unique fluorescence when excited by particular electromagnetic radiation or visible light. Chlorophyll, which can emit fluorescence near the maxima of 685 nm and 730 nm, is abundant in many fruit tissues. When a fruit is bruised, the chlorophyll is destroyed, which lowers the fluorescence excitation of the wounded tissues in comparison to healthy tissues. Through some image processing techniques, such as threshold segment, the brightness of the images recorded from fluorescence imaging are different due to the diverse contents and are used to distinguish the wounded tissues. The application of fluorescence is for the detection of chlorophyll-rich tissues because it can only use chlorophyll as an index to reflect the bruised tissues (Du et al*.,* 2020).

**Table 4: Applications of Fluorescence Imaging**

|  |  |  |  |
| --- | --- | --- | --- |
| **Product** | **Application** | **Wavelength (nm)** | **References** |
| Grapes  | Assessment of anthocyanins in whole Grape (*Vitis vinifera L.)* Bunches  | 550 and 650  | Agati et al*.,* 2008  |
| Mandarin Orange  | Detection of rotten mandarin orange, the extraction and identification of fluorescent substances contained in rotten parts of mandarin orange  | 360-375 and 530 - 550  | Kondo et al*.,* 2009  |
| Tomato | Early discrimination of mature-and immature-green tomatoes (*Solanum lycopersicum L.*) | 365  | Fatchurrahman et al*.,* 2020 |
| Pickling Cucumbers | Detection of chilling injury | 675 and 750  | Lu and Lu, 2021  |

1. **Magnetic Resonance Imaging**

 The high resolution image can be obtained by a strong and uniform magnetic field applied to the hydrogen nucleithat are mainly located in water. The image is formed as a result of the different level of contrast of the object tissues as a response to a magnetic field and radio frequency waves. Based on the nuclear magnetism concept, magnetic resonance imaging creates images by using radio frequencies and applied magnetic fields to interact with the magnetic characteristics of nuclei. By measuring various kinds of object characteristics based on the magnetic properties, such as proton density, chemical shifts, relaxation duration, heteronuclei, and diffusion constants, MRI may analyse molecular dynamics in tissues through several contrast mechanisms. MRI is equipped with magnetic gradient coils that can gather spatial data in order to produce two-dimensional and three-dimensional pictures of the object that exhibit tissues with distinct contrasts based on the different physicochemical qualities for bruise detection and grading (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 monitoring of ripening  | Musse et al*.,* 2009Khoshroo *et al.,* 2011  |

1. **Structured-Illumination Reflectance Imaging**

 A Structure-illumination Reflectance Imaging (SIRI) system uses a digital light projector controlled by a computer to emit phase-shifted sinusoidal patterns onto a sample, and a camera is used to capture the reflectance image from the sample. It mainly consists of a computer, a digital light projector along with a radiometric power supply controller and a back-illuminated electron-multiplying charge-coupled device camera attached with a C-mount fixed focal length lens. A liquid crystal tuneable filter (LCTF) is placed in front of the lens for multispectral imaging, which allows for selecting any wavelength in the spectral range of 650 to 1000 nm. A fibre optic cable is used to channel the output of the lamp into the projector, and a linear polariser is placed in front of the projector, which works together with liquid crystal tuneable filter to suppress specular reflectance. It is operated in an enclosed dark chamber (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  |

1. **Thermal Imaging**

 Thermal Imaging (TI) is based on the fact that all materials emit infrared radiation and measures the infrared radiation emitted from the object rather than reflected infrared light. 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 majority of applications in the food industry call for the high sensitivity that the mid-wave infrared wavelength regions frequently provide. Temperature and emissivity were the main factors that were influenced by the radiation's intensity. It is mainly encompasses of a thermal camera with infrared sensors, signal processing unit, and computer. The infrared sensor detected the infrared radiation emitted by the sample which then converted to the electrical response prior to processing it into an image. The thermal image was 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. Apart from that, it does not need an illumination unit compared to the hyperspectral and multispectral imaging systems since it integrates a heating/cooling source in order to provide a thermal distribution. The selection of wavelength bands is 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 et al*.,* 2008  |
| Detection of early apple bruises  | 8000-14000  | Baranowski et al*.,* 2009  |
| Guava  | Chilling injury  | 700–1000  | Goncalves et al*.,* 2015  |
| Grapes  | Detection of volatile compounds released from decayed grapes  | 10,000- 11,000  | Ding et al*.,* 2017  |
| Mango  | Maturity Grading  | 700-1000  | Naik and Patel, 2017  |
| Blueberry  | Bruise detection  | 700-1000  | Kuzy et al*.,* 2018  |
| Tomato | Disease detection  | 700-1000  | Zhu et al*.,* 2018  |

1. **Machine Vision**

Machine vision is an engineering technology that combines mechanics, optical instrumentation, electromagnetic sensing, and digital image processing technology. The development of machine vision systems is widely used as a nondestructive approach which utilizes image analysis in its operation. Currently, machine vision technology has been widely applied for the detection of external pest damages in agricultural products but because of the challenges involved detecting internal defects.

**Applications of Machine Vision**

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

1. **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. The use of this technology 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 costPoor penetration in materials with high water contentDifficult 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 radiationHigh – resolution visual information of internal structure  | High cost  |
| Structured-illumination Reflectance Imaging  | Enhance the detection resolutionDepth-resolved detection by controlling spatial frequency  | Less speed  |
| Thermal Imaging  | Easy Handling and Portability | Sensitive to environmental conditionRelatively high costs 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 scenesArtificial lighting needed for dim or dark conditions  |

**CONCLUSION**

 The chapter's summary of new imaging methods for the food industry's concerns about food quality and safety. The development of inexpensive multipurpose 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. On the other hand, adding image processing algorithms to specialized technology can cut down on the amount of time spent processing images. Image processing techniques will become more and more crucial in determining the quality of food as a result of quick and inexpensive software and hardware solutions.

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