Assessment of seed quality using non-destructive measurement techniques: a review

Anisur Rahman and Byoung-Kwan Cho*
Department of Biosystems Machinery Engineering, College of Agricultural and Life Science, Chungnam National University, 99 Daehak-ro, Yuseong-gu, Daejeon 305-764, Republic of Korea

Abstract
Seed quality is of great importance in optimizing the cost of crop establishment. Rapid and non-destructive seed quality detection methods must therefore be developed for agriculture and the seed production industry. This review focuses primarily on non-destructive techniques, namely machine vision, spectroscopy, hyperspectral imaging, soft X-ray imaging, thermal imaging and electronic nose techniques, for assessing the quality of agricultural seeds. The fundamentals of these techniques are introduced. Seed quality, including chemical composition, variety identification and classification, insect damage and disease assessment as well as seed viability and germinability of various seeds are discussed. We conclude that non-destructive techniques are accurate detection methods with great potential for seed quality assessment.

Keywords: non-destructive measurement, seed classification, seed damage, seed quality, seed viability

Nomenclature

ADF  acid detergent fiber
ANNR artificial neural network regression
ANN  artificial neural network
BPNN back-propagation neural network
DA  discriminant analysis
DM  dry matter
ECVA  extended canonical variates analysis
FDA  factorial discriminant analysis
ICA  independent component analysis
iECVA interval extended canonical variates analysis
iPLS-DA interval partial least-squares discriminant analysis
iPLSR  interval partial least-squares regression
KPCA kernel principal component analysis
KS  Kennard and Stone
LDA  linear discriminant analysis
LOD  limit of detection
LSD  least significance difference
LS-SVM least-squares support vector machine
LS-SVMR  least-squares support vector machine regression
LW-PCA locally weighted principal component analysis
MD  Mahalanobis distance
MDC Mahalanobis distance classifier
MLMR  maximum likelihood multinomial regression
MLP  multilayer perceptron
MLR  multiple linear regression
MPLS modified partial least-squares
MPLSR modified partial least-squares regression
MSE  mean squared error
NDA  non-linear discriminant analysis
NNN  non-linear neural networks
OMD  organic matter digestibility
PCA  principal component analysis
PCR  principal component regression
PLS  partial least-squares
PLS-DA  partial least-squares discriminant analysis
PLSR partial least-squares regression
QDA  quadratic discriminant analysis
RF  random forest
SAM  spectral angle mapper
SIMCA soft independent modeling class analogy
SSC  soluble sugar content
SWI  single waveband image
SVDD support vector machine description
RMSEP  root mean square error of prediction
R_p  correlation coefficient of prediction
R  coefficient of correlation
R^2 determination coefficient of prediction
R^2_c determination coefficient of calibration
SEP standard error of prediction
RPD  ratio prediction to deviation

Introduction
Seed is a living product and must be grown, harvested and processed correctly to maximize its viability and subsequent crop productivity. Seed quality has a profound effect on the development and yield of a crop...
Good seed quality can increase yield significantly. Seed quality depends on the health, physiology, germinability and physical attributes of seeds, including the presence or absence of disease, chemical composition, insect infestation, and the presence or absence of weed seeds or other plant varieties. Quality of seeds and their products is directly or indirectly related to human health; nevertheless, the evaluation of seed quality parameters is a time-consuming process. For example, calculation of the germination percentage commonly requires manual counting and grading of germinating seedlings by experienced technicians. Therefore, rapid, simple and accurate detection techniques must be developed for farmers and the agro-industry to ensure quality seed during seeding, growth, harvesting, storage and transport to consumers (Huang et al., 2015).

The sowing quality of seed is associated with the germination and growth conditions after sowing and depends on seed composition, kernel maturity, insect infestation, diseases, cleanliness and germination ability (Copeland and McDonald, 1999). The genetic purity of seeds may be detected by molecular identification, DNA analysis, isotope fingerprinting and mineral element analysis (Bradbeer, 1988). Protein electrophoresis, gas chromatography, high-performance liquid chromatography, tetrazolium tests, accelerated ageing and conductivity tests have been employed to evaluate the vigour and germination quality of seeds (Huang et al., 2015). Most of these chemical and physical techniques exhibit high accuracy and good reliability but have certain limitations, such as their high cost, long time requirements and high operator requirements. With the increasing demand for rapid, non-destructive and reliable techniques for evaluation of seed quality in the modern agro-industry, high-performance techniques must be developed for the evaluation of seed quality. A number of non-destructive testing technologies have been developed for evaluation of seed quality (Huang et al., 2015). These non-destructive testing technologies are rapid, accurate, reliable and simple methods for assessing the quality of seeds. This review focuses primarily on non-destructive techniques, namely, machine vision, spectroscopy, hyperspectral imaging, electronic nose, soft X-ray imaging and thermal imaging techniques, which have been used to assess seed quality parameters such as chemical composition, genetic purity and classification, disease and insect infestation, as well as vigour and germinability. The emphasis in this review is also placed on insights into the methods and techniques that have been investigated for evaluating seed qualities.

**Non-destructive techniques for seed quality assessment**

**Machine vision**

Machine vision, also known as ‘computer vision’ or ‘computer image processing’, is an artificial intelligence technique that simulates human vision (Huang et al., 2015). This technique is non-destructive, reliable and rapid and has been proven to be an effective and powerful technique for quality evaluation of food and agricultural products, particularly seeds (Hornberg, 2007). A typical machine vision system consists of four basic components: an illumination system, a sensor or camera, a lens and a computer with frame grabber/digitizer (Fig. 1). Most applications of machine vision address the visible spectrum (380–780 nm) (Gunasekaran et al., 1985). A machine vision system should be capable of identifying and grading seeds based on image external features, such as size, shape, colour and texture. The superiority, disadvantages and feasibility of different image external features should be simultaneously considered to select the most suitable feature for specific applications. Machine vision has already been used, with varying success, to assess seeds of a range of crop and non-crop species. This review focuses mainly on machine vision techniques that can be used to classify seed varieties, disease detection, identification of seed varieties, etc.

**Spectroscopy**

Spectroscopy is used to investigate and measure the spectra produced when matter interacts with, or emits, electromagnetic radiation (Huang et al., 2015). A range of spectroscopic techniques, such as near-infrared- (NIR), mid-infrared- (MIR), fluorescence-, Fourier transform-infrared- (FT-IR) and Raman spectroscopy have been
widely and successfully used as sensitive and fast analytical techniques for authentication and quality analysis of a variety of agricultural seeds (Fig. 2). NIR and MIR spectroscopy are based on molecular overtones and combined vibrations. FT-IR spectroscopy is a technique used to record infrared spectra and detect radiation in the MIR region. FT-IR spectroscopy is an information-rich analytical technique, as it provides a greater amount of chemical information regarding the scanned sample than NIR spectroscopy (Lohumi et al., 2015). Raman spectroscopy is another form of analytical spectroscopy that is suitable for quality and authenticity analysis of agro-food products. This technique can provide specific information needed for identification of sample matrices based on model compounds, such as lipids, proteins and carbohydrates, and is sensitive to minor components (Seo et al., 2016). This review focuses mainly on spectroscopic techniques that can be used to detect seed quality attributes, such as chemical composition, viability and damage by insects and other causes.

**Hyperspectral imaging**

Hyperspectral imaging has recently emerged as a powerful analytical technique for food quality and authenticity analysis. This technique is used to acquire both spectral and spatial information from an object (Wu and Sun, 2013). A hyperspectral imaging system includes light sources, wavelength dispersion devices and detectors. As the centre of a hyperspectral imaging system, wavelength dispersion devices are used to disperse broadband light into different wavelengths (Fig. 3). The detector collects light, which carries useful information from the wavelength dispersion device and measures the intensity of the light by converting radiation energy into electrical signals (Huang et al., 2015). Using hyperspectral imaging, sample analysis is convenient and comparatively fast because a large number of samples are analysed at the same time, whereas spectroscopic methods analyse only one sample at a time (Lohumi et al., 2015). Machine vision and spectroscopy can only provide spatial or spectral information, whereas hyperspectral imaging, which integrates machine vision and spectroscopy advantages, can simultaneously obtain spatial and spectral information by using only one system. In this regard, hyperspectral imaging has been widely used by researchers to evaluate the exterior quality of seeds and predict their internal composition (Mahesh et al., 2011a; Zhu et al., 2011; Huang et al., 2014).
Thermal imaging

Thermal imaging is a technique for converting the invisible radiation pattern of an object into visible images for feature extraction and analysis without establishing contact with the object. Using this method, the surface temperature of any object can be mapped at a high resolution in two dimensions. The thermal data produced may be used directly or indirectly in many ways (Manickavasagan et al., 2008). The application of thermal imaging has gained popularity in the agro-food industry in recent years (Vadivambal and Jayas, 2011). The major advantage of thermal imaging is that it is a non-contact, non-invasive and rapid technique that can be used in online applications (Fig. 4). Thermal cameras are easy to handle and highly accurate temperature measurements are possible (Vadivambal and Jayas, 2011). Using thermal imaging, it is possible to obtain temperature mapping of any particular region of interest with fast response times, which is not possible with thermocouples or other temperature sensors that can only measure spot data. The repeatability of temperature measurements in thermal imaging is high (Ishimwe et al., 2014). In addition, thermal imaging does not require an illumination source, unlike other imaging systems. Nowadays, thermal imaging has a potential application in many operations involved in agriculture, starting from assessing seed quality, especially in detection of diseases, insects and seedling viability, estimating soil water status, estimating crop water stress, scheduling irrigation, determining disease and pathogen affected plants, estimating fruit yield and evaluating maturity of fruits and vegetables (Chelladurai et al., 2010; Manickavasagan et al., 2010; Vadivambal and Jayas, 2011). In spite of the fact that it could be used as a non-contact, non-destructive technique, it has some drawbacks in comparison with other imaging techniques because high resolution thermal imaging is costly and accurate thermal measurements depend on environmental and weather conditions. Thus it may not be possible to develop a universal methodology for its application in seed quality assessment.

Soft X-ray imaging

Electromagnetic waves with wavelengths ranging from 1 to 100 nm (and energies of approximately 0.12 to 12 keV) are called soft X-rays. The low penetration power of these waves and their ability to reveal internal density changes make soft X-rays suitable for use in evaluating agricultural products (Neethirajan et al., 2007). Soft X-ray imaging is a well-known technique that takes a few seconds (3–5 s) to produce an X-ray image. Soft X-ray imaging has begun to be used in the seed industry to detect internal voids, defects, insect infestation and insect damage (Karunakaran et al., 2004; Neethirajan et al., 2006; Mathanker et al., 2013).

Electronic nose

An electronic nose is an instrument consisting of an array of electronic and chemical sensors with partial specificity and a pattern recognition system that is capable of recognizing simple or complex odours (Wilson and Baietto, 2009). These devices typically have arrays

Figure 4. A typical thermal imaging system. From Manickavasagan et al. (2010).
of sensors used to detect and distinguish odours precisely in complex samples and at low cost (Zhou et al., 2012). Electronic nose devices have been employed in a wide variety of applications, including classification of kernels and microbial pathogen detection.

**Quality detection of seeds using non-destructive techniques**

**Quality assessment of seeds: chemical composition**

In recent years, non-destructive sensing techniques, mainly spectroscopy and hyperspectral imaging, have been widely used to determine the internal composition of seeds (Table 1). Previous studies have shown that spectroscopy systems can be applied successfully to determine the protein contents of corn (Armstrong et al., 2011), maize (Baye et al., 2006), common beans (Hacisalihoglu et al., 2010), rice (Wu and Shi, 2004), soybean (Ferreira et al., 2014), peanuts (Wang et al., 2012), jatropha (Vaknin et al., 2011), rapeseed (Velasco and Möllers, 2002), sunflower (Fassio and Cozzolino, 2004), canola (Daun et al., 1994), cotton (Huang et al., 2013), foxtail millet (Yang et al., 2013), flax, safflower, sesame and palm (Pandord et al., 1988). Previous studies have shown that spectroscopy is highly accurate in protein prediction. The coefficients of determination for prediction ($R^2_c$) of a partial least-squares regression (PLSR) model have been found to be 0.98 for corn (Chen et al., 2014), 0.99 for rapeseed (Pandord et al., 1988), 0.96 for cottonseed (Huang et al., 2013), 0.98 for peanut (Pandord et al., 1988) and 0.91 for soybeans (Ferreira et al., 2014). Spectroscopy has also been used to estimate the fibre content of soybean, corn (Armstrong et al., 2011) and rapeseed (Wittkop et al., 2012; Bala and Singh, 2013), and the sucrose content of soybean (Choung, 2010). However, unsatisfactory results have been reported for carbohydrate determination in maize (Baye and Becker 2004; Tallada et al., 2009), rice (Wu and Shi, 2004), foxtail millet (Chen et al., 2013) and soybean (Choung; Ferreira et al., 2013) and made the same conclusions in their study that any changes in the compositional amount among the sample are not translated into differences within the spectra. In recent research, hyperspectral imaging has been used to predict crude protein and crude fat fractions in soybean (Zhu et al., 2011), protein in wheat (Mahesh et al., 2011a) and alpha-amylase activity in wheat (Xing et al., 2009, 2011). Unsatisfactory prediction results have been obtained in some cases using hyperspectral imaging because of the difficulty of extracting the most important object features for assessing the physical structure and chemical composition of samples. The oil content is an important parameter in the internal quality evaluation of most oilseed crops. Spectroscopy within the range of 400–2500 nm has been widely used to determine oil content in peanuts (Sundaram et al., 2010), maize (Tallada et al., 2009), safflower (Rudolph et al., 2012), rapeseed (Velasco and Becker, 1998; Velasco et al., 1999; Petisco et al., 2010), sunflower (Pandord et al., 1988; Pérez-Vich et al., 1998; Fassio and Cozzolino, 2004), jatropha (Vaknin et al., 2011), canola (Daun et al., 1994), cotton (Huang et al., 2013), corn and soybean (Armstrong et al., 2011). The coefficients of determination of the oil prediction model were 0.99, 0.91, 0.98, 0.92, 0.95, 0.98, 0.95, 0.87 and 0.84 for peanut, safflower, rapeseed, sunflower, jatropha, canola, cotton, corn and soybean, respectively. Hyperspectral imaging has also been used to predict the oil and oleic acid concentrations in corn (Weinstock et al., 2006). An NIR hyperspectral imaging system (750–1090 nm) was used to predict the oil content in maize and the determination coefficient of the PLSR model for the determination of oil content was found to be 0.75 (Cogdill et al., 2004). The results indicated outstanding performance of the non-destructive technique in the prediction of the internal composition of the seed. Spectroscopy has also been used to determine the fatty acid content of peanuts (Sundaram et al., 2010), soybean (Patil et al., 2010), safflower (Rudolph et al., 2012), rapeseed (Kim et al., 2007), sunflower (Cantarelli et al., 2009), jatropha (Vaknin et al., 2011), canola and flax (Siemens and Daun, 2005) with high accuracy. The amino acid composition of seeds is also a concern in their quality assessment since high protein content and a rational amino acid composition of seed are a major concern to the plant breeder (Chen et al., 2011). Studies have shown that near-infrared spectroscopy (NIRS) and FT-NIRS can be used successfully in the assessment of amino acid composition in rapeseed (Pandord et al., 1988; Chen et al., 2011), peanuts (Wang et al., 2012), rice (Zhang et al., 2011) and foxtail millet (Yang et al., 2013). An experiment in high-resolution hyperspectral reflectance imagery in the near-infrared region (960–1700 nm) was conducted to predict the amino acid content of fresh soybeans and showed that the best predictions (MSE = 0.305, $R = 0.611$) were obtained using a non-linear artificial neural network (ANN)-based regression model based on the second-derivative spectra data produced for the nitrogen concentration (Monteiro et al., 2007). Spectroscopy has also been used to determine the moisture content of soybean (Pandord et al., 1988; Ferreira et al., 2013; Ferreira et al., 2014), sunflower (Pandord et al., 1988; Fassio and Cozzolino, 2004), peanuts (Sundaram et al., 2010), flax, safflower and cotton (Pandord et al., 1988), as well as the pH of cocoa beans (Sunoj et al., 2016), the mineral contents (K, Mg, Ca and P) of peanuts (Phan-Thien et al., 2011), the seed weight of rapeseed (Velasco et al., 1999), the grain weight of rice and brown rice (Wu and Shi, 2004), the ethanol content of
<table>
<thead>
<tr>
<th>Chemical composition</th>
<th>Seed</th>
<th>Method</th>
<th>Spectra (nm) region</th>
<th>Analysis method</th>
<th>Result</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Protein, starch</td>
<td>Bean</td>
<td>Spectroscopy</td>
<td>907–1689</td>
<td>PLSR</td>
<td>$R_p^2 = 0.80$–0.88</td>
<td>Hacisalihoglu et al., 2010</td>
</tr>
<tr>
<td>Protein, starch, amylose</td>
<td>Bean</td>
<td>Spectroscopy</td>
<td>1000–2500</td>
<td>PCA, PLSR</td>
<td>$R_p^2 = 0.68$–0.91</td>
<td>Plans et al., 2013</td>
</tr>
<tr>
<td>Fatty acid</td>
<td>Canola seed</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>MPLSR</td>
<td>$SEP = 0.42$–0.77%</td>
<td>Siemens and Daun, 2005</td>
</tr>
<tr>
<td>Oil, protein</td>
<td>Canola seed</td>
<td>Spectroscopy</td>
<td>850–1050</td>
<td>PLSR, MLR</td>
<td>$SEP = 0.43$–0.55%, 0.35–0.42%</td>
<td>Daun et al., 1994</td>
</tr>
<tr>
<td>pH, polyphenol</td>
<td>Cocoa bean</td>
<td>FT-NIR spectroscopy</td>
<td>3600–12500 cm$^{-1}$</td>
<td>PLSR</td>
<td>$R_p^2 = 0.80$, 0.85</td>
<td>Sunoj et al., 2016</td>
</tr>
<tr>
<td>Oil, oleic acid</td>
<td>Corn</td>
<td>Hyperspectral imaging</td>
<td>950–1700</td>
<td>PLSR</td>
<td>RMSEP = 0.74%, 14%</td>
<td>Weinstock et al., 2006</td>
</tr>
<tr>
<td>Protein, fat</td>
<td>Corn</td>
<td>Spectroscopy</td>
<td>1000–2500</td>
<td>PLSR</td>
<td>$R_p^2 = 0.98$, 0.94</td>
<td>Chen et al., 2014</td>
</tr>
<tr>
<td>Protein, oil, starch, density</td>
<td>Corn</td>
<td>Spectroscopy</td>
<td>904–1685</td>
<td>PLSR</td>
<td>$R_p^2 = 0.68$–0.91</td>
<td>Armstrong et al., 2011</td>
</tr>
<tr>
<td>DM, protein, ADF, OMD</td>
<td>Corn</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>PCA, PLSR</td>
<td>$R_p = 0.42$–0.92</td>
<td>Fassio et al., 2009</td>
</tr>
<tr>
<td>Moisture, oil, protein, crude fibre</td>
<td>Cotton</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>MLR</td>
<td>$R = 0.96$, 0.99, 0.99, 0.95</td>
<td>Pandord et al., 1988</td>
</tr>
<tr>
<td>Protein, oil</td>
<td>Cotton</td>
<td>Spectroscopy</td>
<td>1100–2498</td>
<td>PLSR, LS-SVMR</td>
<td>$R_p^2 = 0.96$, 0.95</td>
<td>Huang et al., 2013</td>
</tr>
<tr>
<td>Fatty acid</td>
<td>Flax seed</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>MPLSR</td>
<td>$SEP = 0.62$–1.2%</td>
<td>Siemens and Daun, 2005</td>
</tr>
<tr>
<td>Moisture, oil, protein, crude fibre</td>
<td>Flax seed</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>MLR</td>
<td>$R = 0.96$, 0.99, 0.99, 0.98</td>
<td>Pandord et al., 1988</td>
</tr>
<tr>
<td>Protein, carbohydrates, fat</td>
<td>Foxtail millet</td>
<td>Spectroscopy</td>
<td>950–1650</td>
<td>MLR</td>
<td>$R_p^2 = 0.70$–0.94</td>
<td>Chen et al., 2013</td>
</tr>
<tr>
<td>Protein, fat, starch, amino acids</td>
<td>Foxtail millet</td>
<td>Spectroscopy</td>
<td>800–2500</td>
<td>PLSR</td>
<td>$R_p^2 = 0.71$–0.93</td>
<td>Yang et al., 2013</td>
</tr>
<tr>
<td>Protein, oil content, composition</td>
<td>Jatropha</td>
<td>Spectroscopy</td>
<td>1100–2498</td>
<td>MPLSR</td>
<td>$R_p^2 = 0.86$, 0.91–0.95, 0.10–0.73</td>
<td>Vaknin et al., 2011</td>
</tr>
<tr>
<td>Moisture, oil content</td>
<td>Maize</td>
<td>Hyperspectral imaging</td>
<td>750–1090</td>
<td>PLSR</td>
<td>$R_p^2 = 0.87$, 0.75</td>
<td>Cogdill et al., 2004</td>
</tr>
<tr>
<td>Ethanol yield</td>
<td>Maize</td>
<td>Spectroscopy</td>
<td>400–2498</td>
<td>PLSR</td>
<td>RMSEP = 0.56%</td>
<td>Hao et al., 2012</td>
</tr>
<tr>
<td>Protein</td>
<td>Maize</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>MLR</td>
<td>$R_p^2 = 0.94$</td>
<td>Rosales et al., 2011</td>
</tr>
<tr>
<td>Protein, oil, SSC</td>
<td>Maize</td>
<td>Spectroscopy</td>
<td>904–1685</td>
<td>PLSR</td>
<td>$R_p^2 = 0.25$–0.89</td>
<td>Tallada et al., 2009</td>
</tr>
<tr>
<td>Protein, starch</td>
<td>Maize</td>
<td>Spectroscopy</td>
<td>890–1700</td>
<td>PLSR</td>
<td>SEP = 1.7%, 11.5%</td>
<td>Baye et al., 2006</td>
</tr>
<tr>
<td>Mineral: Ca, K, Mg, P</td>
<td>Peanut</td>
<td>Spectroscopy</td>
<td>400–2498</td>
<td>PLSR</td>
<td>$R_p^2 = 0.172$–0.792</td>
<td>Phan-Thien et al., 2011</td>
</tr>
<tr>
<td>Moisture, oil, protein, crude fibre</td>
<td>Peanut</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>MLR</td>
<td>$R = 0.98$, 0.99, 0.99, 0.98</td>
<td>Pandord et al., 1988</td>
</tr>
<tr>
<td>Protein, amino acid</td>
<td>Peanut</td>
<td>Spectroscopy</td>
<td>950–1650</td>
<td>PLSR</td>
<td>$R_p^2 = 0.99$, 0.83–0.96</td>
<td>Wang et al., 2012</td>
</tr>
<tr>
<td>Moisture content</td>
<td>Peanuts</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>PLSR</td>
<td>$R_p^2 = 0.84$–0.97</td>
<td>Sundaram et al., 2010</td>
</tr>
<tr>
<td>Oil, fatty acids</td>
<td>Peanuts</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>PLSR</td>
<td>$R_p^2 = 0.99$</td>
<td>Sundaram et al., 2010</td>
</tr>
<tr>
<td>Moisture, oil, protein, crude fibre</td>
<td>Palm</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>MLR</td>
<td>$R = 0.79$, 0.78, 0.71, 0.57</td>
<td>Pandord et al., 1988</td>
</tr>
<tr>
<td>Amino acid</td>
<td>Rapeseed</td>
<td>Spectroscopy</td>
<td>1100–2498</td>
<td>MPLSR</td>
<td>$R_p^2 = 0.89$–0.98</td>
<td>Chen et al., 2011</td>
</tr>
<tr>
<td>Fatty acid</td>
<td>Rapeseed</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>MPLSR</td>
<td>$R_p^2 = 0.95$–0.98</td>
<td>Velasco and Becker, 1998</td>
</tr>
<tr>
<td>Fatty acid</td>
<td>Rapeseed</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>MPLSR</td>
<td>$R_p^2 = 0.72$–0.98</td>
<td>Kim et al., 2007</td>
</tr>
<tr>
<td>Chemical composition</td>
<td>Seed</td>
<td>Method</td>
<td>Spectra region (nm)</td>
<td>Analysis method (s)</td>
<td>Result</td>
<td>References</td>
</tr>
<tr>
<td>----------------------</td>
<td>---------------</td>
<td>-----------------</td>
<td>--------------------</td>
<td>---------------------</td>
<td>--------</td>
<td>------------</td>
</tr>
<tr>
<td>Fibre content</td>
<td>Rapeseed</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>PCA, MPLSR</td>
<td>$R_p^2 = 0.53-0.81$</td>
<td>Wittkop et al., 2012</td>
</tr>
<tr>
<td>Moisture, oil, protein, crude fibre</td>
<td>Rapeseed</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>MLR</td>
<td>$R = 0.99, 1.0, 0.99, 0.99$</td>
<td>Pandord et al., 1988</td>
</tr>
<tr>
<td>Oil, protein</td>
<td>Rapeseed</td>
<td>Spectroscopy</td>
<td>400–2498</td>
<td>PCA, MPLSR</td>
<td>$R_p^2 = 0.98, 0.96$</td>
<td>Petisco et al., 2010</td>
</tr>
<tr>
<td>Phenol, crude fibre</td>
<td>Rapeseed</td>
<td>FT-NIR spectroscopy</td>
<td>3600–12800 cm$^{-1}$</td>
<td>PLSR</td>
<td>$R_p = 0.96, 0.91$</td>
<td>Bala and Singh, 2013</td>
</tr>
<tr>
<td>Protein</td>
<td>Rapeseed</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>MPLSR</td>
<td>$R_p = 0.94$</td>
<td>Velasco and Möllers, 2002</td>
</tr>
<tr>
<td>Seed weight, oil, fatty acid</td>
<td>Rapeseed</td>
<td>Spectroscopy</td>
<td>1100–1460 and 1560–2500</td>
<td>MLR</td>
<td>$R_p^2 = 0.84-0.95$</td>
<td>Zhang et al., 2011</td>
</tr>
<tr>
<td>Amino acid</td>
<td>Rice</td>
<td>Spectroscopy</td>
<td>1100–2498</td>
<td>PCR</td>
<td>$R_p = 0.67, 0.71, 0.85$</td>
<td>Wu and Shi, 2004</td>
</tr>
<tr>
<td>Grains weight, brown rice weight, amylose content</td>
<td>Rice</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>MLR</td>
<td>$R_p = 0.99, 0.99, 0.99, 0.75$</td>
<td>Pandord et al., 1988</td>
</tr>
<tr>
<td>Starch, protein</td>
<td>Rice</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>PLSR, LS-SVM, ICA</td>
<td>$R_p = 0.89-0.98$</td>
<td>Shao et al., 2011</td>
</tr>
<tr>
<td>Amylose, protein</td>
<td>Rice</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>LS-SVM, ANN</td>
<td>$R_p = 0.82-0.88$</td>
<td>Shao et al., 2009</td>
</tr>
<tr>
<td>Moisture, oil, protein, crude fibre</td>
<td>Safflower</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>MLR</td>
<td>$R_p = 0.85, 0.97, 0.77, 0.84$</td>
<td>Pandord et al., 1988</td>
</tr>
<tr>
<td>Moisture, oil, protein, crude fibre</td>
<td>Sesame</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>MLR</td>
<td>$R_p = 0.99, 0.99, 0.99$</td>
<td>Pandord et al., 1988</td>
</tr>
<tr>
<td>Fatty acid, moisture</td>
<td>Soybean</td>
<td>Hyperspectral imaging</td>
<td>400–1000</td>
<td>PLSR</td>
<td>$R_p = 0.83, 0.97$</td>
<td>Huang et al., 2014</td>
</tr>
<tr>
<td>Fatty acid</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>850–1048</td>
<td>PLSR, ANN, LS-SVM</td>
<td>SEP = 0.42–1.67%</td>
<td>Igne et al., 2008</td>
</tr>
<tr>
<td>Fatty acid</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>850–1048</td>
<td>PLSR, ANN</td>
<td>SEP = 0.01–0.08%</td>
<td>Hurburgh, 2007</td>
</tr>
<tr>
<td>Fatty acid</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>850–1048</td>
<td>PLSR, ANN, SVMR</td>
<td>$R_p^2 = 0.67–0.94$</td>
<td>Kovalenko et al., 2006</td>
</tr>
<tr>
<td>Fatty acid</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>850–1048</td>
<td>MPLSR</td>
<td>$R_p^2 = 0.63–0.89$</td>
<td>Patil et al., 2010</td>
</tr>
<tr>
<td>Moisture, oil, protein, crude fibre</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>MLR</td>
<td>$R_p = 0.92, 0.99, 0.99, 0.76$</td>
<td>Pandord et al., 1988</td>
</tr>
<tr>
<td>Moisture, protein, lipid</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>1000–2500</td>
<td>PLSR</td>
<td>$R_p^2 = 0.50–0.81$</td>
<td>Ferreira et al., 2013</td>
</tr>
<tr>
<td>Moisture, ash, protein, lipid</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>1000–2500</td>
<td>PLSR</td>
<td>$R_p^2 = 0.63–0.91$</td>
<td>Ferreira et al., 2014</td>
</tr>
<tr>
<td>Oil, linoleic, oleic acid</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>MPLSR</td>
<td>$R_p^2 = 0.91, 0.73, 0.68$</td>
<td>Rudolph et al., 2012</td>
</tr>
<tr>
<td>Protein, fat</td>
<td>Soybean</td>
<td>Hyperspectral imaging</td>
<td>850–1700</td>
<td>PLSR</td>
<td>$R_p^2 = 0.9, 0.97$</td>
<td>Zhu et al., 2011</td>
</tr>
<tr>
<td>Protein, oil content</td>
<td>Soybean</td>
<td>Raman spectroscopy</td>
<td>200–1800 cm$^{-1}$</td>
<td>iPLSR</td>
<td>$R_p^2 = 0.92, 0.87$</td>
<td>Lee et al., 2013</td>
</tr>
<tr>
<td>Protein, oil fibre</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>904–1685</td>
<td>PLSR</td>
<td>$R_p^2 = 0.44–0.90$</td>
<td>Armstrong et al., 2011</td>
</tr>
<tr>
<td>Sucrose</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>MPLSR</td>
<td>$R_p = 0.92$</td>
<td>Choung, 2010</td>
</tr>
<tr>
<td>Sweetness, amino acid</td>
<td>Soybean</td>
<td>Hyperspectral imaging</td>
<td>400–1000</td>
<td>ANNR</td>
<td>$R = 0.61, 0.60–0.74$</td>
<td>Monteiro et al., 2007</td>
</tr>
</tbody>
</table>

Continued
### Table 1. Continued

<table>
<thead>
<tr>
<th>Seed Damage</th>
<th>Method</th>
<th>Spectra region</th>
<th>Analysis method</th>
<th>Result</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>MPLSR</td>
<td>$R^2 = 0.94$</td>
<td>Moschner and Biszkup-Korell, 2006</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Fatty acid Sunflower Spectroscopy 400–2500 MPLSR R_p = 0.0.95, 0.96, 0.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Fassio and Cozzolino, 1988</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Pandolfo et al., 1998</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Perez-Vich et al., 2009</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Cantarella et al., 2011</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$R^2 = 0.63–0.82$</td>
<td>Xing et al., 2011</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Mahesh et al., 2011</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$R^2 = 0.54–0.73$</td>
<td>Xing et al., 2009</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1255–2300</td>
<td>PCA, PLSR</td>
<td></td>
<td>Xing et al., 2011</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>13 Dec 2021 at 05:48:11</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$R^2 = 0.68–0.82$</td>
<td>Mahesh et al., 2011</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>100% Mahesh et al., 2011</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1 Dec 2021 at 05:48:11</td>
</tr>
</tbody>
</table>

Quality assessment of seeds: insect damage and diseases

Seed damage by insects, fungi or natural causes, such as germination, are an important factor in seed quality during storage and processing. Seed damage is therefore taken seriously by consumers and the food industry. Various non-destructive techniques such as machine vision, spectroscopy, hyperspectral imaging, soft X-ray imaging, electronic nose and thermal imaging have been widely used in the detection of insect damage, insect infestation and diseases in seeds (Table 2). Machine vision has been used together with back-propagation neural networks based on colour features to detect external defects in rice seeds, such as germs, diseases and incompletely closed glumes, with an accuracy of 98.6–99.2% (Cheng et al., 2006). A machine vision system developed for the detection of damaged wheat kernels based on morphological and textural properties was shown to have a classification accuracy of 91–94% (Delwiche et al., 2013). A machine vision system was also used to detect damaged soybeans based on colour features with an accuracy of 99.6% (Shatadal and Tan, 2003). Recently, spectroscopy has been used to identify defects in corn (Esteve Agelet et al., 2012) and soybean (Sirisomboon et al., 2009). Hyperspectral imaging has been used to detect sprout damage in wheat (Singh et al., 2009a; Xing et al., 2010) and to detect sprouting in barley (Arngren et al., 2011). In a recent study, a machine vision system was used to detect diseases and insects for the purpose of quality sorting of areca nuts with an accuracy of 90.9% (Huang, 2012). Spectroscopy-based methods have also been used to detect and classify fungus-infected maize (Giacomo et al., 2013), wheat (Soto-Cámara et al., 2012) and soybeans (Wang et al., 2004), to determine the percentage of fungal infection in rice (Sirisomboon et al., 2013) and to identify the green mottle mosaic virus in cucumber (Lee et al., 2016). However, this technique has yielded unsatisfactory results for fungal infection determination in rice because the moisture and starch contents in rice affect the overall extent of fungal infection (Sirisomboon et al., 2013). Numerous studies have been conducted using hyperspectral imaging to detect fungal-infected wheat (Singh et al., 2012) and maize
<table>
<thead>
<tr>
<th>Insect damage/diseases</th>
<th>Seed</th>
<th>Method</th>
<th>Feature(s)/spectra region (nm)</th>
<th>Analysis method(s)</th>
<th>Result</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disease detection</td>
<td>Areca nuts</td>
<td>Machine vision</td>
<td>Geometric, colour</td>
<td>BPNN</td>
<td>90.90%</td>
<td>Huang, 2012</td>
</tr>
<tr>
<td>Sprout detection</td>
<td>Barley</td>
<td>Hyperspectral imaging</td>
<td>1002–1626</td>
<td>PCA, NNN, MLMR</td>
<td>&lt;99%</td>
<td>Arngren et al., 2011</td>
</tr>
<tr>
<td>Damaged detection</td>
<td>Corn</td>
<td>Spectroscopy</td>
<td>850–1650</td>
<td>PLSDA, SIMCA, KNN, LS-SVM</td>
<td>96.90%</td>
<td>Kandpal et al., 2015</td>
</tr>
<tr>
<td>Aflatoxin B1</td>
<td>Corn</td>
<td>Hyperspectral imaging</td>
<td>1100–1700</td>
<td>PLS-DA</td>
<td>86%</td>
<td>Lee et al., 2016a</td>
</tr>
<tr>
<td>Fungal infection</td>
<td>Maize</td>
<td>Hyperspectral imaging</td>
<td>400–1000</td>
<td>PCA, DA</td>
<td>–</td>
<td>Del Fiore et al., 2010</td>
</tr>
<tr>
<td>Fungal infection</td>
<td>Maize</td>
<td>Spectroscopy</td>
<td>650–2500</td>
<td>MLR</td>
<td>R² = 0.91</td>
<td>Giacomo and Stefania, 2013</td>
</tr>
<tr>
<td>Fungus-infect</td>
<td>Maize</td>
<td>Spectroscopy &amp; color imaging</td>
<td>904–1685</td>
<td>LDA, ANN</td>
<td>89%, 79%</td>
<td>Tallada et al., 2011</td>
</tr>
<tr>
<td>Aflatoxin B1</td>
<td>Maize</td>
<td>Hyperspectral imaging</td>
<td>1000–2500</td>
<td>PCA, FDA</td>
<td>88–100%</td>
<td>Wang et al., 2014</td>
</tr>
<tr>
<td>Fungal infection</td>
<td>Maize</td>
<td>Hyperspectral imaging</td>
<td>1000–2498</td>
<td>PCA, PLSR</td>
<td>R² = 0.73–0.86</td>
<td>Williams et al., 2012</td>
</tr>
<tr>
<td>Insect-damaged</td>
<td>Mungbean</td>
<td>Hyperspectral imaging</td>
<td>1000–1600</td>
<td>PCA, LDA, QDA</td>
<td>85%, 88%</td>
<td>Kaliramesh et al., 2013</td>
</tr>
<tr>
<td>Defect detection</td>
<td>Rice</td>
<td>Machine vision</td>
<td>Contour, colour</td>
<td>PCBPNN</td>
<td>91–99.4%</td>
<td>Cheng et al., 2006</td>
</tr>
<tr>
<td>Fungal infection</td>
<td>Rice</td>
<td>Spectroscopy</td>
<td>950–1650</td>
<td>PLSR</td>
<td>R = 0.67</td>
<td>Sirisomboon et al., 2013</td>
</tr>
<tr>
<td>Insect-damaged</td>
<td>Soybean</td>
<td>Hyperspectral imaging</td>
<td>900–1700</td>
<td>PCA, LDA, QDA</td>
<td>40–94%</td>
<td>Chelladurai et al., 2014</td>
</tr>
<tr>
<td>Insect-damaged</td>
<td>Soybean</td>
<td>Hyperspectral imaging</td>
<td>400–1000</td>
<td>KS, SVDD</td>
<td>95.60%</td>
<td>Huang et al., 2013</td>
</tr>
<tr>
<td>Bug damage</td>
<td>Soybean</td>
<td>Soft X-ray imaging</td>
<td>Intensity of X-ray image</td>
<td>–</td>
<td>Good</td>
<td>Pinto et al., 2009</td>
</tr>
<tr>
<td>Damaged detection</td>
<td>Soybean</td>
<td>Machine vision</td>
<td>Colour</td>
<td>AN</td>
<td>99.60%</td>
<td>Shatadal and Tan, 2003</td>
</tr>
<tr>
<td>Defect detection</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>600–1100</td>
<td>PCA, PLSDA, SIMCA</td>
<td>72–100%</td>
<td>Sirisomboon et al., 2009</td>
</tr>
<tr>
<td>Bacterial infection</td>
<td>Watermelon</td>
<td>Hyperspectral imaging</td>
<td>400–1000</td>
<td>PLSDA, LS-SVM</td>
<td>91.7%, 90.5%</td>
<td>Wang et al., 2004</td>
</tr>
<tr>
<td>Fusarium detection</td>
<td>Wheat</td>
<td>Hyperspectral imaging</td>
<td>400–1000</td>
<td>PCA, SAM</td>
<td>67%</td>
<td>Bauriegel et al., 2011</td>
</tr>
<tr>
<td>Insect fragments</td>
<td>Wheat</td>
<td>Hyperspectral imaging</td>
<td>1000–1600</td>
<td>PLSR</td>
<td>R² = 0.99</td>
<td>Bhuvaneswari et al., 2011</td>
</tr>
<tr>
<td>Fungal infection</td>
<td>Wheat</td>
<td>Thermal imaging</td>
<td>–</td>
<td>LDA, QDA</td>
<td>96–100%</td>
<td>Chelladurai et al., 2010</td>
</tr>
<tr>
<td>Fungal infection</td>
<td>Wheat</td>
<td>Hyperspectral imaging</td>
<td>400–1700</td>
<td>LDA</td>
<td>95%</td>
<td>Delwiche et al., 2011</td>
</tr>
<tr>
<td>Damaged detection</td>
<td>Wheat</td>
<td>Machine vision</td>
<td>Morphology, texture</td>
<td>LDA, KNN</td>
<td>91–94%</td>
<td>Delwiche et al., 2013</td>
</tr>
<tr>
<td>Insect infestation</td>
<td>Wheat</td>
<td>Soft X-ray imaging</td>
<td>Textural, shape moments, histogram</td>
<td>BPNN</td>
<td>98%</td>
<td>Karunakaran et al., 2004</td>
</tr>
<tr>
<td>Insect infestation</td>
<td>Wheat</td>
<td>Soft X-ray imaging</td>
<td>Textural, histogram</td>
<td>BPNN</td>
<td>86%</td>
<td>Karunakaran et al., 2004</td>
</tr>
<tr>
<td>Insect infestation</td>
<td>Wheat</td>
<td>Thermal imaging</td>
<td>–</td>
<td>LSD</td>
<td>83%</td>
<td>Manickavasagan et al., 2008</td>
</tr>
<tr>
<td>Fungal detection</td>
<td>Wheat</td>
<td>Electronic nose</td>
<td>–</td>
<td>PCA, PLSDA</td>
<td>85.30%</td>
<td>Paolesse et al., 2006</td>
</tr>
<tr>
<td>Insect detection</td>
<td>Wheat</td>
<td>Hyperspectral imaging</td>
<td>1000–1700</td>
<td>PLSDA, iPLSDA</td>
<td>91–100%</td>
<td>Serranti et al., 2013</td>
</tr>
</tbody>
</table>

Continued
### Table 2. Continued

<table>
<thead>
<tr>
<th>Insect damage/diseases</th>
<th>Seed Method</th>
<th>Feature(s)/spectra region</th>
<th>Analysis method(s)</th>
<th>Result</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fungi-damaged wheat</td>
<td>Hyperspectral imaging</td>
<td>400–1000 nm</td>
<td>PCA, LDA</td>
<td>92%</td>
<td>Shahin and Symons, 2011</td>
</tr>
<tr>
<td>Mildew-damaged wheat</td>
<td>Hyperspectral imaging</td>
<td>400–1000 nm</td>
<td>PLSR</td>
<td>96%</td>
<td>Shahin et al., 2009a</td>
</tr>
<tr>
<td>Mildew-damaged wheat</td>
<td>Hyperspectral imaging</td>
<td>400–1000 nm</td>
<td>PCA, LDA, QDA, MD</td>
<td>95.3–99.3%</td>
<td>Singh et al., 2010</td>
</tr>
<tr>
<td>Mildew-damaged wheat</td>
<td>Hyperspectral imaging</td>
<td>1000–1600 nm</td>
<td>LDA, QDA, MD</td>
<td>97.3–100%</td>
<td>Shahin et al., 2009b</td>
</tr>
<tr>
<td>Mildew-damaged wheat</td>
<td>Hyperspectral imaging</td>
<td>1000–1600 nm</td>
<td>LDA, QDA, MD</td>
<td>94%</td>
<td>Singh et al., 2010</td>
</tr>
<tr>
<td>Mildew-damaged wheat</td>
<td>Hyperspectral imaging</td>
<td>1000–1600 nm</td>
<td>PCA, MPLS</td>
<td>88–100%</td>
<td>Xing et al., 2010</td>
</tr>
<tr>
<td>Mildew-damaged wheat</td>
<td>Hyperspectral imaging</td>
<td>1000–1600 nm</td>
<td>PCA, ANN</td>
<td>90–95%</td>
<td>Neethirajan et al., 2007</td>
</tr>
<tr>
<td>Insect identification</td>
<td>Hyperspectral imaging</td>
<td>700–1100 nm</td>
<td>PCA, ANN, QDA</td>
<td>91%</td>
<td>Singh et al., 2010</td>
</tr>
<tr>
<td>Insect-damaged wheat</td>
<td>Hyperspectral imaging</td>
<td>1000–1600 nm</td>
<td>LDA, QDA, MD</td>
<td>85%</td>
<td>Singh et al., 2012</td>
</tr>
<tr>
<td>Insect-damaged wheat</td>
<td>Hyperspectral imaging</td>
<td>1000–1600 nm</td>
<td>LDA, QDA, MD</td>
<td>97.3–100%</td>
<td>Singh et al., 2012</td>
</tr>
<tr>
<td>Fungicide detection</td>
<td>Spectroscopy</td>
<td>400–2500 nm</td>
<td>PCA, MPLS</td>
<td>84%</td>
<td>Soto-Cámara et al., 2012</td>
</tr>
<tr>
<td>Sprout detection</td>
<td>Soft X-ray imaging</td>
<td>–</td>
<td>ANN</td>
<td>90%</td>
<td>Neethirajan et al., 2007</td>
</tr>
</tbody>
</table>

(De Fiore et al., 2010; Williams et al., 2012; Yao et al., 2013) and to detect bacteria-infected watermelon seeds (Lee et al., 2016). One study showed that the electronic nose is a powerful tool for the detection of fungal contamination in wheat; the accuracy obtained using partial least-squares discriminant analysis (PLS-DA) was found to be 85.3% (Paollesse et al., 2006). Recently, chlorophyll fluorescence has been used to sort white cabbage seeds, resulting in 97% germination by removing 13.2% of the seeds with very high chlorophyll fluorescence signal from the seed lot (Jalil et al., 1998). Similar studies have been conducted to evaluate the seed maturity in cabbage (Dell’Aquila et al., 2002), tomato (Jalil et al., 1999), barley (Konstantinova et al., 2002), carrot (Groot et al., 2006) and pepper (Kenanoglu et al., 2013) using chlorophyll fluorescence. Thermal imaging has been used to detect fungal infestations in stored wheat using linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA), with an accuracy of 100% for healthy samples and 96–97% for infected samples (Chelladurai et al., 2010). In a study in which a hyperspectral imaging system (1100–1700 nm) was used to detect aflatoxin B1 (AFB1) contaminants on corn kernels, a PLS-DA was performed, and a minimum classification accuracy of 96.9% was achieved (Kandpal et al., 2015). Similar studies have been performed to detect AFB1 contaminants on the surfaces of healthy maize kernels using a short wavelength infrared (SWIR) hyperspectral imaging system (Wang et al., 2014). The feasibility of short-wave near-infrared hyperspectral (700–1100 nm wavelength range) and digital colour imaging with different statistical discriminant classifiers was investigated for use in the detection of wheat damaged by four different insect species: the rice weevil (Sitophilus oryzae), the lesser grain borer (Rhyzopertha dominica), the rusty grain beetle (Cryptolestes ferrugineus) and the red flour beetle (Tribolium castaneum). Accuracies of 96% were achieved for healthy wheat kernels and 91–100% for insect-damaged wheat kernels (Singh et al., 2010a). Similarly, numerous studies have been performed to detect insect-damaged (Singh et al., 2009a, 2009b, 2010a, 2010b; Serranti et al., 2013) and mildew-damaged (Shahin et al., 2014) wheat using hyperspectral imaging. Hyperspectral imaging has also been used to detect insect-damaged mung bean (Kaliramesh et al., 2013) and insect fragments in semolina (Bhuvaneswari et al., 2011) and soybean (Huang et al., 2013; Chelladurai et al., 2014). Soft X-ray imaging technology has been used to detect red flour beetle infestation in wheat. An accuracy of 86% was achieved using textural features with a back-propagation neural network (BPNN) classifier (Karunakaran et al., 2004b). Soft X-ray imaging has also been used to detect internal wheat seed infestation by insects (Karunakaran et al., 2004a) and bug damage in soybean seeds (Pinto et al., 2009). In a recent study, thermal
imaging was used to detect insect infestation in wheat with an accuracy of 77.6% for infested seeds and 83% for healthy seeds (Manickavasagan et al., 2008). A recent study has shown that multispectral imaging can be used for spinach seeds to discriminate uninfected seeds from infected seeds with 80–100% classification rate (Olesen et al., 2011).

Quality assessment of seeds: variety identification and classification

Variety identification and classification of seed species using non-destructive techniques has been extensively investigated by researchers worldwide (Table 3). Machine vision has been used to identify four wheat varieties using morphological features and colour features with an accuracy of 95.86%, which suggests that morphological features are more effective than colour features in recognizing wheat varieties (Areﬁ et al., 2011). Machine vision has also been used to classify seeds of various species using morphological, colour, textural and wavelet features and to distinguish among species of wheat, barley, oats and rye (Choudhary et al., 2008) and between wheat and barley (Guevara-Hernandez and Gomez-Gil, 2011). Similarly, machine vision has been used to identify nine Iranian wheat seeds based on their varieties, using textural features, with an accuracy of 98.15% (Pourreza et al., 2012) and to recognize five Chinese corn varieties based on their external features (Chen et al., 2010). Machine vision has also been used to identify bean varieties (Venora et al., 2009), discriminate among wheat grain varieties (Zapotoczny, 2011a, 2011b), identify wheat varieties (Zayas et al., 1986; Dubey et al., 2006), classify corn (Jingtao et al., 2012; Pazoki et al., 2013), discriminate among rapeseed varieties (Li et al., 2007; Kurtuluş and Ünal 2015), classify pepper seeds (Kurtuluş et al., 2016) and classify rice varieties (Rad et al., 2011; Hong et al., 2015). Accuracy is an important evaluation parameter in variety identification; most of these studies have reported highly accurate results, in the range of 85–100%. In addition, machine vision has been shown to exhibit an overall accuracy of greater than 80% in grading maize (Yi et al., 2007; Wu et al., 2013) and soybean (Kılıç et al., 2007). Recently, an electronic nose was used to distinguish among varieties of wheat seeds with an accuracy of 100% (Zhou et al., 2012). Thermal imaging was used in a recent study to identify eight western Canadian wheat varieties. The overall classification accuracies of eight-class model, red-class model (four classes), white-class model (four classes), and pairwise (two-class) model comparisons obtained using a quadratic discriminant method were 76, 87, 79 and 95%, respectively, and those obtained using bootstrap and leave-one-out validation methods were 64, 87, 77 and 91%, respectively (Manickavasagan et al., 2010). Hyperspectral imaging systems have been used for accurate and reliable discrimination among varieties of maize seeds (Zhang et al., 2012), for classification of four varieties of maize seeds in different years (Huang et al., 2016), for identification of wheat varieties (Choudhary et al., 2009; Zhu et al., 2012), for differentiation of wheat classes grown in western Canada (Mahesh et al., 2008) and for differentiation among varieties of rice (Kong et al., 2013). Some of these applications have achieved a classification accuracy of 100%. Hyperspectral imaging has also been used by several researchers for hardness classification of maize (Williams et al., 2009; McGoverin et al., 2011). Recently, hyperspectral imaging has been used to distinguish among transgenic soybeans (Esteve Agelet et al., 2012) and rice (Liu et al., 2014). Similarly, a NIRS technique has been used to distinguish among herbicide-resistant genetically modified soybean seeds (Lee and Choung, 2011). It has also been demonstrated that multispectral imaging technique can be used to distinguish transgenic- from non-transgenic rice seeds (Liu et al., 2014).

Quality assessment of seeds: seed viability

A good-quality seed is one that is capable of germination under various conditions. A non-viable seed is one that fails to germinate even under optimal conditions (Bradbeer, 1988). In recent years, non-destructive techniques, mainly spectroscopy and hyperspectral imaging, have been widely used to predict seed viability (Table 4). A machine vision system was used to predict alfalfa and sativa seed germinability using the RGB (red, green, blue) density value with correlation coefficients of 0.982 and 0.984 for alfalfa and sativa, respectively (Behtari et al., 2014). Researchers have also studied soybean and snap bean seed germinability using electric impedance spectroscopy in the frequency range of 60 Hz to 8 MHz (Vozáry et al., 2007). Recently, spectroscopy has been used to distinguish viable gourd (Min and Kang, 2003), cucumber (Mo et al., 2012), patula pine (Tigabu and Odén, 2003), watermelon and pepper seeds (Lohumi et al., 2013; Seo et al., 2016) from their non-viable counterparts, to assess corn seed viability (Ambrose et al., 2016) and to predict the viability of cabbage and radish seeds (Shetty et al., 2011). Most of these studies have reported accuracies of more than 90% in viable seed identification. Hyperspectral imaging systems have also been used for accurate and reliable discrimination of viable and non-viable seeds of corn (Ambrose et al., 2016), radish (Ahn et al., 2012), watermelon (Bae et al., 2016) and pepper (Mo et al., 2014) with accuracies of 95.6, 95, 84.2 and 99.4%, respectively. Recently, a hyperspectral fluorescence imaging technique was used to extract the
### Table 3. Assessment of variety identification and classification in seeds using different non-destructive techniques

<table>
<thead>
<tr>
<th>Variety classification/identification</th>
<th>Seed</th>
<th>Method</th>
<th>Feature(s)/spectra region (nm)</th>
<th>Analysis method(s)</th>
<th>Result</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grading</td>
<td>Bean</td>
<td>Machine vision</td>
<td>Size, colour</td>
<td>ANN</td>
<td>69.1–99.3%</td>
<td>Kiç et al., 2007</td>
</tr>
<tr>
<td>Variety identification</td>
<td>Bean</td>
<td>Machine vision</td>
<td>Morphology</td>
<td>LDA</td>
<td>82.4–100%</td>
<td>Venora et al., 2009</td>
</tr>
<tr>
<td>Variety classification</td>
<td>Corn</td>
<td>Machine vision</td>
<td>Morphology, colour, shape</td>
<td>MLP and Neuro-Fuzzy</td>
<td>94%, 96%</td>
<td>Pazoki et al., 2013</td>
</tr>
<tr>
<td>Variety identification</td>
<td>Corn</td>
<td>Machine vision</td>
<td>Morphology, colour</td>
<td>SVM</td>
<td>97.3–98%</td>
<td>Jingtao et al., 2012</td>
</tr>
<tr>
<td>Variety identification</td>
<td>Maize</td>
<td>Machine vision</td>
<td>Morphology</td>
<td>–</td>
<td>81.9%</td>
<td>Yi et al., 2007</td>
</tr>
<tr>
<td>Variety identification</td>
<td>Maize</td>
<td>Machine vision</td>
<td>Geometric, shape, colour</td>
<td>BPNN</td>
<td>88–100%</td>
<td>Chen et al., 2010</td>
</tr>
<tr>
<td>Grading</td>
<td>Maize</td>
<td>Machine vision</td>
<td>Colour</td>
<td></td>
<td>95%</td>
<td>Wu et al., 2013</td>
</tr>
<tr>
<td>Variety identification</td>
<td>Maize</td>
<td>Machine vision</td>
<td>Geometric, shape, colour</td>
<td></td>
<td></td>
<td>Zhang et al., 2012</td>
</tr>
<tr>
<td>Variety identification</td>
<td>Maize</td>
<td>Hyperspectral imaging</td>
<td>380–1030</td>
<td>PCA, KPCA, LS-SVM, ANN</td>
<td>98.89%</td>
<td></td>
</tr>
<tr>
<td>Hardness</td>
<td>Maize</td>
<td>Hyperspectral imaging</td>
<td>1000–2500</td>
<td>PCA</td>
<td></td>
<td>McGovern and Manley, 2012</td>
</tr>
<tr>
<td>Hardness</td>
<td>Maize</td>
<td>Hyperspectral imaging</td>
<td>960–2498</td>
<td>PCA, PLSDA</td>
<td>RMSEP = 0.18, 0.29</td>
<td>Williams et al., 2009</td>
</tr>
<tr>
<td>Variety classification</td>
<td>Maize</td>
<td>Hyperspectral imaging</td>
<td>400–1000</td>
<td>LS-SVM</td>
<td>94.40%</td>
<td>Huang et al., 2016</td>
</tr>
<tr>
<td>Varieties discrimination</td>
<td>Pepper</td>
<td>Machine vision</td>
<td>Colour, shape and texture</td>
<td>ANN</td>
<td>84.94%</td>
<td>Kurtulmuş et al., 2016</td>
</tr>
<tr>
<td>Variety classification</td>
<td>Rapeseed</td>
<td>Machine vision</td>
<td>Colour</td>
<td>ANN</td>
<td>92.06–100%</td>
<td>Li et al., 2007</td>
</tr>
<tr>
<td>Varieties classification</td>
<td>Rice</td>
<td>Machine vision</td>
<td>Colour, texture</td>
<td>ANN</td>
<td>96.67%</td>
<td>Rad et al., 2011</td>
</tr>
<tr>
<td>GM, non-GM</td>
<td>Rice</td>
<td>Hyperspectral imaging</td>
<td>405–970</td>
<td>PCA, PLSDA, LS-SVM, PCANN</td>
<td>94–100%</td>
<td>Liu et al., 2014</td>
</tr>
<tr>
<td>Variety identification</td>
<td>Rice</td>
<td>Hyperspectral imaging</td>
<td>1039–1612</td>
<td>PLSDA, SIMCA, RF, KNN, SVM, PCA</td>
<td>80–100%</td>
<td>Kong et al., 2013</td>
</tr>
<tr>
<td>Varieties classification</td>
<td>Rice</td>
<td>Machine vision</td>
<td>Morphological, colour, texture</td>
<td>KNN, SVM, RF</td>
<td>90.54%</td>
<td>Hong et al., 2015</td>
</tr>
<tr>
<td>GM, non-GM</td>
<td>Soybean</td>
<td>Hyperspectral imaging</td>
<td>880–1720</td>
<td>LW-PCR, PCA-ANN</td>
<td>72–79%</td>
<td>Esteve Agelet et al., 2012b</td>
</tr>
<tr>
<td>GM, non-GM</td>
<td>Soybean</td>
<td>Spectroscopy</td>
<td>400–2500</td>
<td>PCA, PLSDA, SIMCA</td>
<td>97%</td>
<td>Lee and Choung, 2011</td>
</tr>
<tr>
<td>Classification</td>
<td>Wheat</td>
<td>Machine vision</td>
<td>Morphology, colour</td>
<td>ANN</td>
<td>95.86%</td>
<td>Arefi et al., 2011</td>
</tr>
<tr>
<td>Classification</td>
<td>Wheat</td>
<td>Machine vision</td>
<td>Texture</td>
<td>LDA</td>
<td>98.15%</td>
<td>Pourreza et al., 2012</td>
</tr>
<tr>
<td>Varieties discrimination</td>
<td>Wheat</td>
<td>Machine vision</td>
<td>Geometric</td>
<td>ANN</td>
<td>99–100%</td>
<td>Zapotoczny, 2011b</td>
</tr>
<tr>
<td>Variety identification</td>
<td>Wheat</td>
<td>Machine vision</td>
<td>Shape, size</td>
<td></td>
<td>84–94%</td>
<td>Dubey et al., 2006</td>
</tr>
<tr>
<td>Varieties discrimination</td>
<td>Wheat</td>
<td>Machine vision</td>
<td>Texture</td>
<td>PCA, LDA, NDA, ANN</td>
<td>98%</td>
<td>Zapotoczny, 2011a</td>
</tr>
<tr>
<td>Variety identification</td>
<td>Wheat</td>
<td>Hyperspectral imaging</td>
<td>850–1700</td>
<td>PCA, SIMCA</td>
<td>90–100%</td>
<td>Zhu et al., 2012</td>
</tr>
<tr>
<td>Varieties discrimination</td>
<td>Wheat</td>
<td>Electronic nose</td>
<td>–</td>
<td>PCA, LDA, BPNN</td>
<td>100%</td>
<td>Zhou et al., 2012</td>
</tr>
<tr>
<td>Varieties discrimination</td>
<td>Wheat</td>
<td>Thermal imaging</td>
<td>–</td>
<td>QDA</td>
<td>64–95%</td>
<td>Manickavasagan et al., 2010</td>
</tr>
</tbody>
</table>
fluorescence spectra of cucumber seeds in the 425–700 nm range to discriminate between viable and non-viable cucumber seeds using four types of algorithms. The discrimination accuracies achieved based on the subtraction image, the ratio image and the ratio-subtraction image were 100 and 99.0% for viable and non-viable seeds, respectively (Mo et al., 2015). Hyperspectral imaging has also been used to classify muskmelon seeds based on germination ability with an accuracy of 94.6%, using a PLS-DA classification algorithm (Kandpal et al., 2016). Hyperspectral imaging in the range of 1000–2498 nm was able to predict the viability of barley, wheat and sorghum seed with correlation coefficients of 0.85, 0.92 and 0.87, respectively (McGoverin et al., 2011). Recently, multispectral imaging has been demonstrated to be a potential technique to evaluate castor seed viability with 96% correct classification rate at 19 different wavelengths ranging from 375 to 970 nm (Olesen et al., 2015). Other studies have been conducted, using multispectral imaging to examine germination ability and germ length in spinach seeds; with the use of PLS-DA of images of spinach seeds it was possible to classify large spinach seeds from small-sized and medium-sized seeds (Shetty et al., 2012). Infrared thermography has also been used to predict whether a quiescent seed will germinate or die upon water uptake, and the technique was reported to be able to detect imbibition- and germination-associated biophysical and biochemical changes (Kranner et al., 2010). A similar technique has been used for viability evaluation of lettuce seeds (Kim et al., 2013) and to evaluate germination capacity of leguminous plant seeds (Baranowski et al., 2003).

**Summary and future trends**

This paper provided an overview of previous studies on seed quality assessment using non-destructive measurement techniques, namely chemical composition (Table 1), insect damage and diseases (Table 2), variety identification and classification (Table 3) and viability (Table 4). Machine vision, spectroscopy, hyperspectral imaging, thermal imaging, electronic nose and soft X-ray imaging are the main techniques to determine seed quality. Among them, spectroscopy and hyperspectral imaging techniques for chemical composition, machine vision, hyperspectral imaging, spectroscopy and soft X-ray imaging for insect and diseases detection, machine vision, thermal imaging and hyperspectral imaging for seed variety identification and classification, and spectroscopy and hyperspectral imaging for viability of seeds has been widely used in research, quality assessment, and for industrial purposes. For this, numerous spectroscopy instruments are commercially available. However, most of the
## Table 4. Assessment of seed viability using different non-destructive techniques

<table>
<thead>
<tr>
<th>Application</th>
<th>Seed</th>
<th>Method</th>
<th>Feature(s)/spectra region (nm)</th>
<th>Analysis method(s)</th>
<th>Result</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classify based on germination ability</td>
<td>Muskmelon</td>
<td>Hyperspectral imaging</td>
<td>948–2494</td>
<td>PLS-DA</td>
<td>94.60%</td>
<td>Kandpal <em>et al.</em>, 2016</td>
</tr>
<tr>
<td>Classify the viable and non-viable seeds</td>
<td>Gourd</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>PLS-DA</td>
<td>96%, 95%</td>
<td>Min and Kang, 2003</td>
</tr>
<tr>
<td>Classify the viable and non-viable seeds</td>
<td>Cucumber</td>
<td>Raman spectroscopy</td>
<td>150–1890 cm⁻¹</td>
<td>PLS-DA</td>
<td>100%</td>
<td>Mo <em>et al.</em>, 2012</td>
</tr>
<tr>
<td>Classify the viable and non-viable seeds</td>
<td>Watermelon</td>
<td>Hyperspectral Imaging</td>
<td>1000–2500</td>
<td>PLS-DA</td>
<td>84.20%</td>
<td>Bae <em>et al.</em>, 2016</td>
</tr>
<tr>
<td>Discriminate the viable and empty seeds</td>
<td><em>Potteda</em> pine</td>
<td>Spectroscopy</td>
<td>400–2498</td>
<td>PLS model</td>
<td>96%, 88%</td>
<td>Tigabu and Odén, 2003</td>
</tr>
<tr>
<td>Discriminate the viable and non-viable seeds</td>
<td>Corn</td>
<td>Hyperspectral Imaging</td>
<td>1000–2500</td>
<td>PLS-DA</td>
<td>95.60%</td>
<td>Ambrose <em>et al.</em>, 2016b</td>
</tr>
<tr>
<td>Discriminate the viable and non-viable seeds</td>
<td>Radish</td>
<td>Hyperspectral Imaging</td>
<td>400–1000</td>
<td>PLS-DA</td>
<td>95%</td>
<td>Ahn <em>et al.</em>, 2012</td>
</tr>
<tr>
<td>Discriminate the viable and non-viable seeds</td>
<td>Pepper</td>
<td>Hyperspectral Imaging</td>
<td>400–700</td>
<td>PLS-DA</td>
<td>99.4%</td>
<td>Mo <em>et al.</em>, 2014</td>
</tr>
<tr>
<td>Discriminate the viable and non-viable seeds</td>
<td>Watermelon</td>
<td>FT-NIR spectroscopy</td>
<td>1000–2500</td>
<td>PLS-DA</td>
<td>100%</td>
<td>Lohumi <em>et al.</em>, 2013</td>
</tr>
<tr>
<td>Discriminate the viable and non-viable seeds</td>
<td>Cucumber</td>
<td>Hyperspectral fluorescence imaging</td>
<td>425–700</td>
<td>SWI</td>
<td>99%, 97%</td>
<td>Mo <em>et al.</em>, 2015</td>
</tr>
<tr>
<td>Discriminate the viable and non-viable seeds</td>
<td>Pepper</td>
<td>FT-NIR spectroscopy, Raman spectroscopy</td>
<td>1400–2400, 1800–970 cm⁻¹</td>
<td>PLS-DA</td>
<td>99%</td>
<td>Seo <em>et al.</em>, 2016</td>
</tr>
<tr>
<td>Measure the seed viability</td>
<td>Corn</td>
<td>FT-NIR spectroscopy, Raman spectroscopy</td>
<td>1000–2500, 170–3200 cm⁻¹</td>
<td>PCA, PLS-DA</td>
<td>100%</td>
<td>Ambrose <em>et al.</em>, 2016a</td>
</tr>
<tr>
<td>Predict the viability of seeds</td>
<td>Barley, wheat, sorghum</td>
<td>Hyperspectral Imaging</td>
<td>1000–2498</td>
<td>PCA, PLS-DA</td>
<td>$R = 0.85$, 0.92, 0.87</td>
<td>McGoverin <em>et al.</em>, 2011</td>
</tr>
<tr>
<td>Predict the viability of seeds</td>
<td>Cabbage, radish</td>
<td>Spectroscopy</td>
<td>1100–2500</td>
<td>ECVA, iECVA</td>
<td>Error: 6–8%, 2–3%</td>
<td>Shetty <em>et al.</em>, 2011</td>
</tr>
<tr>
<td>Predicting the seed germinability</td>
<td>Alfalfa, <em>Sativa</em></td>
<td>Machine vision</td>
<td>RGB density value</td>
<td>–</td>
<td>$R = 0.982$, 0.984</td>
<td>Behtari <em>et al.</em>, 2014</td>
</tr>
<tr>
<td>Predicting the seed germinability</td>
<td>Soybean, snap bean</td>
<td>Electrical impedance spectroscopy</td>
<td>60 Hz–8 MHz</td>
<td>–</td>
<td>$R^2 = 0.27–0.49$, 0.44–0.50</td>
<td>Vozáry <em>et al.</em>, 2007</td>
</tr>
</tbody>
</table>

https://doi.org/10.1017/S0960258516000234

Downloaded from https://www.cambridge.org/core. IP address: 18.236.139.98 on 13 Dec 2021 at 05:48:11, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms.
Non-destructive seed quality measurement

Arefi, A., Motlagh, A.M. and Teimourlou, R.F.

Bala, M. and Singh, M.

Armstrong, P.R., Tallada, J.G., Hurburgh, C.R., Hildebrand, D.F. and Specht, J.E.


Non-destructive seed quality measurement


Vadivambal, R. and Jayas, D.S. (2011) Applications of thermal imaging in agriculture and food industry – a review. *Food and Bioprocess Technology* 4, 186–199.


Fourier transform near-infrared reflectance spectroscopy. 
*Food Science and Biotechnology* **22**, 1495–1500.

Yao, H., Hruska, Z., Kincaid, R., Brown, R.L., Bhatnagar, D. and 


