

# Hyperspectral Imaging Techniques on Optical Sorter for Pea Gluten-Free

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Celiac disease (CD) is a very widespread chronic autoimmune disease that causes the body's immune reaction to the intake of gluten: a protein complex present in many cereals, such as barley, wheat and rye. Gluten free products are increasingly in demand on the market, developing more and more interest.

The main problem encountered for the certification of a gluten free product is the sorting of the product in order to guarantee the elimination of 100% of cereal contaminants. The present study has developed and perfected the use of optical systems based on the hyperspectral image analysis technique in order to be able to uniquely identify some spectral characteristics of the products to be analysed, statistically classifying them and separating them from contaminating products. The hyperspectral images were created with VIS (Visible) and NIR (Near infrared) cameras in opposite positions to acquire the reflected radiation on both side of the product. A statistical classifier was created in order to obtain 100% classification of contaminants and the tests carried out with an industrial plant on pea confirmed the result of having eliminated 100% of contaminants with a non-influential product waste (less than 20%).

## 1. Introduction

Celiac disease is a systemic and chronic autoimmune disease that develops in predisposed subjects. This pathology has seen an increase in incidence especially in recent decades and is now estimated between 0.7% and 2.9% in the population (Gatti et al., 2024), with a higher frequency in women and in well-defined groups. This problem arouses growing interest in buyers interested in health and food safety, looking for niche products such as gluten-free products. To classify a product as gluten-free it is necessary to reduce to low quantities the presence of contaminants that present the gluten proteins present in products such as wheat, barley and rye; in fact, in a gluten-free diet, the daily quantity not to be exceeded for an individual is 10 mg.

The technologies currently in use for the separation of contaminants from the product include mechanical systems that allow the classification of materials based on size and the removal of foreign materials (Cheremisinoff et al., 2000). Artificial vision techniques are used to detect geometric parameters, color and surface defects, but are not able to analyze internal defects (Ariana et al., 2008). The limit of these technologies is a function of the homogeneity of the contaminants; increasing the degree of homogeneity of the final product, increases efficiency. Numerous scientific studies have applied the technique of detecting gluten in foods by means of fluorescence spectroscopy which, although it has a high detection sensitivity, up to 0.006 ppm (Varriale et al., 2007), turns out to be a destructive method that does not allow the analysis of the entire production, since it involves the dissolution of a food sample in a cocktail of enzymes mixed with a concentrated solution of gliadins marked with a fluorescent molecule and the subsequent addition of IgG isolated from mice.

The agri-food industry increasingly requires automated process and control systems in order to ensure continuous control over the process (Perone et al., 2021; Romaniello et al., 2021; Tamborrino et al., 2021).

The technology that has found wide development in recent years for the automation of food processes is hyperspectral imaging (Jiang et al., 2023). Numerous studies have involved horticultural products, Amodio et al., 2020, for oil extraction, Leone et al., 2024, and cereal processing, Romaniello et al., 2023, also showing a low cost of management of the process (Kılıç, et al., 2007; Beghi, et al., 2013; Lee et al., 2013; Mendoza et al., 2018; Wei et al., 2020).

The present study aims to use a non-destructive method (Elmasry et al., 2007) to identify the presence of gluten-containing contaminants in pea and then separate them (with mechanical sorting) of the product, reducing the concentration.

Romaniello et al., 2024, performed experimental tests on legumes: broad bean, chickpea and lentil for gluten-free production, achieving optimal results, with 100% separation of substances containing gluten proteins by identifying the reflectance spectra in the visible and near infrared spectrum (VIS/NIR) of legume products and gluten-containing contaminants, in order to create a statistical classifier able to accurately discriminate between the two types of product, based on the internal physical and chemical properties of the same object (Tang, et al., 2023; Haughey, et al., 2023; Dong, et al., 2023).

The statistical model tested was applied on pea confirming the possibility of discriminating the different products.

## 2. Materials and methods

The classification models previously determined on other legumes with classification results higher than 99% were implemented on an industrial optical calibration machine equipped with VIS/NIR sensors in the wavelength range 400–1700 nm in order to discriminate the contaminants present in the pea samples, according to the experimental plan drawn up.

### 2.1 Industrial Hyperspectral Sorter

The hyperspectral sorting machine (Figure 1a) is composed of independent channels crossed by gravity by the product loaded into the hopper. Each channel (Figure 1b) is equipped with n. 2 near-infrared cameras with scanning speeds of up to 15,000 Hz and an optical resolution of 0.06 mm (60 µm) and n. 2 full-color RGB cameras (front and back) with 4096 pixels that work in the visible spectrum and the inspection system recognizes 16 million colors that combined with an optical resolution of 0.06 mm that detect the parameters set in the selection protocol loaded in the machine's PLC and reject the products identified by the software through compressed air jets controlled by solenoid valves. The outgoing products, depending on the selection performed, are collected in separate containers: compliant products and rejected products.

The PLC that manages the sorting machine was programmed by inserting the algorithm compiled on the basis of the statistical classifier developed in the MATLAB environment.



Figure 1a: Automatic industrial sorter

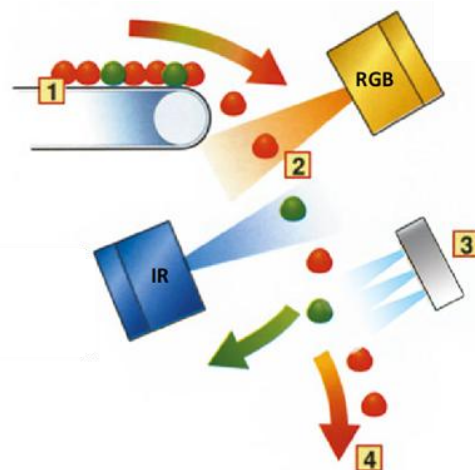


Figure 1b: Scheme of automatic industrial sorter. 1) Vibrating plate, 2) Inclined slide, 3) Compressed air jets 4) Product unloading

## 2.2 Raw material

Homogeneous batches of peas (*Pisum sativum*), Fig. 2, harvested in 2023, were used for the experimental tests. After mechanized harvesting, the peas were sun-dried and stored at a controlled temperature (18°C) in Foggia, Puglia, Italy.



Figure 2: Peas for test

## 2.3 Experimental procedure

The tests, in accordance to experimental plan, were performed with batches of 30 kg of product contaminated as per table 1, with known doses of wheat and stones as further probable contaminants. Each test was repeated 5 times and n. 3 passages of the product inside the sorter.

Table 1 – Sample composition of peas contaminated

Description	Quantity [g]	%	Units
Peas no defects	30,000.00	98.26	-
Peas dotted	243.00	0.80	300
Peas broken	148.20	0.49	240
Stone	101.31	0.33	99
Broad beans	31.50	0.10	90
Caryopses	7.44	0.02	150
<b>Total</b>	<b>30,532.44</b>	<b>100.00</b>	

## 3. Results and discussion

The samples of product were processed by the hyperspectral sorting machine in 3 steps. For each treatment the components that the machine separated were analyzed and verified. The following tables show the quantities of product for the first (table 2), second (table 3) and third passage (table 4) respectively in the sorter.

Table 2 – Sample composition of peas discarded – First selection

Description	Quantity [g]	% of sample	Units	% of contaminant
Peas no defects	2,755.59	9.19	-	-
Peas dotted	95.16	0.32	156	52.00
Peas broken	81.51	0.27	132	55.00
Stones	101.31	0.34	99	100.00
Broad beans	31.50	0.11	90	100.00
Caryopses	7.44	0.02	150	100.00
<b>Total</b>	<b>3,072.51</b>	<b>10.24</b>		

Table 3 – Sample composition of peas discarded – Second selection

Description	Quantity [g]	% of sample	Units	% of contaminant
Peas no defects	1,311.15	4.29	-	-
Peas dotted	24.39	0.08	30	10.00
Peas broken	14.82	0.05	24	10.00
Stones	0.00	0.00	0	0.00
Broad beans	0.00	0.00	0	0.00
Caryopses	0.00	0.00	0	0.00
<b>Total</b>	<b>1,350.36</b>	<b>4.42</b>		

Table 4 – Sample composition of peas discarded

Description	Quantity [g]	% of sample	Units	% of contaminant
Peas no defects	1,743.21	5.81	-	-
Peas dotted	141.51	0.06	174	58.00
Peas broken	87.06	0.29	141	58.75
Stones	0.00	0.00	0	0.00
Broad beans	0.00	0.00	0	0.00
Caryopses	0.00	0.00	0	0.00
<b>Total</b>	<b>1,971.78</b>	<b>6.57</b>		

The selection criteria set on the sorter concerned geometry, color and material type. A correct setting of these parameters allows a good degree of identification and therefore selection of the product.

Analyzing the data reported in the table for the three consecutive product passages inside the sorter, already from the first selection the identification and therefore the separation of 100% of contaminants such as stones, broad beans and caryopses is recorded. The results on pea defects are also encouraging as they allow a substantial reduction of the seeds that present such aesthetic imperfections.

Figure 3 graphically reports the residual trend of the contaminants, highlighting a substantial result after the first passage in the sorter.

Figure 4a and 4b show the results of the selection, respectively the selected peas product and the rejected product with the contaminants.

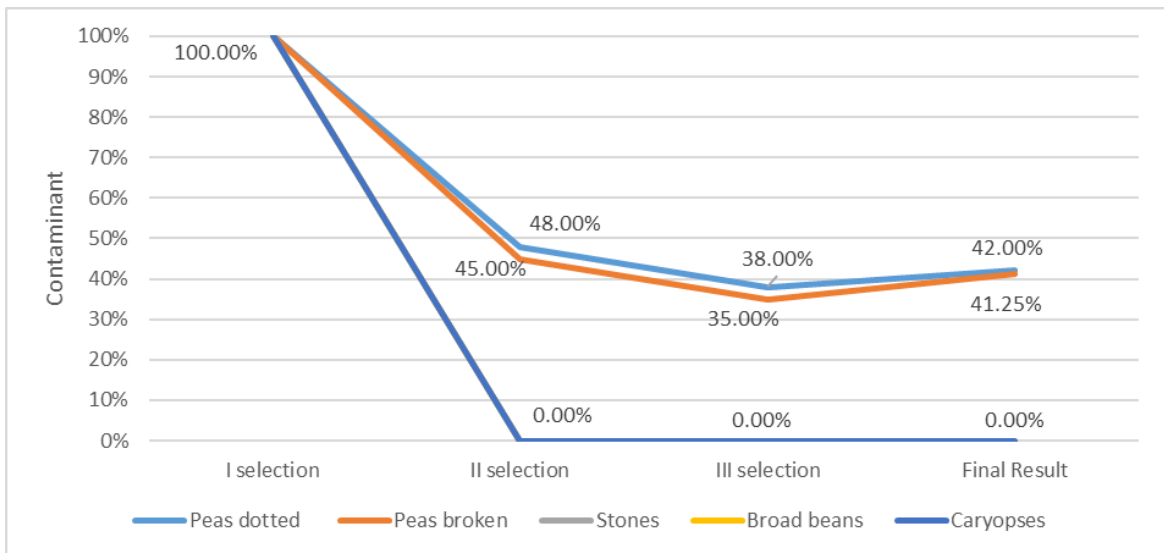


Figure 3: Residual contaminants for peas discrimination

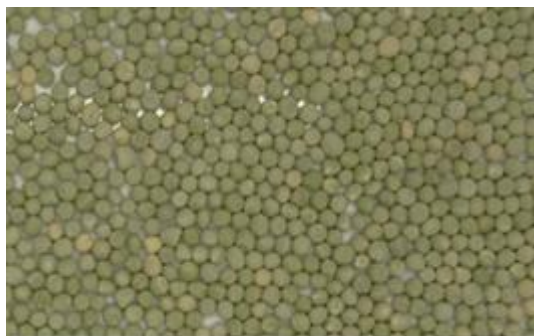


Figure 4a: Peas selected



Figure 4b: Discard

#### 4. Conclusions

The growing sensitivity towards niche products and the ever-increasing spread of Celiac disease among the world population has raised the need to be able to market gluten-free products.

This classification requires very stringent product selection processes that must have a low value of gluten proteins inside it.

Optical selection techniques, in particular hyperspectral imaging, make it possible to perform a non-destructive analysis of the product, with low costs and in real time on the entire product to be processed. The analysis performed with n. 2 near-infrared cameras with scanning speeds of up to 15,000 Hz and n. 2 full-color RGB cameras allows for total screening of the product and therefore the identification of any contaminants or defects on the product itself.

The analysis model, already used for other legumes, has been successfully extended to pea.

This model is based on the geometric, color and chemical analysis of the analyzed product.

The treatment required n. 3 consecutive passes of the product in the sorter, obtaining the elimination of 100% of contaminants such as stones, broad beans and caryopses already in the first pass in the machine, thus allowing to define the product as gluten free. In the two subsequent passes, work continued on the selection of product defects, even if most of them had already been eliminated in the first pass. The low cost, the speed of analysis and selection and the total automation of the process make this type of analysis easy to use in the industrial sector.

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#### References

- Gatti, S., Rubio-Tapia, A., Makharia, G., Catassi, C. (2024) 'Patient and Community Health Global Burden in a World With More Celiac Disease', *Gastroenterology*, Volume 167, Issue 1, Pages 23-33, ISSN 0016-5085, <https://doi.org/10.1053/j.gastro.2024.01.035>.
- Cheremisinoff, N.P. (2000) 'Chapter 6—Mechanical Separation Equipment'. In *Handbook of Chemical Processing Equipment*; Elsevier: Amsterdam, The Netherlands, pp. 334–434. ISBN 9780750671262.
- Ariana, D.P. and Lu, R. (2008) 'Quality evaluation of pickling cucumbers using hyperspectral reflectance and transmittance imaging: Part I. development of a prototype'. *Sens. Instrum. Food Qual. Saf.*, 144–151.
- Varriale, A., Rossi, M., Staiano, M., Terpetschnig, E., Barbieri, B., Rossi, M., and D'Auria, S. (2007) 'Fluorescence correlation spectroscopy assay for gliadin in food'. *Anal Chem.*, 79, 4687–4689.
- Perone, C., Romaniello, R., Leone, A., Catalano, P., and Tamborrino, A. (2021) 'CFD Analysis of a Tubular Heat Exchanger for the Conditioning of Olive Paste'. *Appl. Sci.*, 11, 1858. <https://doi.org/10.3390/app11041858>.
- Romaniello, R., Perone, C., Tamborrino, A., Berardi, A., Leone, A., Di Taranto, A., and Iammarino, M. (2021) 'Additives Individuation in Raw Ham Using Image Analysis', *Chem. Eng. Trans*, 87, 217-222.
- Tamborrino, A., Catalano, F., Berardi, A., and Bianchi, B. (2021) 'New modelling approach for the energy and steam consumption evaluation in a fresh pasta industry'. *Chem. Eng. Trans*. 2021, 87, 409–414.
- Jiang, Z., Lv, A., Zhong, L., Yang, J., Xu, X., Li, Y., Liu, Y., Fan, Q., Shao, Q. and Zhang, A. (2023) 'Rapid Prediction of Adulteration Content in *Atractylodis rhizoma* Based on Data and Image Features Fusions from Near-Infrared Spectroscopy and Hyperspectral Imaging Techniques'. *Foods*, 12, 2904.

- Amodio, M.L., Berardi, A., Ricci, I., Babellahi, F. and Colelli, G. (2020). Use of hyperspectral imaging for the discrimination of artichoke by cultivar and harvest time. *Acta Hortic.* 1284, 165-172 <https://doi.org/10.17660/ActaHortic.2020.1284.22>.
- Leone, A., Berardi, A., Antonelli, G., Dellisanti, C.D., and Tamborrino, A. (2024) 'NIR Spectroscopy for the Online Monitoring of Water and Olive Oil Content in Pomace during the Extraction Process'. *Appl. Syst. Innov.*, 7, 96. <https://doi.org/10.3390/asi7050096>.
- Romaniello, R., Barrasso, A.E., Berardi, A., Perone, C., Tamborrino, A., Catalano, F., and Baiano, A. (2023). 'Hyperspectral Imaging System to Online Monitoring the Soy Flour Content in a Functional Pasta'. *Journal of Agricultural Engineering* 54 (4). <https://doi.org/10.4081/jae.2023.1535>.
- Kılıç, K., Boyacı, H., Köksel, H. and Küsmenoğlu, I. (2007) 'A classification system for beans using computer vision system and artificial neural networks'. *J. Food Eng.* 2007, 78, 897–904.
- Beghi, R., Giovenzana, V., Civelli, R., Cini, E. and Guidetti, R. (2013) 'Characterisation of olive fruit for the milling process by using visible/near infrared spectroscopy'. *J. Agric. Eng.*, 44, e8.
- Lee, H., Cho, B.-K., Kim, M.S., Lee, W.-H., Tewari, J., Bae, H., Sohn, S.-I. and Chi, H.-Y. (2013) 'Prediction of crude protein and oil content of soybeans using Raman spectroscopy'. *Sens. Actuators B*, 185, 694–700.
- Mendoza, F.A., Cichy, K.A., Sprague, C., Goffnett, A., Lu, R. and Kelly, J.D. (2018) 'Prediction of canned black bean texture (*Phaseolus vulgaris* L.) from intact dry seeds using visible/near infrared spectroscopy and hyperspectral imaging data'. *J. Sci. Food Agric.*, 98, 283–290.
- Wei, X., Zheng, W., Zhu, S., Zhou, S., Wu, W. and Xie, Z. (2020) 'Application of terahertz spectrum and interval partial least squares method in the identification of genetically modified soybeans'. *Spectrochim. Acta A Mol. Biomol. Spectrosc.*, 238, 118453.
- Romaniello, R., Barrasso, A.E., Perone, C., Tamborrino, A., Berardi, A. and Leone, A. (2024) 'Optimisation of an Industrial Optical Sorter of Legumes for Gluten-Free Production Using Hyperspectral Imaging Techniques'. *Foods*, 13, 404. <https://doi.org/10.3390/foods13030404>.
- Tang, X., Rao, L., Xie, L., Yan, M., Chen, Z., Liu, S., Chen, L., Xiao, S., Ding, N. and Zhang, Z. (2023) 'Quantification and visualization of meat quality traits in pork using hyperspectral imaging'. *Meat Sci.*, 196, 109052.
- Haughey, S.A., Montgomery, H., Moser, B., Logan, N. and Elliott, C.T. (2023) 'Utilization of Hyperspectral Imaging with Chemometrics to Assess Beef Maturity'. *Foods*, 12, 4500.
- Dong, F., Bi, Y., Hao, J., Liu, S., Yi, W., Yu, W., Lv, Y., Cui, J., Li, H. and Xian, J. (2023) 'A new comprehensive quantitative index for the assessment of essential amino acid quality in beef using Vis-NIR hyperspectral imaging combined with LSTM'. *Food Chem.*, 440, 138040.
- Elmasry, G., Wang, N., Elsayed, A. and Ngadi, N. (2007) 'Hyperspectral imaging for non-destructive determination of some quality attributes for strawberry'. *J. Food Eng.*, 81, 98–107.