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Review

Monitoring and Optimization of the Process of Drying Fruits and Vegetables Using Computer Vision: A Review

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Abstract: An overview is given regarding the most recent use of non-destructive techniques during drying used to monitor quality changes in fruits and vegetables. Quality changes were commonly investigated in order to improve the sensory properties (i.e., appearance, texture, flavor and aroma), nutritive values, chemical constituents and mechanical properties of drying products. The application of single-point spectroscopy coupled with drying was discussed by virtue of its potentiality to improve the overall efficiency of the process. With a similar purpose, the implementation of a machine vision (MV) system used to inspect foods during drying was investigated; MV, indeed, can easily monitor physical changes (e.g., color, size, texture and shape) in fruits and vegetables during the drying process. Hyperspectral imaging spectroscopy is a sophisticated technology since it is able to combine the advantages of spectroscopy and machine vision. As a consequence, its application to drying of fruits and vegetables was reviewed. Finally, attention was focused on the implementation of sensors in an on-line process based on the technologies mentioned above. This is a necessary step in order to turn the conventional dryer into a smart dryer, which is a more sustainable way to produce high quality dried fruits and vegetables.

Keywords: non-destructive technique; visible-near infrared spectroscopy (Vis-NIR); chemometrics; hyper-/multi-spectral imaging spectroscopy; drying process optimization; quality changes during drying

1. Introduction

Drying is one of the most energy-consuming, being nonlinear in the changes in water content, unit operations in postharvest processing, and it has been used since ancient times. Drying is a complex operation that involves removal of moisture. During drying, two processes occur simultaneously [1]:

(1) transfer of energy, mostly as heat, generally from the surrounding environment and/or an energy source to the wet solid;
(2) transfer of mass, as moisture, from inside of the solid to the surface and its subsequent evaporation due to the process described in Point 1.

The aim of food drying is the reduction of the amount of free-water to slow down deteriorative processes, which are principally caused by microbial growth, chemical reaction and/or enzymatic activity. Fruits and vegetables are particularly susceptible to deteriorative processes, since their initial water content range is from 74–90% w/w [2], and then, water activity allows microbial growth (>0.60). Drying, then, can positively affect fruits' and vegetables' shelf-life. Furthermore, it can reduce the cost of storage and transport, due to the loss of the original shape and weight. However, despite these advantages, the process may cause damage and severe changes in the physicochemical and organoleptic properties of the products [3]. Indeed, there are changes in flavor, color, shrinkage and with no adequate control, oxidation of fat and degradation of nutritional compounds [1,3,4].

The very first drying method was solar drying (SD), which required many windy and sunny days to dry the food. Despite this limitation, the method is still used (e.g., production of dried tomatoes in the south of Italy). Nowadays, however, several types of dryers have been developed (e.g., hot-air-convective, microwave, infrared, osmotic and freeze dryers), and the selection among them is important to obtain a quality product [1,3]. Hot-air drying (AD) is the most conventional drying method, and due to the high temperature and long drying cycle, there are usually important losses of flavor, color and nutritional compounds (e.g., vitamin C, carotenoids and phenolic compounds) [4,5]. Microwave (MW) and infrared drying (IR-D) offer some advantages over AD (e.g., better efficiency and faster drying rate) [1]. However, the energy transfer in the drying process is not homogeneous; this results in a disadvantage, which is difficult to eradicate due to the molecular structure and the dielectric properties of the dried products [6]. Osmotic dehydration (OD) is a process often used in combination with other drying methods, which using sugar syrup or brine to remove water, offering some advantages in terms of energy savings and retention of color, aroma and nutritional compounds [7]. Finally, freeze drying (FD) is one of the best methods in order to remove the largest amount of water from products [3,8], and moreover, it works at low pressure and temperature. For this reason, FD is also the best solution to preserve foods' quality. However, it is also the dryer that requires the most amount of energy to perform the unit operation [3]. For this reason, it is not convenient to use this technology to preserve low cost fruits and vegetables (e.g., carrots, potatoes, onion and the like).

Energy consumption for all the drying processes discussed above is high due to the huge amount of latent heat required for phase transformation of moisture. Thus, the optimization of the operating temperature and the implementation of heat-recovery systems are fundamental in order to get maximum earnings with the lowest environmental impact. However, conventional dryers are far from the optimization of the energy utilization. Frequently, indeed, the food industry over-dries the product, even when it is not necessary to remove such an amount of moisture in order to preserve food-stocks well. Normally, choosing the right amount of moisture enables one to preserve the commodities for a long time and, at the same time, retains the nutrients better, avoiding unnecessary exposition to high temperature [9]. Nowadays, on the market, there is a wide offering of drying devices. Industrial dryers are usually equipped with sensors (e.g., humidity and temperature sensors). The aim of these sensors is to monitor air temperature and relative humidity inside and outside of the drying chamber [10]. These dryers are hardly ever linked to instrumentation able to monitor on-line changes of the products, with the exception of load cells for weight loss [7,10]. This gap opens several possibilities to enhance drying performances.

Single-point spectroscopy in the visible and near infrared region (Vis-NIR) [11], machine vision (MV) [12] and the combination of these technologies (i.e., hyper- and multi-spectral imaging (HSI, MSI) [13]) are devices able to non-destructively assess quality changes during drying. Furthermore, they are simple to use even for non-specialized operators, even if they require a calibration step to work properly [11–13]. In the literature, the application of these devices is adopted for the monitoring of moisture content [14,15], shrinkage [16,17], color [15,16], size and shape [16,18], as well as the change of soluble solid content [14,19–21], carotenoids [21], vitamin C [22] or phenolic compounds [23,24].

The simultaneous and instant monitoring of processing parameters (e.g., flow rate, air humidity and temperature, sample weight) and product parameters (e.g., color, shrinkage, soluble solid content, water activity, etc.) allows a better modulation of the response of the dryer, energy savings and, at the same time, higher quality dried products. A dryer with such characteristic is by definition a smart dryer [25].

The aim of this work is to present the most recent innovation in the use of non-destructive techniques such as MV, Vis-NIR and HSI in order to control the quality changes and safety aspect with respect to fruits and vegetables before, during and after the drying process, with the goal of obtaining a smart modulation of the process itself. Finally, attention is briefly focused on the quality aspects of the organic dried product because, despite consumer demand, there is a lack of guidelines for processing organic food [26], and to our knowledge, very few works in the literature have been written on this topic.

2. Literature Review

We developed a search strategy in Scopus [27], PubMed [28] and Google Scholar [29], using Boolean combinations (i.e., using the AND logical operator) of three search words (i.e., drying, dryer and dehydration) with the following terms: quality, foodstuffs, vegetables, fruits, food, non-destructive technique, machine vision, image analysis, hyperspectral camera, near infrared spectroscopy, UV-Vis spectroscopy, quality inspection, moisture content, water activity, chemometrics, principal component analysis, image pre-processing, quality changes, shrinkage, color, algorithm, regression, prediction, automation, data-processing, segmentation, texture, nutritional changes, physio-chemical changes, organic and organic legislation. Only articles published from 1999 onwards were taken into account, except for those that were necessary to write about the history of instrumentation and historical applications.

3. Fundamentals of Food-Drying

In the optimization of the drying process, many parameters are considered, in order to reach the following objectives: an increase of foodstuff stability, a reduction of storage and transport costs, energy savings and, of course, a high-quality product [30]. The total cost of a drying process and the quality of the final foodstuff often are competing parameters, especially for low cost processed food. The main aspects in terms of energy and quality for fruits and vegetables are discussed below.

3.1. Quality Aspect in Drying

During drying of fruits and vegetables, many physicochemical changes occur, such as: changes in color due to enzymatic or non-enzymatic browning reactions, changes in texture and shrinkage and loss and/or degradation of nutritional compounds (e.g., ascorbic acid, carotenoids, phenolic compounds and the like) [31].

3.1.1. Nutritional Quality Changes

The nutritional quality of fruits and vegetables depends on their chemical composition, which shows a wide range of variation depending on the species, cultivar and maturity stage. Heat processing, moreover, leads to the degradation and/or isomerization of most of the chemical compounds. Due to the complexity of the matrices, some chemical compounds are chosen as markers of nutritional quality [32]. For fruit and vegetables, ascorbic acid, carotenoids, vitamin E and phenolic content are generally used as markers.

Vitamin C

Ascorbic acid (AA), also known as vitamin C, is an essential nutrient in the human diet. Since fruits and vegetables have a high content of AA, it is commonly used as a quality marker. AA is an antioxidant, heat labile and water soluble compound and is able to regenerate tocopherols (vitamin E), from its oxidized form [33]. High temperature, long drying cycle and exposure to oxygen cause a strong reduction of its concentration in fruit and vegetables. Tomato, indeed, after drying at 75 °C loses about half of its original AA content [34]. Furthermore, it has been observed, in a study on fluted pumpkin leaves, that high temperature over a short-time at low pH leads to a better retention of AA than a lower temperature over a long process at high pH [35]. During hot-air drying, vitamin C losses are greater than the ones related to freeze drying [36]. A slight loss of AA occurs during blanching in hot water due its water-solubility. However, the pretreated sample retained better AA during drying [30].

Carotenoids

Carotenoids are a large class of tetraterpenes responsible for the bright red, yellow and orange color in many fruits and vegetables. Due to their highly hydrophobic nature, they are mainly present within the lipid membrane or in complexes with proteins [37]. There are more than 600 compounds classified as carotenoids, and most of them are human precursors of vitamin A. In plants, they help in photosynthesis and prevent the oxidation of chlorophylls; in human beings, consumption of β-carotene and lutein, the two most important dietary carotenoids, reduces the risk of lung cancer and chronic eye diseases like cataracts [38]. Slight decreases in total carotenoids content were observed during hot-air drying of carrots [39]; moreover, coupled blanching and drying releases carotenoids from lipid membranes and complexes, resulting in better bio-availability [40,41]. Despite this positive effect, heat induces the isomerization of carotenoids from trans to cis, which is more susceptible to oxidation [42]. Finally, it was seen that the lycopene concentration decreases more in FD than AD or MW drying [43].

Phenols

Phenols are a large class of compounds that have at least an aromatic ring with one or more hydroxy-substituents; they may include functional derivatives (e.g., esters). Phenol compounds have antioxidant activity, and in plants, they act as a defense mechanism against pathogens and parasites; for this reason, the peel commonly has a higher level of phenols than the flesh [44]. Commonly, they are also associated with sensorial characteristics (i.e., astringency, color, etc.) [23]. Fruits and vegetables rich in phenols are commonly blue or red. The regular consumption of fruits and vegetables rich in phenols is associated with a reduction in the risk of developing chronic diseases, such as cancer and cardiovascular disease [45]. Significant losses of phenols occur during mechanical processing (e.g., peeling, slicing or shredding); all these steps expose phenols to oxygen directly [46]. Higher loss of phenolics occurs in AD compared with FD and MW drying. This is because it requires a higher temperature and a long drying time [4,47].

Vitamin E

Vitamin E comprises a group of fat-soluble compounds that include both tocopherols and tocotrienols. α-tocopherols are the most abundant in the human body [48].Vitamin E compounds are highly susceptible to oxygen and light exposure during processing and storage [32]. Fatty foods, broccoli and leafy vegetables are good sources of this vitamin. During drying of chestnut at low temperature (e.g., 50 °C for 10 h), it was seen that vitamin E content decreased just slightly [49]. Furthermore, around a 10% vitamin E loss was reported during cooking and microwaving of bean [50].

3.1.2. Color Changes

Color preservation is crucial to make processed fruit and vegetables attractive and acceptable. Indeed, it is the first attribute considered by the consumer to make a buying decision [51]. For this reason, several researches have, as a matter of study, considered color conservation during post-harvest handling and processing of fruits and vegetables [51]. During drying, many phenomena are responsible of color changes. The most common ones are pigment degradation (e.g., chlorophylls and carotenoids) [52] and the occurrence of browning, due both to enzymatic and non-enzymatic reactions [53].

Chlorophylls and Carotenoids

The color of green and yellow/red/orange vegetables is mainly due to pigments closely related to chlorophylls and carotenoids, respectively [54]. These pigments are easily degraded during post-harvest processing by light, heat, oxygen and enzymes [55]. However, it should be noted that the type of product, origin, pre-treatment and type of drying affect the degradation rate of chlorophylls and carotenoids [54] Furthermore, high temperature and low pH stimulate the conversion of chlorophylls into pheophytins by replacing the central magnesium in the chlorin ring with two hydrogen ions [56]; when chlorophyll is converted into pheophytin, the color changes from light-bright green to olive brown. The conversion rate of pheophytins' formation seems to be slowed down at a water activity (a_w) lower than 0.32 [52]. In addition to this reaction, chlorophyll degradation is related to fat peroxidation. In this reaction, lipoxidase and oxygen play the major role [57].

Enzymatic Browning

Polyphenol oxidase (PPO, EC-1.10.32) and peroxidases (POD, EC number 1.11.1.x) are mainly responsible for enzymatic browning. The pathway results in phenols' degradation and starts with the conversion of amino acid L-phenylalanine to trans-cinnamic acid by enzyme phenylalanine lyase (PAL, EC. 4.3.1.5) [58,59]. After this step is the conversion of trans-cinnamic acid by PPO to ortho-quinones, which spontaneously polymerize to melanins, which are brown pigments responsible for tissue browning [60,61]. In the food processing industry, the results of the activity of these enzymes are often undesirable. For example, a high level of melanins, which are enzymatic browning products, is responsible for the brownish color and off-flavor. One exception is made for Sultana grapes, because consumers seem to prefer brown dried grapes [62]. Several solutions were adopted to inhibit enzyme activity: the use of heat as pre-treatment, to inactivate the enzyme, and the use of sulfur dioxide or sulfites, which are able to complex an intermediate product, the o-quinones [63]. Another way to reduce this adverse phenomenon is to lower the pH of the products using acid (e.g., citric, malic, phosphoric and ascorbic acid) or combining different unit operations (e.g., OD with AD) [64].

Non-Enzymatic Browning

Non-enzymatic browning (NEB) is a series of chemical reactions that occur during a thermal process, resulting in changes in color, texture, antioxidant compounds and aroma [65,66]. The most important non-enzymatic processes are caramelization, which involves pyrolysis of sugars, and the Maillard reaction (MR) [67]. Louis Maillard was the French chemist who first described the MR, in 1913, while John E. Hodge was the first one to describe its chemical pathway, in 1953. The initial stage of MR involves a reaction between a reducing sugar and free amino group (e.g., amino acids, polypeptides and protein) to give N-substituted glucosamine, which then rearranges to form the Amadori and Heyn's products [68]. MR is a complex net of parallel and consecutive chemical reactions, which are related to product characteristics (e.g., pH, moisture content, etc.) and the processing parameters (e.g., temperature and heat exposure time) [66,69]. At a pH lower than 7.0, the reaction primarily leads to the formation of furfural and hydroxy-methylfurfural [66,68,70], while at a pH higher than 7.0, 4-hydroxy-5-methyl-2,3-dihydrofuran-3-one (HMFone) and fission products (e.g., acetol, pyruvaldehyde and diacetyl) are mainly formed [66,69]. Despite the pathway, all these compounds are highly reactive and, thus, are involved in further reactions responsible for the development of brown pigments (e.g., melanoidins) [70]. Commonly, NEB is monitored as follow:

- content of sugar (e.g., sucrose, fructose and glucose) [70,71],
- HMF [70,72] and furfural [72],
- spectral measurement at 420 nm to measure the browning development [70–73].

NEB often reduces the quality of processed foods [74] with some exceptions, e.g., roasted coffee and bakery products, in which MR is responsible for better color, taste and aroma [75].

3.1.3. Physical Changes

During drying, physical changes occur, and often, they strongly influence drying product characteristics. The main physical changes (i.e., shrinkage and texture) are discussed below.

Shrinkage

During drying, fruits and vegetables lose water, and the cellular membranes collapse. The result is a reduction in the shape and size of food tissues, commonly called shrinkage [76]. Moisture gradually moves from the center of the food tissues to the external surfaces [77]. Several studies confirmed that there is a linear correlation between moisture content (MC) and shrinkage [17,78,79]. During the initial stage of AD, shrinkage increases rapidly; the value then slowly increases until it reaches an equilibrium point [80]. It was observed that a stronger shrinkage phenomena occurs in MW and AD dryers than in FD [77,81]. This is because the raised temperature increased the rate of cellular shrinkage following an Arrhenius-type behavior [17]. However, in a study performed on strawberries, a similar rehydration behavior was noticed after MW and FD [82].

Texture

Textural parameters of fruits and vegetables are perceived with the sense of touch and hearing, either when the product is picked up with the hand or placed in the mouth and chewed [83]. Texture is the result of complex interactions among food components at micro- and macro-structural levels [84]; using tomatoes as an example, the greatest contributors to the texture are the insoluble solids, which are derived from the cell walls [50]. Other parameters are related to changes in texture (e.g., the structure of the tissue, turgor pressure, porosity, cellular orientation and composition). During drying of fruits and vegetables, several changes in texture are common (e.g., hardness, cohesiveness, springiness and chewiness) [85].

The main parameter to evaluate texture change is firmness, which is commonly measured using a texture profile analyzer (TPA) [59,86]. The high temperature and long drying time in AD often result in heat-damage and losses in texture [47]. During AD of apple slices, three phases in texture were observed: softening, in which gradual changes in firmness appear, uniform hardness and hardening [87]. The last step is due to a limited moisture diffusion rate [87]. In a study made on carrots, it was deducted that MW was faster and the product showed better textural properties compared with AD [88].

Moisture Content (w) and Water Activity (a_w)

Moisture content, or water content (w), is an indicator of the amount of water contained in a solid sample (e.g., soil, fruit and vegetables). Moisture changes during drying are usually expressed as dry basis of moisture content (MC_d), which corresponds to the ratio between the amount of water in the sample (m_w) over the residual solid content (m_{RSC}), both expressed in the same unit (e.g., g/g or kg/kg).

$$MC_d = \frac{m_w}{m_{RSC}}, \tag{1}$$

However, regarding other food industry applications, moisture content is commonly expressed as wet basis (MC_w), which is equal to the ratio between the amount of water in the sample (m_w) over the total weight of the sample (m_{tot}).

$$MC_w = \frac{m_w}{m_{tot}} = \frac{m_w}{m_w + m_{RSC}}, \tag{2}$$

The relationship between MC_d and MC_w is described by the following equation:

$$MC_d = \frac{MC_w}{1 - MC_w}, \tag{3}$$

During drying, m_w decreases, and m_{RSC} remains constant. However, microbial growth is more related to the amount of free-water contained in food rather than the total water amount [89]. In order to control microbial growth, then, another parameter should be introduced: the water activity (a_w), which is represent as the ratio between the vapor pressure of water in a substance (P_a) over the vapor pressure of pure water (P_0) under identical thermodynamic conditions.

$$a_W = \frac{P_a}{P_0} \quad (4)$$

Following a_w ensures not only microbial growth control, but also the shelf-life of food, the enzymatic activity and the modulation of chemical reaction rates [77]. The relationship between moisture content and water activity during drying is complex, non-linear and unique for each food product. This is due to colligative, capillary and surface effects [90]. At a fixed temperature, the two parameters can be plotted, and the resulting graph is called the moisture sorption isotherm, as shown in Figure 1.

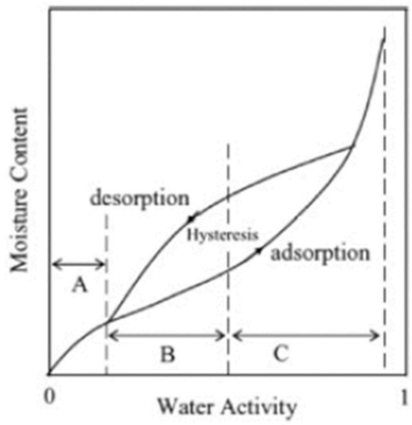

Figure 1. Sorption isotherm for a typical food product. The difference between the adsorption (wetting) and desorption (drying) curve is called hysteresis [91].

3.2. Energy Aspects in Drying

Drying is one of the most energy intensive unit operations, as it requires 12% of the total energy demand for manufacturing processes in developed countries [92]. For a common dryer, the major cost during its lifetime is the energy consumed, which is roughly five-times its capital cost [93]. Furthermore, most of the energy used in the drying process derives from fossil fuels, therefore leading to greenhouse gas (GHG) emission, which negatively affects the environment. The European Union (EU) is strongly interested in the reduction of GHG emissions. The directive 2012/27/EU establishes a set of common measures for UE members in order to reach at least the 20% energy efficiency target, at all stages of the energy chain, from its production to its final consumption, by 2020.

For dryers, energy efficiency (η), is defined as the energy required rom moisture evaporation at the solids' feed temperature, (E_r), divided by the total energy supplied to the dryer (E_s), as shown in Equation (5) [94]:

$$\eta = \frac{E_r}{E_s}, \quad (5)$$

Energy efficiency (η) is an average parameter and is not representative of the process when there are changes in temperature. To describe the process better, instantaneous energy efficiency formulas (η_{ins}), Equation (6), should be used [94,95].

$$\eta_{ins} = \frac{\mathrm{E}_r(\mathrm{t})}{\mathrm{E}_s(\mathrm{t})}, \quad (6)$$

Energy efficiency is then the integration of Equation (4) by time, as shown in Equation (7):

$$\eta = \frac{1}{t}\int_0^t \eta_{ins}(t)dt, \tag{7}$$

For convective drying, assuming the drying system as adiabatic (i.e., with no exchange of heat with the surroundings), energy efficiency can be expressed as thermal efficiency, Equation (8):

$$\eta = \frac{T1 - T2}{T1 - T0}, \tag{8}$$

where $T0$, $T1$ and $T2$ are respectively: ambient, inlet and outlet temperature. For microwave-vacuum, drying efficiency (DE) was calculated by Yongsawatdigul and Gunasekaran (1996) as shown in Equation (9) [96]:

$$DE = \frac{tP\left(1 - w_f\right)}{M_i\left(w - w_f\right)} * 10^{-6}\ (MJ/kg\ H_2O), \tag{9}$$

where t (s) is the total time of applied microwave, P (W) is the power applied, w_f and w_i are the amount of moisture at the initial and final stage and M_i is the initial mass of the sample. However, it should be noted that although Yongsawatdigul and Gunasekaran (1996) assumed Equation (9) as drying efficiency, the equation represents an energy consumption rate.

Finally, probably the most useful indicator for energy efficiency is the specific moisture extraction ratio, Equation (10) (SMER), [97], which is expressed in kg kW^{-1} h^{-1}:

$$SMER = \frac{Amount\ of\ water\ Evaporated}{Energy\ Used}, \tag{10}$$

A dryer's energy demand depends largely on the configuration, energy efficiency and weather fluctuations. However, since thermal efficiency is generally low (for convective dryers, below 50%) [98], it is reasonable to expect an energy optimization of such processes as feasible. Reducing energy consumption, cost and environmental impact of dryers may be achieved in different ways, i.e., by:

- dewatering the food prior to the drying process;
- reducing inlet and outlet gas humidity;
- reducing heat losses;
- recovering heat between hot and cold streams;
- adopting lower cost and/or renewable heat sources, such as solar energy and biofuel;
- combining heat and power to reduce drying time drastically;
- using smart drying technology to avoid over-drying.

Smart drying technology may be obtained in many ways (e.g., biomimetic systems, computer vision, spectroscopy, magnetic resonance imaging and a control system for the drying environment) [25]. The idea of smart drying technology is to obtain real-time information related to the process and the product as a means to simultaneously modulate the drying process. The result is a standardized high-quality dried product [25].

4. Fundamental of Computer Vision

Human beings use their eyes to see and visually sense the world around them. Computer vision (CV) is the science that aims to give a similar capability to a machine or computer. Its application concerns the automatic extraction, analysis and understanding of useful information from a single or a sequence of images, using an algorithmic basis to achieve automatic visual understanding [99].

Since the early 1960s, with the advent of the digital computer, vision was recognized as an important tool to evaluate quality in food production, and its use was constantly increased. It is possible to evaluate the visual characteristic and defects in food products rapidly and inexpensively in a non-destructive way [100]. Nowadays, CV is used in several different fields (e.g., food industry, robotics, medical diagnosis and industrial robotic systems).

A CV system is generally composed, as shown in Figure 2, by five elements: an illumination system, a sensor or a camera, a digitizer (only if the camera it is not digital), a computer and software capable of processing the image. Similar to human vision, CV is strongly affected by several factors (i.e., light source, background, direction of light, size of the area containing the same color and differences between individual perception) [101]. To reduce these defects and increase the accuracy of a CV system, it is necessary to use an illumination chamber [102].

The food industry continues to be among the fastest-growing segments of computer vision application, and it ranks among the top ten industries that uses computer vision systems [103]. This is due to the easy implementation of this technology in a broad range of applications, the simplicity of use, the rapid inspection rate and the feasibility to inspect a product non-destructively [99–103].

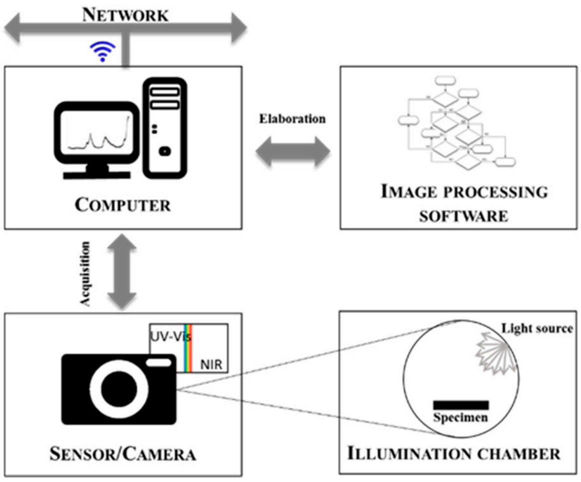

Figure 2. Elements of a computer vision (CV) system.

4.1. Analysis of Images in the Visible Region

External changes and defects on fruits and vegetables are often characterized by differences in color, shape and size. Commonly, a red, green and blue color space (RGB) camera, linked to a machine vision system, makes it possible to inspect external products in a rapid, accurate and fast way. RGB cameras emulate the human eye's capacity to capture images [104]. In fact, they acquire three wavelengths in the VIS region by using filters centered at 700, 560.1 and 465 nm (respectively, red, green and blue) [71]. These systems are simple, low cost and fast, and their models show good classification performance for a broad range of applications [105]. Unfortunately, CV systems have several drawbacks; when defects have a similar color to non-defects or when the objects are similar (e.g., same shape, color and the like), image analysis often fails to distinguish them. Furthermore, since RGB cameras acquire images only in the visible region, this spectral region is not suitable for an internal investigation of the object [106]. Thus, if the defect is invisible in the Vis region (e.g., oil oxidation), it is not detectable by the system.

4.2. Single-Point Spectroscopy

Spectroscopy is the study of the interaction of matter and electromagnetic radiation (ER). The interaction occurs in several ways (i.e., reflectance, transmittance, absorbance or scatter of polychromatic or monochromatic radiation), as shown in Figure 3.

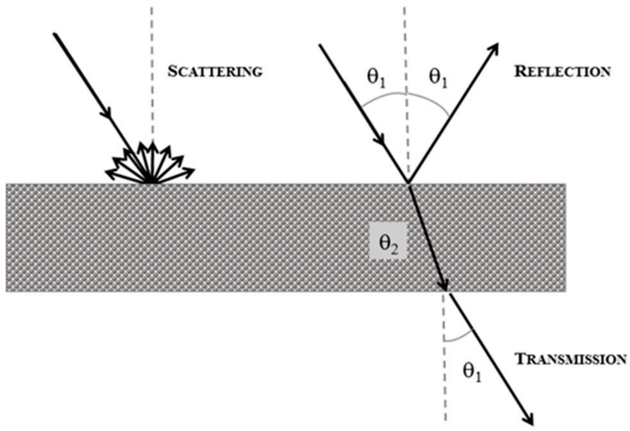

Figure 3. Interaction between matter and electromagnetic radiation (ER).

Different electromagnetic regions give different information related to the chemical composition of the sample. This being because each chemical bond absorbs light energy at specific wavelengths. As an example, pigments (e.g., chlorophylls, carotenoids and anthocyanins), mainly absorb in the visible spectral range, while water, carbohydrates, fats and proteins have absorption bands in the NIR region [107,108]. For food quality evaluation (e.g., quality control and authenticity), the ultraviolet (UV), visible (Vis) and near infrared (NIR) regions are the main spectral regions used [109].

4.2.1. Single-Point UV-Vis Spectroscopy

The Ultraviolet-visible (UV-Vis) region is a spectral region of the electromagnetic spectrum that covers wavelengths from 200 to 780 nm. Absorption of light in this region promotes the electronic transition of external electrons [107]. Both absorption and emission spectroscopy are routinely performed in a post-harvest laboratory for food-quality purposes. Absorption UV-Vis spectroscopy is commonly used in analytical food quality detection methods, for quantitative determination of different chromophores, (i.e., π-electron systems, conjugated unsaturation, aromatic compounds and conjugated non-bonding electron systems) [110]. Usually, UV-Vis spectroscopy is used for the solution, but there are studies also using this spectral range with a reduced amount of liquid, solid and gas [111].

Fluorescence consists of the excitation of a molecule that quickly returns to the ground state, losing a photon during the process. It is often used due to its high selectivity and sensitivity; indeed, in the solutions, the limit of detection is generally at the level of ppb (part per billion) [112]. In non-destructive food analysis, fluorescence offers a spectral signature containing information of the food's molecular structure. To extract this information, a chemometric approach is necessary [113].

4.2.2. Single-Point NIR Spectroscopy

The near infrared region covers wavelengths from 780–2500 nm. It is collocated between the visible and the medium infrared region. Infrared absorption leads to the vibrational transition of molecules (e.g., bending and stretching vibrations). NIR is the most energetic part of infrared radiation. The NIR spectrum is essentially composed of overtones and combination bands of specific bonds (i.e., C-H, C-C, C=C, C=O, C-O, N-H, O-H and S-H) commonly present in most organic and inorganic molecules [114–116]. Table 1 summaries the main investigable molecular classes using single-point NIR spectroscopy.

Water is the most important chemical constituent of fruits and vegetables; consequently, due to symmetric and asymmetric stretching and bending of the OH group at 979, 1200, 1453, 1780 and 1938 nm, the NIR region (780–2500 nm) is strongly affected by the water molecule [126]. NIR spectroscopy is a secondary method that requires calibration against reference methods for the determination of physicochemical parameters. However, during NIR measurements, spectral data may be affected by baseline shifts due to scattering effects related to the particle size differences and tissue heterogeneities, shifts of peaks towards lower wavelengths with increasing temperature, as well as noise and other irrelevant information due to instrumental bias. All these issues could make the assignment of a functional group to specific absorption bands difficult [130,131], thus affecting the development of well-performing prediction models. In this context, spectral preprocessing (i.e., mathematical transformation of spectral data) helps with enhancing spectral quality and amplifying the information carried out by spectra.

Table 1. Overtone bands for common molecular classes investigated by NIR.

Molecular Classes/Molecule	Bond	Features (nm)		Reference
		1st Overtone	2nd Overtone	
Aliphatic hydrocarbons Aromatic hydrocarbons	C-H C-H	1700 1685	1150 1143	[117]
Olefins (1-octene) Olefins	C-H C-H	1620 1680	 1180	[118]
Norbornene	C-H	1645–1675		[119]
Water	O-H	1453	979	[120]
Alcohol and phenols	O-H	1405–1425	945–985	[121]
Silanols	O-H	1385		[122]
Primary amines (R-NH2) Secondary amines (R2-NH)	N-H N-H	1500 and 1530 1520–1540	1000 	[123]
Aromatic amines (Ar-NH2)	N-H	1450–1490	1020	[124]
Cyclic amines (pyrroles, indoles, carbazoles)	N-H	1450		[125]
Ethanamide (CH3CONH2) *N*-methyl ethanamide (CH3CONHCH3)	N-H N-H	1430 and 1490 1475		[126]
Wheat protein	N-H	1500 and 1570		[127]
Aldehydes and ketones Esters Peptides Carboxylic acids	C=O C=O C=O C=O	2900	1960 1900–1950 1920 1900	[128]
Epoxides	C-O	1640–1650		[129]
Organophosphorus compounds	P-H	1891		
Aliphatic and aromatic thiols Phosphorus-thiol group	S-H P-S-H	1970–1980 1970 and 1999		[126]

4.2.3. Advantages and Disadvantages of Single-Point Spectroscopy

UV-Vis spectroscopy is widely used due to its high versatility, easy handling, fast scan rate and automation feasibility. However, it is a technique with low selectivity for the analytes, and often, it is necessary to couple it with other devices (e.g., chromatography) and/or process the dataset through chemometrics in order to obtain clear information [107,109,117]. NIR spectroscopy has many advantages (i.e., minimal processing of the sample, fast scan rate, feasibility of automating the process in an on-line device, multi-analytical and non-destructive analysis). However, there are also some drawbacks: Vis-NIR spectra are unreadable without preprocessing and multivariate analysis; moreover, the technique is not very sensitive; the limits of detection indeed are in the order of 10% range [132]; furthermore, as mentioned above, the setting up of robust calibration is a mandatory step to obtain good predictions.

Finally, both spectroscopic techniques give information about the composition of food products, but they can spot only a relatively small area of samples. Even when spectra are acquired in different areas of the sample, the result is the average chemical composition [106]. Often, the spatial distribution of quality parameters is the information desired, in the fruit and vegetable processing industry.

4.3. Hyper- and Multi-Spectral Imaging

Hyperspectral imaging systems are devices able to obtain both spectroscopic and spatial information [133,134]. The data-structure of the hyperspectral image is called the hypercube, which is the 3D image containing two spatial and one spectroscopic dimensions, as shown in Figure 4.

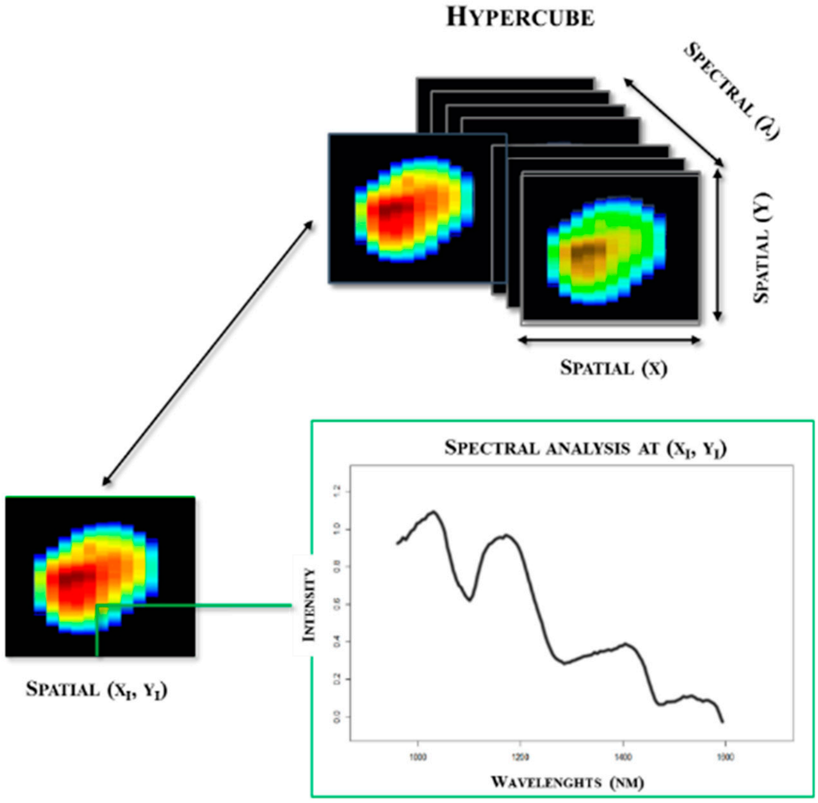

Figure 4. Schematic representation of a hypercube.

HSI devices in food-analysis work in the Vis/NIR region, each using absorption and emission spectroscopy [135]. However, due to scattering effects, emission spectroscopy in fruit and vegetable tissues is less sensible than in homogeneous liquid matrix [136].

The main advantage of HSI is the feasibility of monitoring both external and internal quality parameters. With this device, it is feasible to distinguish and analyze objects with similar color, shape, size and overlapping spectra. The drawbacks are related to the long acquisition time needed, the high amount of redundant information and, thus, the huge amount of data acquired. These drawbacks limit HSI in on-line processing. Furthermore the computational time to develop the prediction model increases considerably [99]. The development of an MSI system can reduce these drawbacks, mainly due to its possibility to select the most significative wavelengths (from 3–15) in order to predict the physicochemical attributes of interest [137]. MSI has several advantages compared to HSI (i.e., faster scan rate, feasibility of on-line application in the food processing industry, less computer memory required to acquire and process the images) [138]. The drawbacks are related to the device lacking flexibility. Generally, these are built by researchers according to the specific imaging task. Moreover, it is necessary to have an HSI system to use prior to the development of the MSI device.

4.4. Data Processing and Chemometrics

Regardless the device used, a chemometric approach is required to pre-process the signal and to obtain a regression and classification model able to describe the changes in the quality of interest [131]. Image and HSI analyses require an additional step, as summarized in Figure 5.

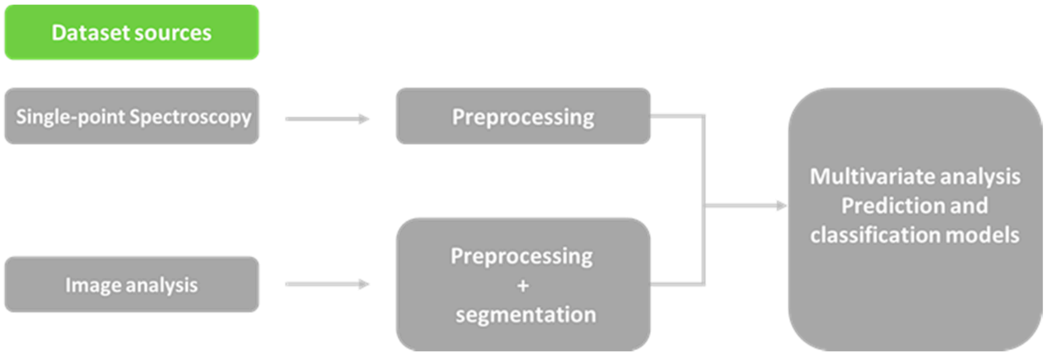

Figure 5. Schematic representation of single-point and hyperspectral image (HSI) processing.

Preprocessing is required to clean the dataset of undesired physical phenomena (e.g., light scattering, unwanted spectral variations and baseline shifts) [139]. The result of preprocessing is often an improvement of the signal-to-noise ratio (S/N ratio). Usually, in the food-science application of CV, four kinds of preprocessing methods are used (i.e., noise reduction, baseline correction, resolution enhancement, centering and normalization) [139,140].

- Noise reduction methods (e.g., moving-average and Savitzky–Golay smoothing) can reduce high-frequency noises associated with instrument detectors and electronic circuits.
- Baseline correction methods (e.g., Savitzky–Golay filters for derivative, multiplicative scatter correction (MSC), standard normal variate (SNV)) are used to reduce or eliminate multiplicative and additive scatter factors and noises.
- Resolution enhancement methods (e.g., first and second derivatives and Fourier self-deconvolution) point out information from overlapping bands.
- Mean centering and normalization are preprocessing methods frequently used because they are simple and effective ways to enhance information prior to multivariate analysis.

After the preprocessing step, spectra are processed using chemometrics. For qualitative analysis, the most prevalent algorithm is software independent modelling class analogy (SIMCA), which is based on principal component analysis (PCA) [130]. For quantitative purposes, the most typical linear methods are multilinear regression (MLR), principal component regression (PCR) [131] and partial least square regression (PLS) [141,142]. If a non-linear regression model seems more suitable, artificial neural network (ANN) and the kernel-based technique (e.g., support vector machine (SVM)) can be used [19]. Furthermore, image segmentation (the ability to distinguish the desired object in the matrix) is the most important operation to obtain accurate classification models in computer vision. Segmentation can be done manually by using commercial software packages (e.g., Photoshop (Adobe systems Incorporated, San Jose, CA, USA), Aphelion (AAI, Inc., Saint Contest, Normandy, France) or MATLAB (The MathWorks Inc., Natick, MA, USA)), but in this way, the step takes a long time to be performed, and thus, it is not suitable for on-line processing [143]. For this reason, several algorithms were developed to automate the segmentation process. Generally, this can be done in three different ways: thresholding, edge-based segmentation and region-based segmentation.

- Thresholding is the simplest segmentation method; pixels are partitioned depending on their intensity value. The Otsu method is an algorithm that works on this principle and is generally used for food quality inspection [144].
- Edge-based segmentation methods attempt to find the edges directly by their high gradient magnitudes [145].
- Region-based segmentation is based on pixel-level similarity, following criteria such as grey level, color and texture to identify a single object in images [146].

Nowadays, despite the broad range of algorithms used in CV image analysis, an ideal solution able to ensure good accuracy and efficiency in all the food products has still not been found. Generally, during the development of a CV system, various image preprocessing, segmentation and classification algorithms should be tested to find the best solution for the specific scenario.

5. Applications

Single-point spectroscopy and computer vision, including multi- and hyper-spectral vision systems, have been widely used in the fruit and vegetable industry for quality and safety control [15,146–150]. The subsequent section is focused on the application of these devices for monitoring fruit and vegetable quality during drying.

5.1. Quality Control of Fruit during Drying

Table 2 gives an overview of the application of single-point spectroscopy and machine vision to monitor the quality of fruits during drying.

Romano et al., in 2016, investigated the feasibility of implementing three laser backscattering sources in the Vis/NIR range at 473, 532 and 785 nm for a convective dryer, for quality assessment of two golden-colored kinds of fruit: mango and litchi [151]. Linear mixed model analysis using the Lorentzian distribution showed that 473 nm was adequate for detecting browning changes, 785 nm was suitable to predict hardness and both 532 and 785 nm were able to follow moisture changes both for mango and litchi. The coefficient of determination (R^2) for browning, moisture content and hardness were, respectively: R^2 = 0.63; 0.91; 0.70 for mango and R^2 = 0.81; 0.80; 0.55 for litchi. These results indicate the potential feasibility of the technique for the authors' intended purposes, although an R^2 value lower than 0.80 usually indicates poor performances and that improvements were still required. This application of Vis/NIR spectroscopy presents several advantages: it is rapid, inexpensive, in-line transferable, easily implementable in existing drying systems, non-destructive, multi-analytical and able to improve energy efficiency by avoiding over-drying and quality losses.

Barzaghi et al., in 2008, developed a method able to quantify residual moisture on osmo-air dehydrated apple rings and to discriminate them on the basis of the osmotic solution used as pretreatments [152]. Apple rings, prior to air drying, were dipped several times (i.e., 30, 60, 90 min) in three different sugar solutions. Air drying had been performed then at three different temperatures (i.e., 70, 80, 90 °C). After the treatments, apple rings were packed in polypropylene film under vacuum in order to avoid water absorption phenomena. NIR spectra were recorded directly on packed apple rings by using an FT-NIR spectrometer (NIRFlex 500, Büchi Italia, Assago, Italy).This method showed the following metrics: R^2 = 0.93, regression point displacement (RPD) = 3.33; a value of RPD above three corresponds to good prediction accuracy [19]. The method could identify the cultivar and sugar composition of the final product, using the PLS discriminant algorithm. According to the author, this method is promising and could be used to measure sample constituents, (e.g., as water content changes during drying) and to control the product shelf-life without opening the package.

Pu and Sun, in 2015, investigated the feasibility of using Vis/NIR hyperspectral imaging to visualize moisture distribution in mango slices during microwave-vacuum drying [13]. Two Vis/NIR ranges were investigated in this study: 400–1000 nm and 880–1720 nm. PLS was applied to correlate the mean spectrum of each slice with the reference moisture content. The second spectral region (880–1720 nm) showed the best prediction performances in terms of the coefficient of determination in prediction (R^2p) and root mean square error in prediction (RMSEP): R^2p = 0.97 and RMSEP = 4.80%. Furthermore, different algorithms were tested to reduce the number of wavelengths used to perform the regression; the best result was obtained by using competitive adaptive reweighted sampling (CARS): this model indeed was built using just two wavelengths (1342, 1405 nm), and the prediction performance was as good as the full wavelength model. Starting from this result, the multispectral device can be built and rapid, non-destructive moisture content determination can be done and visualized during the drying process.

Table 2. Monitoring of fruits during drying using spectroscopy and image analysis techniques. AD, air drying; MSI, multispectral imaging; RMSEP, root mean square error in prediction.

Products	Dryer Type	CV Device	Features	Resolution	Attribute(s)	Algorithm	Metric		Reference
							Error Metric	R^2	
Mango (var. Nam Dokmai)	AD	Vis-NIR	473, 532 and 875 nm	5 nm	Browning index,	–	–	0.63	[151]
					w			0.91	
					Hardness (h)			0.70	
Litchi (var. Chinensis Sonn.)	AD	Vis-NIR	473, 532 and 875 nm	5 nm	Browning index,			0.81	
					w			0.80	
					h			0.55	
Apple (var. Golden delicious and Pink lady)	OD + AD	NIR	1000–2500 nm	0.8–5 nm	w	PLS-DA	3.33 (RPD)	0.93	[152]
							13.79 (RER)		
Mango (var. Nam Dokmai)	MVD	HSI	880–1720 nm	7 nm	w	PLS	4.716	0.97	[13]
		MSI	1342, 1405 nm		w	PLS	5.582	0.96	
Apple (var. Granny Smith)	AD	CV	RGB	1280 × 1024 pixels	L*	COM	<5% (SE)	0.91	[12]
					a*			0.94	
					b*			0.95	
Apple (var. Empire)	AD	CV	RGB	640 × 480 pixels	Area	–	–	1	[153]
					Thickness			0.97	
					Volume			0.95	
					Hue angle			1	
					L*			0.90	
					Chroma (C*)			0.94	
					Texture			0.90	
Apple (var. Jonagold)	AD	CV	Visible	1280 × 768 pixels	ΔE*	Third order polynomial		0.95	[154]
					Shrinkage		P = 0.04	0.68	
Sultana grape (var. *Vitis vinifera* L)	AD	CV	Visible	–	w	Page's model	–	0.99	[155]
					Shrinkage			0.99	
					ΔE*			0.95	
Apple (var. Idared)	AD	NIR	740–1400 nm	9 nm	w, (dry bulb)	PLS	RMSEP < 5.09, RPD = 5.09	0.98	[156]
					w, (wet bulb)		RMSEP < 24.82, RPD = 6.63	0.99	
		MSI	532, 635, 650, 780, 808, 850, 1064 nm	5 nm	w, (dry bulb)	PLS	RMSEP 38.41	0.94	
					w, (wet bulb)		RMSEP 13.2	0.71	

MVD = microwave vacuum drying; OD = osmo-air dehydration; COM = Co-occurrence matrices; RPD = regression point displacement; RER = range error ratio.

Fernández et al., in 2005, analyzed the effect of drying in terms of shrinkage, color and image texture of the apple disc, via a standardized image acquisition system and image analysis [12]. All morphological features (i.e., shape, dimension) changed smoothly during the first 6–8 h of drying, and samples became less uniform in color during that period. The authors developed a classification model to identify different drying based on Euclidean distance. After 6-h of drying, external features remain almost constant. Seven classes (0, 1, 2, 3, 4, 5, $\geq$6 h) were considered in the classification model. The training set consisted of 72 images and 39 random samples. Ninety-five percent of the test samples were correctly classified into their respective classes.

Sampson et al., in 2014, developed a low cost dual-view CV system with a fish-eye lens for monitoring apple slices during the drying process [153]. The authors decided to use the fish-eye lens in order to obtain a low cost wide field-of-view and two identical cameras (model TL-BW3N8D-0.5W TSD Co.) positioned perpendicularly to obtain 3D imaging information. The aims of this work were to obtain: a perpendicular CV system to evaluate volume and image textural changes and a prediction model for moisture content and color changes. The results suggested that volume can be accurately measured by the proposed method, but it is not suitable to predict the end of the drying process. The uniformity of intensity of the image feature was a better predictor ($R > 0.94$).

Sturm et al., 2012, developed and optimized a convective hot-air dryer, for routine processing of apple slices by using computer vision [154]. Several dryers and product parameters (i.e., air temperature, air velocity, color changes and shrinkage) were investigated. Air velocity showed a significant influence on product quality; at a fixed temperature, increasing air velocity reduced processing time and damage to the product. The prediction model for total color difference ΔE^* followed a third order polynomial trend and showed an $R^2 = 0.95$. The shrinkage prediction model followed a first order polynomial trend, and the coefficient of determination was $R^2 = 0.68$.

Behroozi Khazaei et al., in 2013, applied a method based on computer vision with a low cost Smart Cloud Camera (SCC-101 PA) to follow grape hot-air drying [155]. Shrinkage, ΔE^* and moisture content changes were evaluated. Experimental data were acquired by capturing images at different drying temperatures (i.e., 40, 50 and 60 °C). Good prediction models were obtained for shrinkage, moisture content and color changes, demonstrating the feasibility of the on-line evaluation of such parameters during the drying process. The coefficients of determination indeed were respectively: $R^2 = 0.99$; 0.99; 0.95.

Dénes et al., in 2012, evaluated changes in laser-induced diffuse reflectance on apple discs during the hot-air drying process [156]. Samples were measured with an NIR spectrometer (MetriNIR 10-17 ST) and a machine vision system based on laser-induced scattering. NIR spectra were acquired in the following range: 740–1700 nm with 2-nm steps. PLS regression was tested, and the models showed very good performance in predicting moisture content with the following metrics $R^2 = 0.99$, RPD = 6.63, RMSEP = 24.82. The multispectral device is based on a high performance monochromatic CCD IP camera (Photon Focus MV1-D1312, gray scale resolution of 12-bit, max. spatial resolution of 1312 $\times$ 1082 pixels, spectral sensitivity from 320–1080 nm) with an L-SV-L5014MP megapixel lens of fixed focus, optimized for Vis-NIR application. Seven laser diode modules emitting at seven different spectral bands were used (532, 635, 650, 780, 808, 850, 1064, 532, 635, 650, 780, 808, 850, 1064 nm). PLS regression was performed with the following metrics: $R^2 = 0.99$, RPD = 6.72, RMSEP = 24.48. Both methods proved themselves to be accurate and rapid for predicting moisture content (dry and wet bulb) on apple slices during drying.

5.2. Quality Control of Vegetables during Drying

Table 3 gives an overview of the application of single-point spectroscopy and machine vision to monitor the quality of vegetables during drying:

Table 3. Monitoring of vegetables during drying using spectroscopy and image analysis techniques.

Species	Dryer Type	CV Device	Features	Resolution	Attribute(s)	Algorithm	Metric		Reference
							Error Metric	R^2	
Yellow pepper (var. *Capsicum annuum*)	AD	CV (CCD camera + laser diode)	Visible (CCD camera; 532 and 635 nm)	1280 × 1024 pixels	w	–	7.28	0.93	[157]
					L*		–	0.9	
					a*			0.93	
					b*			0.72	
Green pepper (var. *Capsicum annuum*)	AD	CV (CCD camera + laser diode)	Visible (CCD camera; 532 and 635 nm)	1280 × 1024 pixels	w (635 nm)		8.77	0.9	
					L*		–	0.87	
					a*			0.97	
					b*			Low	
Red pepper (var. *Capsicum annuum*)	AD	CV (CCD camera + laser diode)	Visible (CCD camera; 532 and 635 nm)	1280 × 1024 pixels	w (532 nm)		9.95	0.89	
					L*		–	Low	
					a*			Low	
					b*			Low	
Soybean (var. *Glycine max*)	MVD	HSI	400–1000 nm	0.12 mm/pixel	Color	Segmentation PLS	RMSEP = 1.0	0.74	[15]
				0.64 mm/pixel	w		RMSEP = 4.7	0.94	
Ginseng (var. *Panax ginseng*), (var. *Panax quinquefolium*)	AD	NIR	1100–2500 nm	8 nm	w	First derivative, SNV, PLS	SEP = 0.14	1	[11]
Potato (var. *Solarium tuberosum*)	IR	CV (digital camera)	Visible range	3648 × 2736 pixels	Shape	Image processing, segmentation	–		[158]
					Shrinkage				
Ginseng (var. *Panax ginseng*)	AD	CV (CCD camera)	Visible range	1040 × 1392 pixels	Density, shrinkage, porosity	Image processing, segmentation	–		[159]
Potato (var. *Solarium tuberosum*)	AD	Computer vision (black/white video camera)	Visible range	510 × 492 pixels	Shrinkage	Segmentation	BIAS = 0.6%	0.99	[160]
Cauliflower (var. Snow March)							BIAS = 0.6%	0.97	
Carrot (var. *Daucus carota*)	MVD	CV (CCD digital camera)	Visible range	3264 × 2448 pixels	Shrinkage, color	–	–	1	[16]
Carrot (var. *Daucus carota*)	AD	MSI	19 wavelengths from 405–970 nm	–	w, color	PLS, LS-SVM, BPNN	RMSEP = 1.482	0.99	[161]

MVD = microwave vacuum drying; OD = osmo-air dehydration; COM = co-occurrence matrices; RPD = regression point displacement; RER = range error ratio.

Romano et al., in 2012, evaluated the use of a CCD camera combined with two laser diodes emitting at 532 and 635 nm for monitoring changes in moisture content and color in red, green and yellow pepper during hot-air drying [157]. Results showed excellent correlations for yellow pepper (R^2 = 0.93 and RMSEP = 7.28). However, green and red pepper changes during drying were not well predicted respectively by green and red LED. However, the 635-nm LED can predict green pepper moisture changes (R2 = 0.90 and RMSEP = 8.77), and 532 nm can predict red pepper w (R^2 = 0.89 and RMSEP = 9.95). Scattering phenomena were observed due to changes of tissue structure during drying. CV was validated as a promising way to monitor changes in L* (R^2 = 0.87 and R2 = 0.90) and a (R^2 = 0.93 and R^2 = 0.97) during drying for yellow and green pepper. The result of this work suggested that alteration in tissue structure and the wavelengths selected had a remarkable effect on moisture changes' predictability.

M. Huang et al., in 2014, developed a hyperspectral method for predicting color and moisture content on soybeans during MVD [15]. HSI images were acquired within the following range: 400–1000 nm for 270 samples. Soybean images were acquired and automatically segmented (via the active contour model). Mean reflectance and image entropy were obtained, tested separately and in combination for predicting (using PLS regression) color and moisture contents. The best prediction results were given by mean reflectance data, with the following metrics (R^2p = 0.74 and RMSEP = 1.0% for color and R^2p = 0.94 and RMSEP = 4.7% for moisture content). Entropy data regression and its combination with mean reflectance data did not improve the prediction ability of the model. However, the results indicate that the evaluation of color and moisture changes via the hyperspectral technique on soybean during drying is feasible.

Ren and Chen, in 1997, developed a single-point NIR method to determinate moisture content in ginseng roots of different cultivars: Asian ginseng (*Panax ginseng*) roots, freeze-dried Asian ginseng roots, red Asian ginseng roots and hot-air dried American ginseng (*Panax quinquefolium*) roots [11]. Single-point NIR spectra were acquired in the following range: 1100–2500 nm using an NIR system (Model 6500, Perstorp Analytical Inc., Silver Spring, MD, USA) at 8-nm intervals. Spectra were recorded as the logarithm of the reciprocal reflectance, log (1/R). A high prediction model was obtained: R^2p = 1 and RMSEP = 0.18%.

Hafezi et al., in 2015, standardized an image acquisition system in order to monitor shrinkage changes in potato slices during vacuum-infrared drying [158]. Three factors were varied during the experiments: infrared radiation power (100, 150, 200 W), absolute pressure levels (20, 80, 140, 760 mmHg) and slice thickness (1, 2, 3 mm). During the drying process, surface area reduction was mostly affected by the thickness of potato slices. The results showed that all the factors had significant effects on the potato slices. Furthermore, the percentage reduction of surface area, which is related to shrinkage, can be used as a parameter to measure shrinkage changes. Finally, it was observed that an increase in infrared power and a reduction of absolute pressure at a given thickness led to a reduction of the drying time. However, deformation of the product surface was more evident using this setup.

Martynenko, in 2008, evaluated porosity changes in ginseng roots during hot-air dehydration by using real-time imaging and mass measurements [159]. Porosity changes were evaluated from the moisture-shrinkage-porosity correlation. It was found that any deviation from the linear shrinkage-moisture relationship was due to changes in porosity. Moreover, temperature effects on porosity changes were investigated; it was demonstrated that density and porosity changes were evaluable from real-time volume and mass measurement. Drying at 38 °C resulted in an increase of porosity of 20–25% with the inversion point at the critical moisture content (0.3 g/g), after which there was a significant decrease of porosity (range of 10–15%). However, drying at 50 °C led to a constant porosity until moisture content of 0.5 g/g, after which a strong hardening of the ginseng roots was observed. The discrepancy of this method to evaluate porosity changes and official methods did not exceed 5%.

Mulet et al., in 2000, evaluated the effect of shape (cubes, parallelepipeds and cylinders) on potato and cauliflower stem shrinkage during drying [160]. A basic image analysis was developed to monitor changes in shape during the drying process. Caliper and image analysis data showed a very good correlation with no bias. Furthermore, it was observed that shape influenced shrinkage depending on the x-axis. The difference in shrinkage between directions was greater for cauliflowers, probably due to the alignment of fibers along the axis.

Nahimana and Zhang, in 2011, developed a computer vision method to monitor shrinkage and color change during MVD of carrots [16]. The aim of this article was to evaluate drying characteristics and loss of product qualities with simple and accurate models. Visual color was quantified using Hunter CIE Lab coordinates, and carotenoids contents were determined via a UV-Vis spectrophotometer. Drying time varied from 24–42 min. It was seen that circularity, solidity, major and minor axes varied significantly during drying. Results indicated that the drying rate increased with the increasing of microwave power. Moreover, microwave drying proved to have a better rehydration capacity, as it was observed that the products were more porous and less shrunken. Furthermore, MVD led to a significant whitening index and carotenoid losses, in agreement with what is reported in the literature.

Liu et al., in 2016, evaluated the feasibility of a multispectral method for the real-time determination of color changes and moisture distribution among carrots slices during AD [161]. Twenty wavelengths were used in the spectral region between 405 and 970 nm for the color change detection and moisture content prediction of carrot slices during the dehydration process. Moreover, the authors' aim was to compare three prediction algorithms: PLS, nonlinear least square-support vector machine (LS-SVM) and back propagation neural network (BPNN) for predicting the accuracy of moisture content. The authors demonstrated that MSI, combined with chemometrics, is a valid tool to non-destructively determine color change and moisture content in carrot slices without any preliminary sample preparation. The best prediction model was the BPNN with the following metrics: $R^2p = 0.99$, RMSEP = 1.48% and RPD = 11.38. The results were very promising and suggested the feasibility of such technology for food-industry purposes.

To summarize, CV is a valid method to non-destructively monitor the external attributes during drying. It is often used also to develop the discrimination model, able to classify the products based on external attributes. NIR and HSI, instead, were principally used to detect changes in moisture and its distribution in fruits and vegetables. MSI development is promising due to its low cost, faster scan rate and good prediction results. However, in all the studies found in the literature, only color and moisture content were investigated with these devices. In other fields instead, these devices were successfully used (e.g., in quality and safety [15,116,150], as well as in post-harvest control of fresh fruits and vegetables using NIR [19,138,162,163] and HSI [164,165] to monitor a broad range of physicochemical changes such as: sugar content [166], protein content [167,168], starch index [135] and several related nutritional compounds [169,170]. For this reason, it seems reasonable to develop a model able to detect the same compounds and their changes during the drying process.

6. Conclusions

The continuously growing demand for high quality processed food in recent years, together with the food industry's necessity to restrain the quality assurance cost, has led to several technical solutions and standard operation procedures able to simultaneously increase products' quality and reduce resource consumption. Non-destructive techniques, such as CV and NIRs, can follow the process on-line, resulting in a greener solution in order to perform quality control for several industrial processes. Generally, smart drying systems based on computer vision are used to follow moisture content, color and shrinkage changes. However, even if these systems can obtain more information during the process, especially related to the chemical composition of the product, few works can be found in the literature.

An effort in such a direction was done by Moscetti et al., in 2017, demonstrating the feasibility of the real-time measurement of several quality attributes (e.g., carotenoid contents, Soluble Solid

Content, (SSC) lightness and hue angle) in organic carrots (var. Romance) during hot-air drying using near infrared spectroscopy [171]. Further effort in this direction may be useful not only to improve the smart drying technologies, but also to fulfil the lack of guidelines in organic food processing, reducing the gap between conventional and organic drying products.

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