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Advanced Detection Techniques Using Artificial Intelligence in Processing of Berries

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Abstract
Berries are delicious and nutritious, making them among the popular fruits. There are various types of berries, the most common ones include blueberries, strawberries, raspberries, blackberries, grapes, and currants. Fresh berries combine high nutritional value and perishability. The processing of berries ensures high quality and enhanced marketability of the product. Sorting, disinfection, and decontamination are essential processes that many types of fruits such as citrus fruits, berries, pomes, and drupes must undergo to ensure improved quality, uniformity, and microbiological safety of the product. Drying and freezing are excellent processing methods to extend the shelf life of berries which also provide new options to the consumer of a wide variety of berries. With the demand for high quality and automatic high-throughput detection of the quality of fruit products, intelligent and rapid detection of various parameters during processing has become the development direction of modern food processing. Therefore, this paper reviews the application of advanced detection technologies, artificial intelligence-based methods for detection and prediction during berry sorting, drying, disinfecting, sterilizing, and freezing processing. These advanced detection techniques include computer vision system, near infrared, hyperspectral imaging, thermal imaging, low-field nuclear magnetic resonance, magnetic resonance imaging, electronic nose, and X-ray computed tomography. These artificial intelligence methods include mathematical modeling, chemometrics, machine learning, deep learning, and artificial neural networks. In general, advanced detection techniques incorporating artificial intelligence have not yet penetrated into all aspects of commercial berry processing, which include drying, disinfecting, sterilizing, and freezing processes.

Keywords Berries · Detection technology · Artificial intelligence · Sorting · Disinfection · Decontamination · Drying · Freezing

Abbreviations

ADE	Advanced detection equipment
AI	Artificial intelligence
ANFIS	Adaptive neuro fuzzy inference system
ANN	Artificial neural network
BPNN	Back-propagation neural network
CARS	Competitive adaptive reweighted sampling
CCD	Charge-coupled device
CFBP	Cascade forward back propagation
CFD	Computational fluid dynamics
CFS	Correlation-based feature selection subset
CNN	Convolutional neural network
CONS	Consistency subset
CT	Computed tomography
CVS	Computer vision system
DAE	Deep autoencoder
DSC	Differential scanning calorimetry
DT	Decision tree
E-nose	Electronic nose
FCN	Fully convolutional network
FEM	Finite element modeling
FFBP	Feed forward back propagation

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FL	Fuzzy logic
FNN	Feedforward neural network
FTIR	Fourier transform infrared spectroscopy
GAN	Generative adversarial network
GGCM	Gray level-gradient co-occurrence matrix
GLCM	Gray level co-occurrence matrix
HSI	Hyperspectral imaging
iPLSR	Interval partial least squares regression
KNN	K-nearest neighbors
LDA	Linear discriminant analysis
LF-NMR	Low-field nuclear magnetic resonance
LIBS	Laser-induced breakdown spectroscopy
LR	Linear regression
LS-SVM	Least-squares support vector machine
LS-SVR	Least-squares support vector regression
LWR	Locally weighted regression
MLP	Multi-layer perceptron
MRAFC	Model reference adaptive fuzzy control
MRI	Magnetic resonance imaging
NIR	Near infrared
OES	Optical emission spectrometry
PCA	Principal components analysis
PLS	Partial least squares
PLSR	Partial least squares regression
PNN	Probabilistic neural network
RBFNN	Radial basis function neural network
RF	Random forest
RFR	Random forest regression
RMSE	Root mean square error
RNN	Recurrent neural network
RPD	Residual prediction deviation
RT-qPCR	Real-time quantitative PCR
SMO	Sequential minimal optimization
SPA	Successive projection algorithm
SSC	Soluble solid content
SVM	Support vector machine
SVR	Support vector regression
UVE	Uninformative variable elimination
VC	Vitamin C
WT	Wavelet transform

Introduction

Berry fruits represent a very diverse group, such as grape, currant, goji (wolfberry), blueberry, strawberry, raspberry, cranberry, mulberry, blackberry, gooseberry, chokeberry, bayberry, bilberry, and cherry tomato among many more [1]. Berry fruits are rich in a wide variety of nutritious bioactive compounds, such as vitamins, anthocyanins, polyphenols, and organic acids [2, 3]. Many berries can be consumed directly as fresh foods; however, due to their perishable and seasonal nature, many berries are processed after harvest into a variety of more storable products such as frozen berries, dried berries, berry juice, and berry jams.

Berries have high water content and contain sugars which make them susceptible to contamination from spoilage bacteria and viruses during and after harvest [1]. Sorting is one of the essential berries processing procedures. This work is performed based on quality parameters such as ripeness, size, shape, damage, and decay of raw berries. Sorting operations can reduce the impact of inconsistent appearance, vulnerability, and perishable nature of raw berries on the berry processing and consumption system. In general, after the sorting step, raw berries must be cleaned, disinfected, and inspected to ensure cleanliness and microbiological safety before they are suitable for consumption as ready-to-eat fresh berries or for undergoing further processing. Several outbreaks in Europe linked to berries have been attributed to the presence of norovirus [4], hepatitis A virus [5], and other food-borne pathogens [6] on berry products, which is a reminder to pay more attention to the microbial inactivation of berries. Drying and freezing of berries is an excellent processing method that extends the shelf life of berry products and also brings popular and novel processed berry products to consumers.

During processing, effects can occur on the color, texture, structure, chemical content, and biological activity of berries, which determine the quality of the product. Detecting and analyzing the influence of different processing methods on these parameters can contribute to ensuring high overall quality of the end products, improving processing techniques, and enhancing processing efficiency. Because of rising labor costs as well as inherent subjectivity and inconsistency in human handling, intelligent detection technology can provide rapid and accurate results, which guarantees high quality products. For high-capacity processing of berries, current trend in modern food processing industry is to monitor the parameters of the process with intelligent and efficient detection technology and to further optimize control of the process. Use of advanced detection equipment (ADE) and artificial intelligence (AI) will soon accelerate this trend. In this review, ADE is defined as a category of non-destructive rapid detection equipment, which distinguishes them from traditional physical and chemical analytical methods. These ADEs are generally implemented by electromagnetic spectrum-based detection equipment and sensor devices to obtain appropriate physical and chemical information during berry processing. However, the information obtained by ADE is often multi-dimensional, complex, and does not present the final detection results in a straightforward manner. Chemometrics, machine learning, and deep learning methods based on AI techniques can mine physicochemical characteristics by analyzing and reducing the dimensionality of the vast amount of data generated from ADE [7]. In addition, mathematical modeling and computer simulations are applied to analyze and predict parameters during berry drying, disinfecting, and freezing processing. AI, as a tool that can be run independently, allows the use of data obtained by traditional detection means as input variables for modeling and prediction using AI models [8]. Soft sensing is the concept of AI technology applied in the field of measurement and control engineering, which can be used as an alternative for process variables that cannot be measured at all or only by very sophisticated equipment because of technical limitations, measurement delays, and complicated environments [8, 9]. In general, the collaboration between ADE and AI is the trend of intelligent detection in modern food processing. That is, the detection data of berries are obtained by ADE, and then analyzed and processed using smart AI-based algorithms to get the expected detection results.

The content and status of important parameters (internal moisture of berries, microorganisms) in the processing of berries determine the processing performance and product quality. However, real-time, non-destructive, and accurate detection of internal moisture and microorganisms still present some challenges for current detection equipment and technologies. Therefore, fewer ADEs and AI are needed for detecting purposes in berry drying, freezing, and disinfecting processing as opposed to the varied intelligent detection techniques in sorting.

Detection Technologies

In modern processing of berries, ADE is gradually replacing traditional experimental measurements as the newer detection techniques save labor and cost while providing better precision. These advanced detection methods cover a wide range from computer vision systems (CVSs), near infrared (NIR), hyperspectral imaging (HSI), thermal imaging, nuclear magnetic resonance (NMR) to X-ray computed tomography (CT). In addition, sensor technologies such as electronic nose (E-nose) and sound sensors also play an important role in berry processing [10]. In the following section, we summarize briefly key features of these technologies.

Computer Vision Systems

Computer vision system, also commonly referred to as machine vision system, is being used extensively for post-harvest fruit quality measurements [11, 12]. CVS consists of an integrated mechanical-optical-electronic-software system that includes mechanical devices, optical instruments, electromagnetic sensing, and image processing [13]. CCD digital camera is a common image acquisition device in CVS, and the wavelength operating range almost overlaps with the visible spectrum [14]. CVS first acquires digitized images of food materials through cameras, and then inputs them into a computer for image processing and analysis to detect the appearance characteristics of the food [13]. It mainly focuses on applications in quality inspection and sorting of products, including foreign materials, shape [15], size, color [16, 17], ripeness [18, 19], rottenness [20], and external damage. However, the narrow working range of the visible spectrum makes it impossible for CVS to detect the internal structure of food. Although the skin of blueberries is thin, the high absorption and scattering of the skin prevents the spectrum between 500 and 700 nm from penetrating to the interior, which makes it difficult to use to differentiate internal bruises [21].

Near Infrared

NIR refers to the absorption spectrum between the visible spectrum and the mid-infrared, in the wavelength range of 780–2526 nm. NIR spectroscopy is an analytical method suitable for the prediction of both chemical and physical properties of samples. The change in NIR-active compounds (same or a class of structurally similar) concentration correlates with the amount of change in NIR spectral data [22]. The absorption of the NIR spectrum is related to the vibration of hydrogen-containing groups (O–H, N–H, C–H) in organic molecules, which can indicate the chemical composition in food materials [23]. Therefore, NIR spectroscopy can be performed for the quantitative determination of the chemical composition of berries. However, due to the low penetration depth of NIR radiation, the NIR technique is not well suited to measure quality attributes such as sugars or acids in fruits with thick skin or complex internal structure [24]. In addition, NIR can be applied to the detection of hardness or internal bruises. The principle that NIR spectroscopy can distinguish blueberry hardness is that different structures of berries change the path of incident light and further change the NIR spectral pattern [25].

Hyperspectral Imaging

HSI systems measure data from hundreds of narrow spectral bands. Unlike common 3-channel cameras, which return three data points from each pixel, hyperspectral cameras can collect hundreds of data points per pixel. The spectral resolution of hyperspectral is usually less than 10 nm, which not only provides a wealth of information but also results in the generation of a large amount of redundant data [26, 27]. In the application, the redundant hyperspectral data need to be downscaled to select representative key wavelengths relevant to the detection target, and then fed into the prediction model [28, 29]. In addition, it is also available to perform automatic feature extraction and prediction of HSI data using deep learning approaches such as convolutional neural network (CNN) [30, 31]. HSI can be used to detect product quality in sorting processes, as well as quantitative detection of nutrient content. The detection HSI spectra provide complex information generally related to the vibrational behavior of the chemical bonds associated with food components [32].

Thermal Imaging

The basic feature of thermal imaging is to capture the infrared radiation emitted, transmitted, and reflected by the object, and to analyze and use the received infrared radiation data of the object and its surroundings to build a pseudo-color image. The visual imaging feature of product temperature monitoring makes it feasible to use thermal imaging for monitoring the body temperature of berries in thermal processing, such as the decontamination process of berries using the microwave plasma torch [33]. Thermal imaging could also be performed for the detection of internal bruises of berries. The principle that thermal imaging can be employed to detect bruises is that bruised tissues have higher thermal diffusivity than healthy tissues [34]. During the heating phase of thermal imaging detection, thermal radiation first reaches the surface of the berry and then conducts to the relatively cooler internal tissues. In healthy berries, intact cell walls and organized cell layers impede this heat transfer. In contrast, in berries with bruises, the ruptured cell walls and tissues provide a better conductive medium and ultimately more heat is absorbed internally, resulting in lower berry skin temperatures. These inferences can be explained by the thermal window theory [34].

Low-Field Nuclear Magnetic Resonance (LF-NMR) and Magnetic Resonance Imaging (MRI)

LF-NMR is a time-domain NMR measurement that exploits the differences in molecular mobility between different food components, as reflected in the transverse relaxation times (T_2) of protons (usually the hydrogen nuclei of water) [35]. MRI is a pseudo-color imaging that can show the density of hydrogen protons in water and is used to reflect images of water content in food, water distribution, and its texture. Moreover, MRI can present the signals of different water phases (free water/bound water) in food [36]. Water is contained in all foodstuffs, which has an important influence on the physical properties of food during processing. The physical properties and content of water compared to other food components determine the dominance of water in food composition [37]. LF-NMR is an emerging tool for non-destructive detection of moisture content, moisture migration, water status, and distribution during food processing and storage. The applications of LF-NMR in berries processing detection discussed in this paper cover the processing of drying [38–41] and freezing [42, 43] as well as the analysis of decay [44, 45], during which water undergoes various changes.

Miscellaneous Techniques

E-nose is a non-destructive and rapid detection technique that uses sensor arrays, chemometrics, and AI algorithms for odor detection and identification. The application of E-nose in fresh food covers food classification, flavor detection, and spoilage evaluation [46]. Fruits are rich in volatile aromas and the E-nose allows to detect changes or distinguish differences in volatile compounds in fruits. Application scenarios of E-nose in berries include ripeness detection [47], disease detection [48], producing area identification [49], volatile odor change monitoring during drying [50], and others.

X-ray CT or X-ray micro-computed tomography (μCT or micro-CT) is a technique for non-destructive visualization of internal structures. The resolution of X-ray μCT can be as high as several hundred nanometers. X-ray CT shows the structure of a cross-section of food tissue based on its absorption of different radiation doses of X-rays or presents a three-dimensional structure by computer 3D reconstruction [51]. For example, X-ray micro-CT quantified the growth of 3D ice crystals in frozen carrots [52], and synchrotron X-ray CT scanners showed the 3D microstructure of ice crystals and air cells in ice cream in real-time imaging [53]. In berry processing, desktop X-ray CT and synchrotron X-ray CT were used to detect ice crystals and microstructures in the frozen processing of strawberries [54].

These aforementioned ADEs provide a large amount of data on berries, but these data are usually high-dimensional, complex, and difficult to understand intuitively. AI-based algorithms can analyze and interpret this intricate first-hand data from ADE, and model predictions based on conventional parameters.

Artificial Intelligence-Based Techniques

In scientific terms, AI is a wide-ranging branch of computer science that includes time-honored simple linear regression (mathematical models), not just most of the AI examples one hears about today such as autonomous driving and intelligent robots. Many AI algorithms have been successfully applied in berry processing; they include mathematical regression models, chemometrics, machine learning, artificial neural network (ANN), and deep learning, and the relationships between these AI subfields are presented in Fig. 1.

Mathematical Modeling

Mathematical models are based on description of complex scientific processes through concise mathematical equations and are generally useful in scenarios where detection and/or desired performance is difficult to achieve. With the development of mathematical modeling software and computer

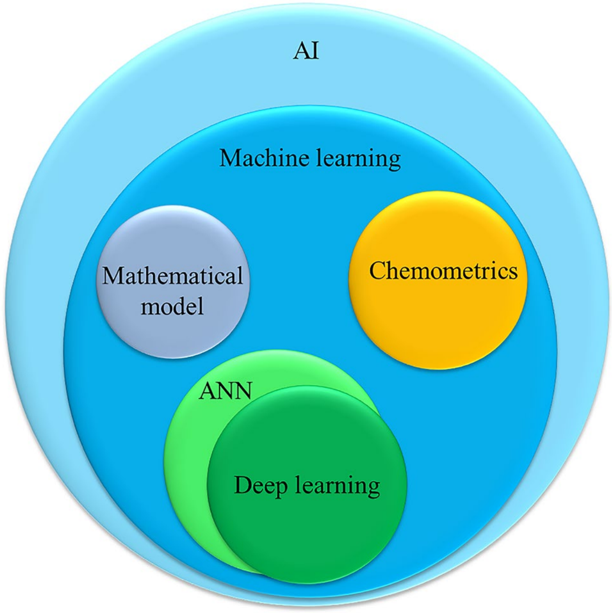


Fig. 1 The relationship between AI, machine learning, mathematical model, chemometrics, ANN, and deep learning. AI, artificial intelligence; ANN, artificial neural network

technology, the ability of mathematical modeling to describe complex problems has become reliable. Food processing is complex but validated mathematical models can now be developed and used with confidence to describe the kinetics, heat transfer, mass transfer, heat treatment at high and low temperatures, non-thermal decontamination, etc. [55–58]. Furthermore, computational fluid dynamics (CFD) also provides a valuable tool for simulation of various food processing operations. Several reviews have appeared in recent years on the application of mathematical models (e.g., fruit drying [59, 60], vacuum cooling [61], freezing [62, 63], and microbial inactivation [64–67]) and CFD simulations (drying [68–70], chilling and freezing [71], and microbial inactivation [72, 73]) in food processing. Real-time qualitative and quantitative measurements of moisture, microorganisms, ice crystals, and microstructure changes in berry drying, disinfecting, and freezing processing, respectively, all pose great challenges to ADE. Mathematical models can provide a viable tool to tackle complex scenarios, although literature on the application of CFD in berry processing is still rather limited. Several research papers have proposed and tested mathematical models for the prediction of the dynamics of moisture content in berry drying with multiple drying condition parameters as input variables [39, 74–76]. For example, Sun et al. [59] summarized nine mathematical models reported in the literature for the berry drying process, most of which are exponential family nonlinear models. The prediction of microbial inactivation curves and decontamination time in berry disinfecting was also achieved with the assistance of mathematical models [77–80]. Zhao et al. [81] used mathematical models to analyze the heat transfer during freezing of bayberry, and predicted the freezing time–temperature curve.

Chemometrics

Chemometrics can be classified as a machine learning. It is basically a set of tools that use mathematics, statistics, and computing to process data generated by chemical processes and to maximize the extraction of useful chemical information. Modern testing instruments generate massive amounts of data, but the accuracy of prediction models may be reduced due to too much redundant data and similar data [82]. The dimensionality reduction algorithm in chemometrics solves the curse of dimensionality by feature selection and feature extraction [31], which is important for the simplification and robustness improvement of the model [28]. The common feature selection methods include competitive adaptive reweighted sampling (CARS), successive projection algorithm (SPA), and uninformative variable elimination (UVE), and the reduced dimensional variables are a subset of the original feature variables. There are common feature extraction methods such as linear discriminant analysis (LDA), principal components analysis (PCA), and partial least squares (PLS), which achieve dimensionality reduction by converting the original feature variables into new feature variables. A large variety of chemometric-based feature selection and feature extraction methods are applied to the dimensionality reduction of the electromagnetic spectrum in berry sorting processes [28, 29, 44]. There are also some other ways of dimensionality reduction based on traditional machine learning. In addition to the chemometric dimensionality reduction algorithm, there are some other dimensionality reduction methods, which are given together in Table 1.

Traditional Machine Learning

Machine learning is the core of AI and allows the construction of models for detection and prediction [83]. Figure 2 presents the classification of machine learning and its relevant applications in berry processing. Machine learning can be classified into unsupervised learning with dimensionality reduction and clustering as subsets, and supervised learning with classification and regression as subsets [84]. Unlike deep learning algorithms, traditional machine learning techniques usually need to be supplemented with additional feature selection or feature extraction methods. After the dimensionality reduction process, the data are fed to classification or regression models for prediction. Classification and regression are used for qualitative detection of categorical variables and quantitative prediction of

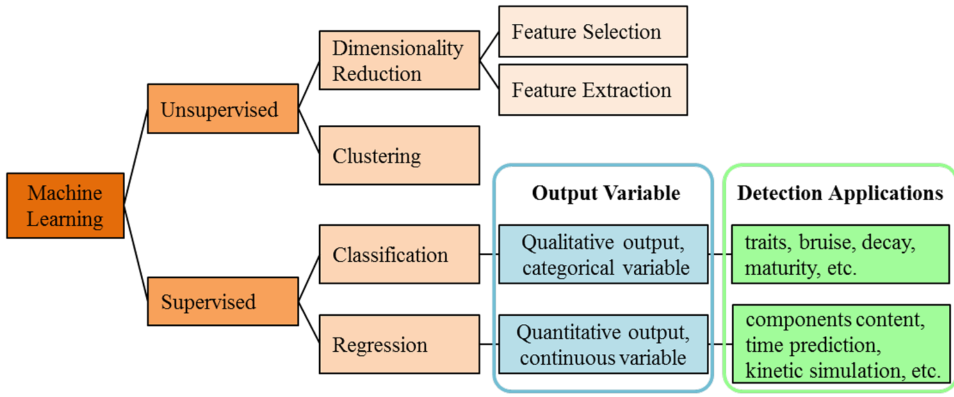
Table 1 Advanced detection techniques using artificial intelligence in berry fruits sorting

Aim	Product	Detect technology	Feature selection/feature extraction	Classification/regression algorithm(s)	Results	Ref
Trait	Grape	CVS	Dendrogram	RF	Integrated quality traits (color change, dehydration, rachis browning, and desiccation) to characterize the quality level for table grapes	[16]
	Strawberry	CVS	-	Customized 3-layer network	Automatic strawberry shape and size quantitative estimation, and qualitative classification	[15]
	Blueberry	NIR	Random frog	5 active learning algorithms, LS-SVM	Suitable for blueberry hardness classification, simple but robust classifier for hard and soft blueberries	[25]
Bruise	Blueberry	HSI	RF, permutation + LDA	FCN, SVM	FCN models have superior performance in calyx segmentation, early bruise detection, and bruise ratio quantification compared with SVM	[89]
	Blueberry	NIR	-	Monte Carlo multi-layered	Simulated photon interaction with fruit tissues for bruising detection using Monte Carlo multi-layered	[21]
	Blueberry	HSI	CNN, customized	CNN, SMO, LR, RF, bagging, MLP	HSI and two deep CNNs were used to detect internal bruise of blueberries. These two CNNs have better classification performance, accuracy, and F1-score than five conventional machine learning algorithms	[30]
	Blueberry	Thermal imaging	Relief	LDA, SVM, RF, KNN, logistic regression	Pulsed thermography and several different feature classifiers were used to identify bruises on blueberries	[34]
Decay	Blueberry	HSI, LF-NMR	CARS, SPA	PLS-DA, PNN, BPNN	The information obtained from advanced detection techniques (HSI and LF-NMR) was fused and several AI detection models (PLS-DA, PNN, and BPNN) were built to detect blueberry decay	[44]
	Strawberry	HSI	CARS, SPA, UVE, CARS-SPA	SVM, RF; PLSR, SVR, RFR	Ten representative wavelengths reflecting the storage time of strawberries were selected from the 260 bands obtained from the HSI. Classification and regression models were developed using algorithms for strawberry storage time prediction	[28]
	Blueberry	LF-NMR, MRI	Gray histogram, GLCM, GGCM	BPNN	LF-NMR and MRI were used to detect blueberries and obtain features, and to identify fruit decay and predict decay class using the BPNN model	[45]
	Strawberry	NIR-HSI	SPA	SVR, SVM	The key wavelengths for NIR-HSI generation were selected by successive projection algorithm. The prediction of fungal decay classification was also performed based on the results of quantitative analysis of fructose, glucose, sucrose, and water-soluble sugar content	[102]

Table 1 (continued)

Aim	Product	Detect technology	Feature selection/feature extraction	Classification/regression algorithm(s)	Results	Ref
Maturity	White berry and blackberry	E-nose	-	ANN	The structure of the ANN is 10–11-5, where the 10 sensor arrays of the electronic nose are the input layer and the 5 ripeness levels of the berries are the output layer	[47]
	Mulberry	CVS	CFS, CONS	ANN, SVM	The CVS, ANN, and SVM classifiers can be effective in mulberry grading	[19]
	Strawberry	HSI	PCA, CARS, SPA	PLS-DA, LS-SVM	Portable HSI was used for the prediction of three maturation stages using PLS-DA and LS-SVM classifiers after extracting the effective wavelengths	[29]
	Gooseberry	CVS	PCA	RBFNN, DT, SVM, KNN	Four AI methods and three color spaces (RGB, HSV, and L*a*b*) were used to classify the ripeness of gooseberry based on CVS	[18]
Composition & content	Mulberry	HSI	Customized	PLSR, LS-SVR	The HSI method can provide an alternative to chemical methods for the rapid quantitative determination of the four pectin polysaccharides in mulberry	[101]
	Raspberry	NIR	PCA	PLSR	A near-infrared prediction method for anthocyanin and SSC content in raspberry was developed	[100]
	Goji	NIR-HSI	CNN, DAE, SPA, CARS, PCA, WT	CNN, PLSR, LS-SVR	Quantitative prediction of phenolics, flavonoids, and anthocyanins in dry black goji berries using HSI, CNN, and traditional methods	[31]
	Strawberry	HSI	CARS, UVE	PLSR, SVR, LWR	Prediction of SSC, pH, and VC of strawberries by spectral, color, and texture features	[98]
	Grape	NIR	PCA	PLSR, iPLSR	Analysis of intact table grape in texture-related (crunchiness as textural hardness) and chemical-related (sweetness as SSC) parameters. The PLSR and iPLSR models satisfactorily predict the SSC and "hardness" parameter	[22]
	Cherry tomato	NIR	PCA	PLSR, SVR, ELM	Prediction of firmness, SSC, and pH of cherry tomato by portable NIR spectrometer and chemometric algorithms	[90]

Fig. 2 The classification of machine learning and its relevant detection applications in berry processing



continuous variables, respectively. In the berry processing, applications of classification include detection of berry traits, bruise, decay, and maturity, and the results are classified into two to multiple classes (binary classification and multinomial classification, respectively). The application of regression includes the detection of berry chemical components content, moisture content, pesticide residue content, microbial content, processing time prediction, and kinetic simulation. A variety of classification and regression model algorithms based on traditional machine learning are listed in Table 1. However, probably due to the lack of relevant ADEs, there are fewer traditional machine learning algorithms applied in berry drying, decontamination, and freezing processing except for some mathematical models. The performance of classification models is mainly evaluated by accuracy, precision, recall, and F1-score [30], while the performance of regression models is mainly evaluated by R^2, root mean square error (RMSE), and residual prediction deviation (RPD) [38]. Figure 3 shows the traditional machine learning for classification of thermal image data after feature extraction and feature selection in blueberry bruise detection.

ANNs and Deep Learning

ANN and deep learning are at the forefront of AI technology development, and have penetrated into various areas including intelligent food processing [85]. ANN is a simplified algorithmic model of biological neurons, and ANN consists of an input layer, one or more hidden layers, and an output layer [86]. Deep learning is a form of machine learning that uses ANN as the underlying architecture and has multiple hidden layers. Deep learning has powerful feature learning (automatic feature extraction), classification, and regression capabilities, which are more advantageous than traditional machine learning algorithms and manual feature extractors (chemometrics-based dimensionality reduction algorithms, etc.) [31, 87]. Deep learning can be categorized into three main types: CNN, recurrent neural network (RNN), and generative adversarial network (GAN) [88]. Wang et al. [30] quickly detected internal damage of blueberry with the help of CNN and HSI, where CNN not only implicitly extracted image features through the convolutional layer but also acted as a classifier. Fully convolutional networks (FCNs) can learn information in both the spectral and spatial

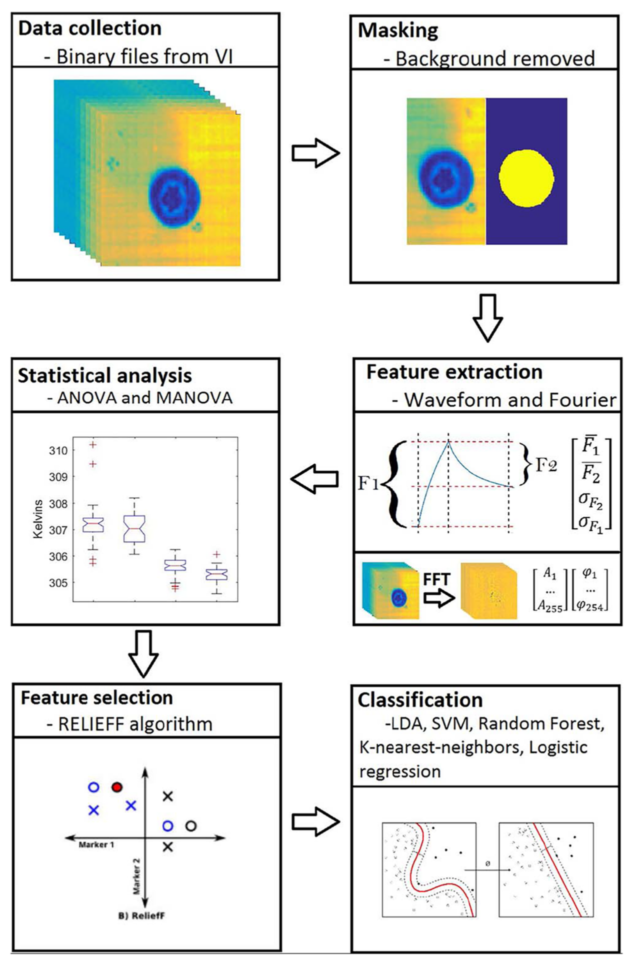


Fig. 3 Digital processing flow for blueberry bruise detection by thermal imaging [34]

dimensions, whereas support vector machine (SVM) classifiers are limited to learning information from predefined features [89].

Moreover, with the advancement of ANN research, some common neural networks such as back-propagation neural network (BPNN), radial basis function neural network (RBFNN), probabilistic neural networks (PNNs), and extreme learning machine (ELM) [90] have been developed. Various ANN and deep learning specific algorithms provide an excellent tool for berry sorting, quantitative detection of chemical composition, and prediction of key parameters in drying and freezing processing (Tables 1, 2 and 4). However, ANN and deep learning require a large amount of data for training to get a good prediction performance, so it is also not a general-purpose algorithm, especially when the amount of training data is quite limited.

Miscellaneous

Fuzzy logic (FL) simulates the process of human reasoning without requiring precise inputs and is suitable for systems that are difficult to model mathematically [91]. The main mechanism of FL is If–Then rule, and FL are considered as AI, but not machine learning. Rad et al. [74] predicted the moisture ratio of white mulberry fruit using the FL model with conventional parameters from the convective-infrared drying process as input.

Adaptive neuro fuzzy inference system (ANFIS) integrates the principles of ANN and FL and has the advantages of both. Taghinezhad et al. [92] used ANFIS to predict the energy and exergy parameters during drying of blackberries by combined hot air-infrared dryer with ultrasound pretreatment, where the ANFIS method was more accurate than ANN. ANFIS is also an effective controller for complex systems. Riverol et al. [93] reported the adaptive advanced control of ANFIS in a fluidized bed freezer for strawberry freezing process, which performed better than the classical state feedback controller.

Processing Applications

This paper provides a comprehensive yet concise review of the intelligent detection technologies and AI methodologies applied in four distinct processing procedures for berries: sorting (Table 1), drying (Table 2), disinfection (Table 3), and freezing (Table 4). The quantitative detection of the chemical composition of various berries is generally carried out for fresh berries. Pesticide residue detection can be used as an indicator of the effectiveness of washing/disinfecting. In this paper, the quantitative detection of chemical components and pesticide residue detection were classified into sorting (Table 1) and disinfection (Table 3) of berry processing procedures, respectively.

Sorting

During the berry harvest season, manual harvesting or rapid harvesting using large agricultural machinery can result in inconsistent quality of the collected berries. The fragile skin and juicy nature of berries also pose challenges in their stable storage. The sorting of berries is therefore an important part of the berry pretreatment process and the first step in berry quality control.

The application of intelligent detection technologies and AI methods in sorting of berry fruits is showed in Table 1. The detection in the berries sorting can be broadly divided into two major aims: classification of physical characteristics and quantification of chemical composition. The detection aims of physical characteristics include trait (shape, size, color, hardness), bruise, decay, and maturity. On the other hand, the quantitative detection of chemical nutrient components includes soluble solid content (SSC) [95–97], vitamin C (VC) [98], pH [98], chlorophylls [99], anthocyanins [100], polysaccharides [101, 102], flavonoids [31], and phenolic [31, 103].

A typical full sorting system includes a product flow conveyor, detection equipment, AI algorithms, and removal mechanics. Detection technology is the key to any sorting system, as its accuracy and speed of detection determine the overall performance and efficiency as well as cost-effectiveness of the whole sorting system. In the sorting processes, almost all of these ADEs are based on electromagnetic spectroscopy, such as CVS, NIR, HSI, thermal imaging, and LF-NMR. In addition, a variety of AI-based dimensionality reduction algorithms, and classification and regression models are used to process data from detection devices. The coupling of these ADE and AI technologies gives the sorting system the advantage of being accurate, non-destructive, non-contact, and fast, ensuring a high-throughput sorting process. Figure 4 shows the process of blueberry decay detection, which can represent the general ADE and AI-based classification modeling process [44]. Firstly, the raw spectral information and relaxation parameters information of blueberries were obtained by HSI and LF-NMR, respectively. Then, the CARS algorithm and SPA algorithm were used to dimensionality reduction of the raw spectral information to obtain the characteristic wavelength, and use it and the selected LF-NMR parameters by Pearson correlation and Spearman correlation as input variables. Finally, these input variables were put into PLS-DA, PNN, and BPNN three models for classification modeling, and then the decay of blueberry was detected.

Table 2 Advanced detection techniques using artificial intelligence in berry fruits drying

Product	Drying method	Detect technology/input parameters	AI-based methods	Results	Ref
Raspberry	Pulse-spouted microwave freeze drying	LF-NMR, MRI	PLSR, BPNN	The drying process was monitored using LF-NMR, and the parameters obtained from the monitoring were fed into a BPNN model to predict the drying end-points	[38]
Mulberry	Hot air drying	LF-NMR, MRI	Mathematical model, PLSR	Based on the parameters obtained from the LF-NMR and MRI during the detection drying process, the mathematical model simulated the drying kinetics, and the PLSR predicted the color of the product	[39]
Blueberry	Pulsed vacuum drying	LF-NMR, MRI	Not given	Monitoring and parametric analysis of pulsed vacuum drying and hot air drying blueberry processes were carried out using LF-NMR and MRI. No further predictive analysis was available	[40]
Blueberry	Pulse-spouted microwave freeze drying	LF-NMR, NIR	BPNN	The freeze-drying process was detected using LF-NMR and NIR, and the sublimation/desorption drying transition points and drying end-points were predicted using BP-ANN models	[41]
Blueberry	Osmo–air dehydration	NIR	PCA	NIR spectra of whole blueberries were acquired under diffuse reflection to monitor changes in the main components (water and sugar) during osmotic–air dehydration of blueberries, and to distinguish untreated and osmo-dehydrated blueberries	[111]
Blueberry	Air convective drying	CVS	-	The color and shrinkage of blueberries at different drying temperatures were measured in real time using CVS. No evaluation of CVS performance	[112]
Grape	Thin-layer drying	CVS, conventional parameters (air drying temperature, velocity, shrinkage, moisture content)	ANN, LR	Shrinkage of grapes was detected using CVS. The moisture content of grapes after a certain time interval of drying was predicted using ANN and multivariate LR with four conventional parameters as inputs	[113]
Strawberry	Convection drying	Capacitor microphone	ANN	Detect the acoustic spectra of dried strawberry products based on sound spectrum with the help of capacitor microphone and recognition of the crispness of dried strawberries using ANN models	[10]

Table 2 (continued)

Product	Drying method	Detect technology/input parameters	AI-based methods	Results	Ref
Blackberry	Hot air-infrared drying	Hot air temperature, ultrasound pretreatment time, drying time	ANN, ANFIS	The ANFIS model predicts more accurately than the ANN model, with predicted parameters including energy utilization ratio, energy utilization, exergy loss, and exergy efficiency	[92]
White mulberry	Infrared-convective drying	Air temperature, air velocity, infrared power	ANN	Two ANN models for predicting the moisture diffusivity or specific energy consumption of white mulberry during the drying process	[105]
Raspberry	Microwave-assisted fluidized bed drying	Inlet air temperature, microwave power, inlet air flow rate, starting time of microwave input, and amount of material	ANN	The physicochemical properties of raspberry dried products were predicted using ANN modeling with drying condition parameters as input. The prediction aims included drying time, rehydration capacity, density, porosity, hardness, water activity, phenolic compounds content, anthocyanins content, and antioxidant activity	[107]
White mulberry	Thin-layer convective-infrared drying	Air temperature, air velocity, infrared power, drying time	ANN, FL, mathematical model	The moisture ratio of dried white mulberry was predicted using three models simulated with drying condition parameters as input	[74]
Raspberry	Microwave- and ultrasound-assisted convective non-stationary-hybrid drying	Initial, instantaneous, and equilibrium moisture contents, total weight loss, total drying time	Mathematical models	Four nonlinear regression mathematical models were used to describe seven drying process kinetic simulations, and the moisture ratio was evaluated	[106]
Cranberry	Microwave-vacuum drying	Moisture content, drying rate constant, drying time	Mathematical models	Two nonlinear regression mathematical models were used to simulate the drying kinetics and moisture ratio was predicted, and the results showed that the Page model was more appropriate	[76]

Table 3 Advanced detection techniques using artificial intelligence in berry fruits disinfection and decontamination processing

Aims	Product	Disinfect treatment/pesticide	Detect technology	AI-based methods	Results	Ref
Mathematical modeling of disinfection kinetic curves	Chokeberry	Corona discharge plasma jet	Plate count	First-order inactivation model	Corona discharge plasma jet treatment reduces initial microbial contamination on chokeberry by 99%, and a first-order kinetic model can describe the inactivation profile of aerobic bacteria, yeasts, and molds during decontamination	[77]
	Strawberry	Mild heat wash	Plate count	Secondary model based on linear regression	Four models were used to fit inactivation curves under different disinfection treatments. A Weibull model was used to describe the survival kinetics of *S. typhimurium* by washing temperature	[78]
	Raspberry	Steam-ultrasound	Plaque count	Log-linear model	The survival of two viruses was simulated using a log-linear model to predict the inactivation time of viruses under different steam-ultrasound treatments	[79]
	Strawberry	UV-C radiation	-	CFD, biphasic linear model, first-order model	In the decontamination process, radiation model (CFD modeling) was used to predict the UV radiation intensity and inactivation model (biphasic linear model and first-order model) to simulate the inactivation process to evaluate the time required for inactivation	[80]

Table 3 (continued)

Aims	Product	Disinfect treatment/pesticide	Detect technology	AI-based methods	Results	Ref
Several relevant parameters detection	Strawberry, cherry, and blueberry	Microwave plasma torch	Thermal imaging, OES	Boltzmann plot method	Thermal images generated by an infrared camera to monitor the temperature during berry disinfection. Active species and plasma parameters during the berry decontamination treatment were detected by OES and Boltzmann plot methods	[33]
	Grape	Atmospheric-pressure plasmas	FTIR, ozone detector, OES	Not given	To study the disinfection mechanism, electrical measurements and OES were used to analyze the parameters of the air plasma. FTIR and ozone detectors were used to detect the composition of the air after decontamination	[173]
Pesticide residue content	Strawberry	Boscalid and pyraclostrobin	NIR	PCA, PLSR	A rapid detection of pesticide residues in strawberries based on NIR technology was established	[174]
	Mulberry	Thiophanate-methyl	LIBS, HSI	PCA, PLSR	A rapid method for the determination of thiophanate-methyl residues in mulberry by LIBS and HSI was established, and the pesticide residues were analyzed qualitatively and quantitatively using chemometric	[175]

Table 4 Advanced detection techniques using artificial intelligence in berry fruits freezing

Product	Freezing method	Detect technology/input variables	AI-based methods	Results	Ref
Blueberry	Ultra-low-temperature refrigerators and immersion in liquid nitrogen	LF-NMR	Not given	LF-NMR analysis was used to determine the water distribution and migration of blueberry under four freeze–thaw treatments. The T_2 relaxation time of water inside and outside the cells was shortened compared to that of fresh blueberries, indicating lower liquidity	[43]
Strawberry	Conventional rapid freezing and supercooled freezing	Desktop X-ray CT, synchrotron X-ray CT	Not given	Evaluation of ice crystals and microscopic pore structures of strawberry samples prepared by conventional freezing and supercooled freezing methods by two X-ray CTs showed that supercooled freezing caused less damage to strawberry cells	[54]
Bayberry	Domestic freezer and liquid nitrogen cryogenic food freezer	Not given	Mathematical model	The heat transfer process of frozen prunes was analyzed by numerical simulation, and the time–temperature curve of frozen bayberry was predicted. The experimental results showed that the faster the freezing speed was, the better the quality was	[81]
Strawberry	Fluidized bed freezer	Not given	MRAFC, ANFIS	Two adaptive control techniques in a fluidized bed freezer: model reference adaptive fuzzy control and adaptive-network-based fuzzy inference system	[93]
Any food	Conventional rapid freezing and supercooled freezing	10 input variables	ANN	Ten parameters related to any shape of food were used as inputs to the ANN model to predict the freezing time	[176]
Any food	Datasets from other reports	7 input variables	ANN, GA	Prediction of foods freezing and thawing times	[177]
Any food	-	-	Finite element method	The finite element method is applied to simulate the heat transfer during freezing and to predict the freezing time. The application examples do not include fruits	[170]

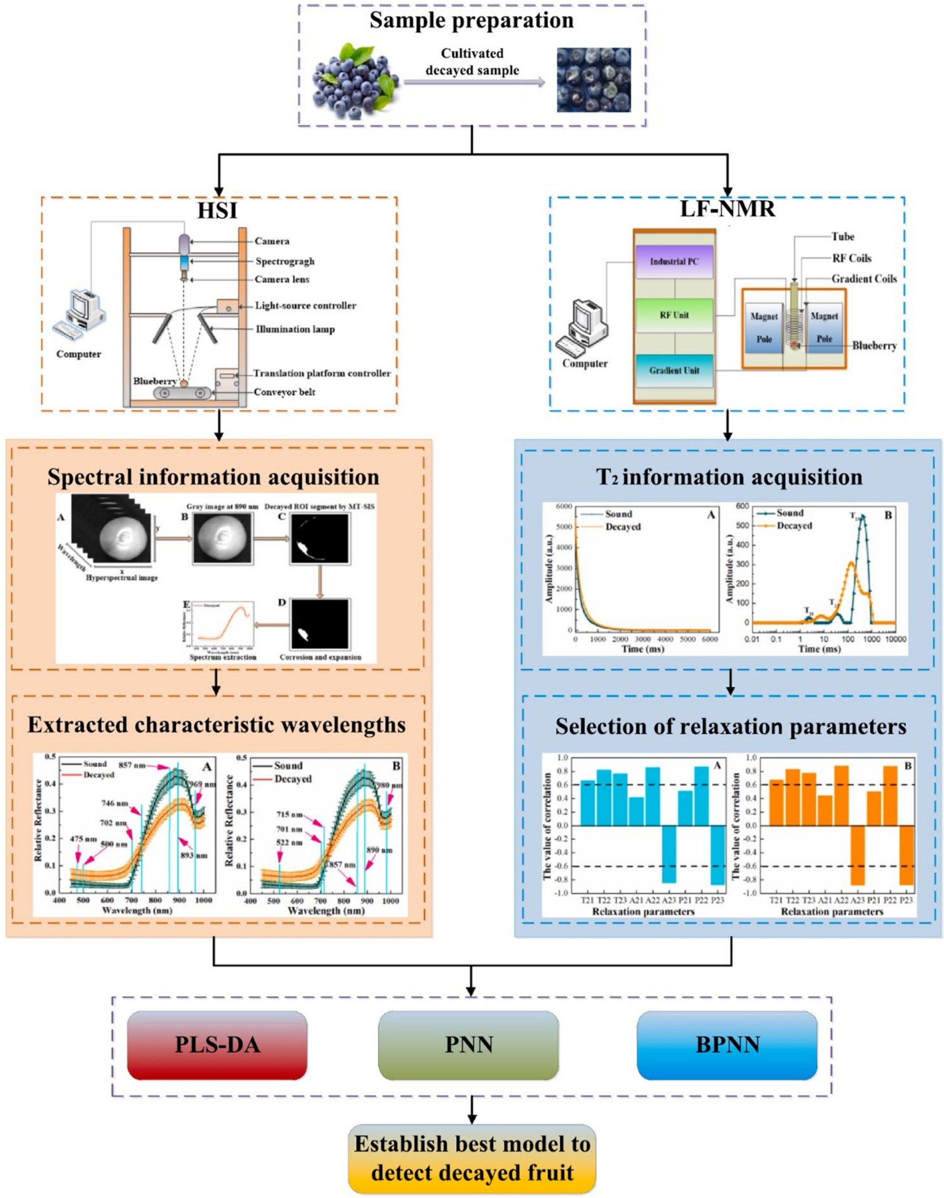
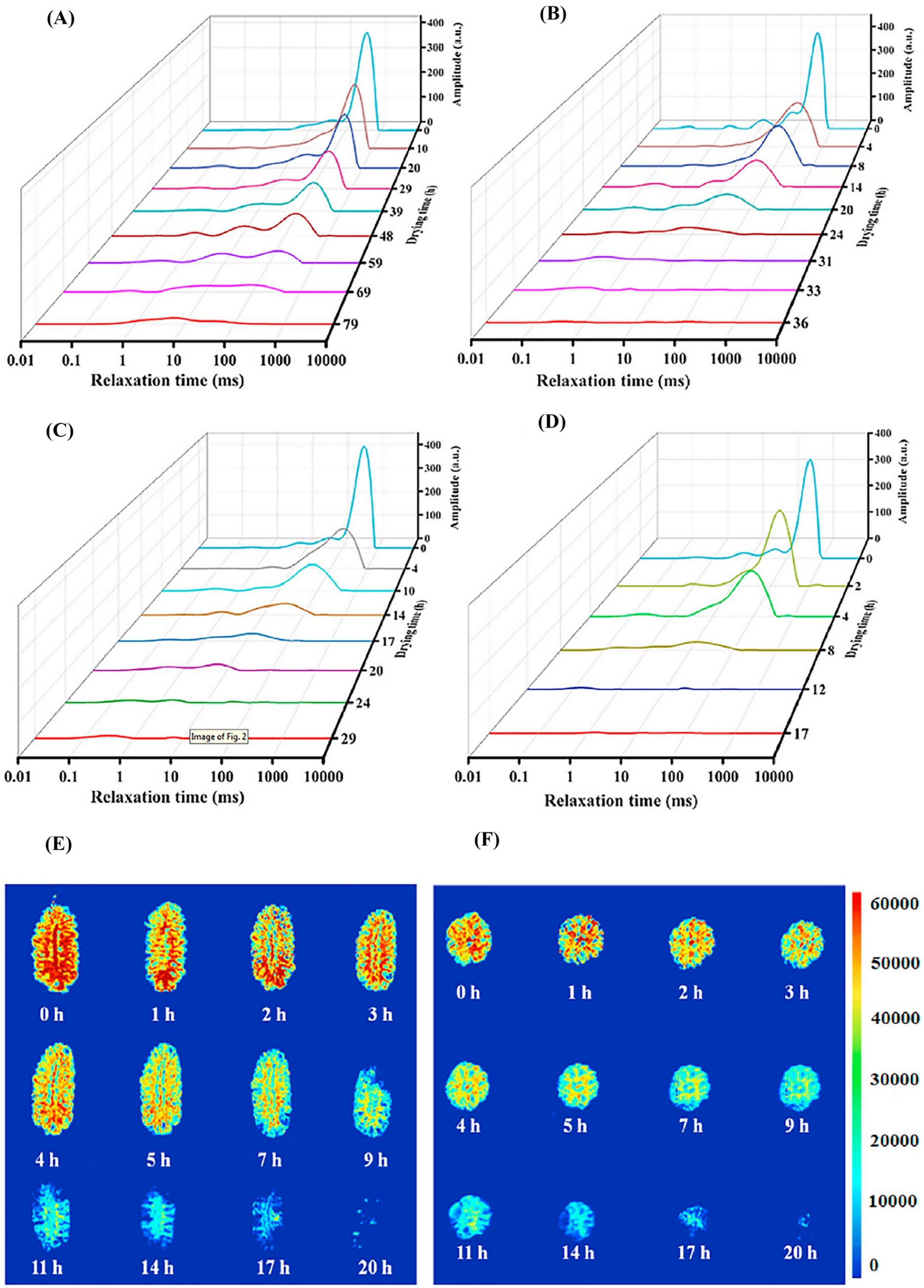


Fig. 4 Flowchart of detecting decayed blueberry [44]. HSI, hyperspectral imaging; LF-NMR, low-field nuclear magnetic resonance; T_2, transverse relaxation time; PLS-DA, partial least squares discriminate analysis; PNN, probabilistic neural network; BPNN, back-propagation neural network

Drying

Drying is one of the most common methods for preserving berries [59]. A variety of traditional and emerging drying techniques are used for berry drying, including hot air convection drying [39, 105, 106], vacuum drying [40, 75], fluidized bed drying [107], freeze drying [108, 109], and various physical field-assisted drying methods [38, 92]. Freeze drying is generally considered to be the best method of dehydration, but it is also an energy-intensive and lengthy process [94, 104]. The low moisture content and low water activity properties imparted by drying bring many advantages to dried food products, including long-term storage, novel product formats, convenient handling, and reduces cost of transportation [114]. However, there are also potential product defects such as shrinkage, discoloration, case hardening, flavor, and thermosensitive components loss [122, 130]. The parameters such as moisture content, moisture distribution, drying temperature, drying rate, and drying end-point during the berry drying process affect the final quality of the dried product [41]. In summary, the drying process is complex, dynamic, unsteady, highly nonlinear, strongly interactive, successively interconnected, and multivariable thermal process whose underlying mechanisms are not yet perfectly understood [110]. Therefore, rapid and intelligent detection of drying conditions and drying food parameters during drying is very important to ensure the quality of dried products. The detection of berry moisture information (content, types, migration, etc.) during the drying process is the most valuable aspect in monitoring the


(A)
(B)
(C)
(D)
(E)
(F)
Amplitude (a.u.)
Drying time (h)
Relaxation time (ms)
0.01 0.1 1 10 100 1000 10000
0 100 200 300 400
0 10 20 29 39 48 59 69 79
0 4 8 14 20 24 31 33 36
0 4 10 14 17 20 24 29
0 2 4 8 12 17
Image of Fig. 2
0 h 1 h 2 h 3 h
4 h 5 h 7 h 9 h
11 h 14 h 17 h 20 h
60000 50000 40000 30000 20000 10000 0

◂**Fig. 5** Application of LF-NMR and MRI in the detection of mulberries drying [39]. T_2 curves for mulberries dried at different temperatures: **A** 40 °C; **B** 50 °C; **C** 60 °C; and **D** 70 °C. MRI images of mulberries dried at 50 °C: **E** longitudinal section; **F** cross section. LF-NMR, low-field nuclear magnetic resonance; MRI, magnetic resonance imaging; T_2, transverse relaxation time

drying process. LF-NMR technology has become a novel detection tool in the field of food drying with the advantage of specific detection of water hydrogen nuclei. Figure 5 shows the application of LF-NMR and MRI in detecting the drying of mulberries. The MRI images visualized the process of moisture content reduction in drying. The transverse relaxation parameters of LF-NMR can be used as input variables for predictive models: for drying kinetic simulations [39], and for prediction of drying end-points [38] and sublimation/desorption drying transition points [41] in the berry freeze-drying process.

Table 2 presents several advanced detection techniques and AI-based methods applied in berry drying. The detection techniques used in the drying process can be broadly classified as LF-NMR/MRI [38–41], NIR [41, 111], CVS [112, 113], capacitor microphone [10], and directly giving the conventional parameters related to drying. The obtained detection data are then used for predictive modeling using ANN, mathematical models, and other AI-based algorithms to detect key points, moisture information, nutrient components content, changes in appearance, crispiness, drying efficacy, and drying kinetic simulations during the berries drying process.

Disinfection and Decontamination

Berries that have not undergone microbial inactivation procedures can cause various decay problems and a short shelf life. Also, pathogenic viruses are able to survive on unsterilized berries, which would pose a health risk to humans [6]. Frozen berries have been implicated as the food vehicle in outbreaks of hepatitis A virus [5] and norovirus [115] infections in recent decades. Berry disinfection and decontamination options can be categorized as disinfectant decontamination, thermal decontamination, and non-thermal decontamination. Disinfectant decontamination includes gaseous chlorine dioxide [116, 117], acetic acid [118], peracetic acid [119], and others [120]. Thermal decontamination is rarely applied due to the richness of the heat-sensitive components of berries. Much research has been devoted to developing novel non-thermal decontamination methods that allow microorganisms to be inactivated under mild conditions, thereby better preserving the sensory and nutritional activity of the fruits. Some of the non-thermal decontamination methods of fruits listed here include application of plasma [121], microwave [33], high hydrostatic pressure [123], irradiation [124], pulsed light [125], ozone [126], ultraviolet [127], and hydrothermodynamic cavitation [128]. Perez-Lavalle et al. [129] have reviewed the individual and combined non-thermal and physical techniques for microbial inactivation applied to fresh blueberries which are also applicable to most other berries as well.

Due to the nature of microorganisms that are not easily detected quickly and accurately, the assessment of the microbial inactivation performance of berries has been dominated by the traditional time-consuming plate counts [77, 131–135]. Real-time quantitative PCR (RT-qPCR) is a standard method for the detection of hepatitis A virus and norovirus in berry fruit [136, 137]. However, a full RT-qPCR procedure can take several hours and does not allow for true real-time detection [128]. The increasing concerns over food-borne outbreaks necessitate rapid, on-site, and sensitive methods for the detection of microorganisms in food matrices [138, 139]. In recent years, biosensors have become a hot topic of research in the field of food safety testing [140, 141]. However, these fast and sensitive biosensors are hardly employed in berry decontamination, probably due to the complexity of sample pretreatment. In addition to the detection in the microbiological field, the decontamination process also has an impact on the biochemical substances of the berries [142, 143]. Park et al. [77] found that cold plasma treatment of chokeberries resulted in a significant decrease in anthocyanin content, while soluble solids content and pH were not affected. In berry processing, decontamination of berries includes washing and disinfection, and is always performed together. Sarangapani et al. [144] found that cold plasma application has the ability to eliminate microorganisms from blueberries and also degrade residues of the pesticides boscalid and imidacloprid. Therefore, the pesticide residue content on the berry surface might also be an indicator for the evaluation of the washing and sterilizing effect.

Selected articles on mathematical modeling of disinfection kinetic curves, parameter monitoring of plasma disinfection, and pesticide residue content detection about berries were reviewed and are summarized briefly in Table 3. As of now, the presentation of ADE-based intelligent detection in fruit disinfection/decontamination processes is rare.

Freezing

Freezing is a common method of preserving berry fruits to maintain freshness and nutrition and to achieve increased shelf life. The freezing process is a complex, multi-stage process that basically follows five basic steps: cooling period, supercooling period, ice nucleation, latent heat thermal storage process, and ice sensible heat thermal storage process [145]. Typical temperature–time curves for typical food freezing are displayed in Fig. 6 [145]. The freezing conditions and physical field-assisted freezing determine the

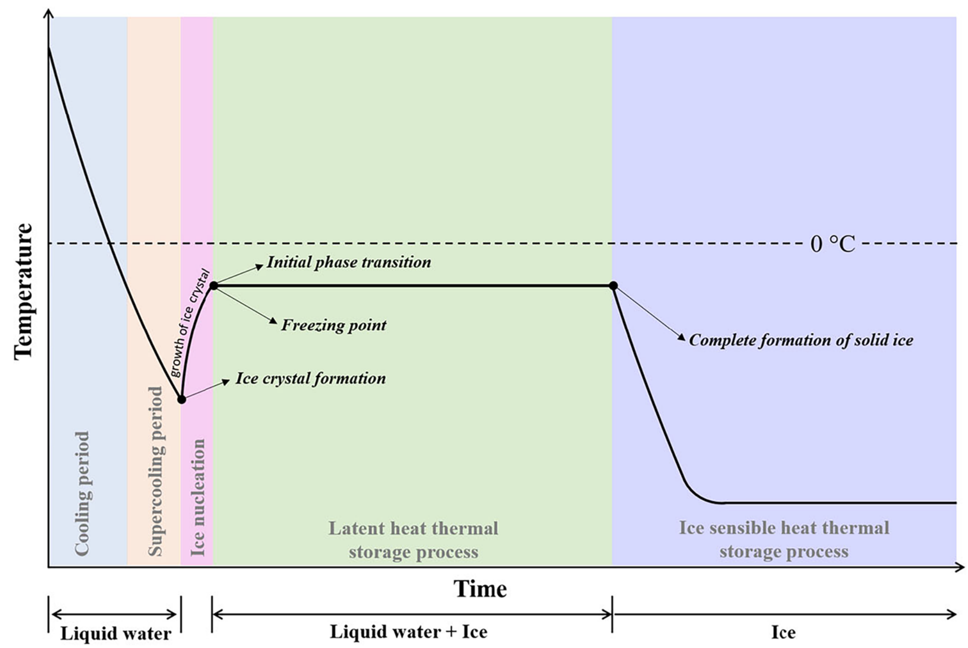


Fig. 6 A typical temperature–time curve for food freezing [145]

final status of the ice crystals formed, whose structure and distribution have a critical impact on frozen berries quality [146, 147]. Freezing causes the berries to dehydrate leading to surface frosting; so the berries should be allowed to freeze quickly to minimize dehydration losses. Meanwhile, rapid freezing can form a large number of small ice crystals that do not harm cell membranes [148, 149]. van der Sman [150] describes the freezing operation and ice crystal formation, how the freezing rate affects the size of the ice crystals and thus the quality of the food. Physical field-assisted freezing techniques are considered as a strategy to control the freezing method to improve the quality of the frozen product [151–154]. These novel aids include pressure transfer, magnetic field [146, 155], electric field [156], electrostatic [157], microwave [158], radio frequency [159], and ultrasound [160].

To obtain good quality frozen berries, the freezing process ideally needs much information that should be detected dynamically, including freezing temperature curve, freezing speed, ice crystal growth process, ice crystal structure and distribution, freezing rate, and microstructure. The measurement of the internal temperature of food products during the freezing process is the most important measurement, but currently, it is almost exclusively performed with invasive temperature probes [54, 81]. This method of temperature measurement may not be suitable for small, fragile, and juicy berries, as it causes significant structural damage and will affect the accurate measurement of the internal temperature. However, as of now, there is no better solution. Table 4 shows some detection techniques and AI-based methods applied in berry freezing. In berry freezing, LF-NMR and MRI have been performed to detect the distribution and migration of water in blueberries during cold storage and freeze–thaw [42, 43]. On the whole, there are still fewer studies that use ADE and AI-based methods for frozen berry detection.

Recently, several new and improved detection technologies have demonstrated applicability in food freezing, such as LF-NMR/MRI, X-ray CT, and Raman spectroscopy. LF-NMR and MRI techniques have also been used to evaluate the water dynamics [161], water migration [162], and freezing storage time [163] of meat during freezing processing. MRI can obtain information about the moisture state of ice crystals and demonstrate the structure of ice crystals, which is an important detection tool in the freezing process [147, 164]. X-ray CT can detect and visualize the microstructure of frozen foods such as minced beef [165], strawberry [54], carrots [52], apples and potatoes [166], bell peppers, and cucumbers [167]. Raman spectroscopy allows the rapid measurement of sensory and physicochemical properties of frozen foods without any pretreatment [168]. In addition, mathematical-based methods such as mathematical modeling, finite element modeling (FEM), and CFD provide valuable solutions for freezing curves simulation, freezing time prediction, and high-performance freezing system design in freezing processes. Zhao et al. [62] have reviewed the mechanisms of ice crystal formation, propagation, and glass transition during food freezing and discussed mathematical models of heat and mass transfer for predicting freezing time and optimizing freezing conditions. Rodriguez et al. [169] present mathematical simulation modeling of a magnetic field-assisted frozen food process to evaluate the magnetic field strength and magnetic field distribution in the frozen space and frozen material. FEM has become a widely used numerical simulation tool for monitoring and controlling changes in food quality during freezing and thawing processes [170]. CFD models for heat and mass transfer in hydrofluidization systems during food chilling and freezing were reviewed by Peralta et al. [71]. Differential scanning calorimetry (DSC) [164], various microscopes [164, 171, 172], etc. are also used to detect the physicochemical or structural properties of frozen foods for the purpose of frozen product quality and freezing damage assessment. Nonetheless, DSC and various microscopic structural determination techniques are in use although they require some degree of destructive pretreatment of the sample prior to measurement.

Conclusion and Future Trends

Berries are one of the most popular fruits. Their perishability and seasonality requires processing of fresh berries to improve quality, shelf life, and market value. This paper reviews various smart detection techniques and methods in berry sorting (trait classification, defect detection, chemical component quantification), drying, disinfection/decontamination, and freezing. Rapid non-destructive testing of product quality and process parameters in berry processing provides a reference for improving product quality, understanding processing principles, and optimizing the processing conditions. These modern intelligent detection technologies and methods cover a diverse range of ADEs and AI-based methods. Hardware-based detection equipment gives first-hand data on berries, and AI-based methods use this raw data to then perform classification or regression modeling predictions. Some mathematical models and ANN algorithms use conventional detection parameters for modeling predictions. In addition, some novel advanced computational tools such as deep learning, FEM, and CFD also provide viable solutions for intelligent detection and simulation in berry processing. Following are some recommendations based on this review. For the quantitative detection of chemical composition, almost all detection targets were performed on fresh berries. Considering the principles and the non-destructive and rapid advantages of these ADE and AI-based methods, it is feasible to monitor changes in nutrient composition during drying, disinfection, and freezing of berries in future studies. The monitoring of changes in the chemical components of berry processing will provide a reference for the design and improvement of berries processing systems. The powerful feature learning and prediction capabilities of deep learning tend to perform better compared to traditional machine learning when a large amount of data is available for training. With enhanced computer performance, the application of deep learning in berry detection should be explored more widely and actively. The most urgent problem to be solved is the serious lack of detection equipment in the fields of drying, disinfecting, and freezing processing, which requires the equipment manufacturers and researchers to make efforts to develop and explore novel rapid and non-destructive tools. Finally, validated computer simulation techniques as CFD should be utilized in the optimization and design of berry processing systems.

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Declarations

Conflict of Interest The authors declare no competing interests.

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