Optical grain sorting machines: review of principles of operation and classification

Dmytro Galka, Andrii Sharan

National University of Food Technologies, Kyiv, Ukraine

Keywords:

Grain
Sorting machine
Optical
Impurities
Classification

Article history:

Received 18.05.2025
Received in revised form 23.10.2025
Accepted 31.12.2025

Corresponding author:

Dmytro Galka
E-mail: dima.halka@gmail.com

DOI:
10.24263/2310-1008-2025-13-2-12

Abstract

Introduction. This review summarizes the operating principles and current engineering solutions of Optical Grain Sorting Machines and synthesizes a practical classification to support equipment selection and process tuning for specific crops and quality and safety targets.

Materials and methods. A staged literature search and screening workflow was applied in Web of Science, Scopus, and Google Scholar using Ukrainian and English keyword combinations and predefined relevance criteria, with a primary focus on 2010-2025 publications. The selected evidence was then extracted and systematized to synthesize a generalized classification of Optical Grain Sorting Machines.

Results and discussion. Optical Grain Sorting Machines can be described as a set of functional subsystems: feeding/stream formation, optical acquisition, decision making, rejection and routing, cleaning/diagnostics, and control/integration. Sorting grain targets fall into distinct groups, separating defective kernels from plant, mineral, technogenic, and biological contaminants. Optical Grain Sorting Machines can be compared within a single multidimensional classification defined by six axes: sorting type, structural design and flow handling, automation/intelligent-control level, application focus, crop specificity, and optical-system characteristics. Sorting cues are summarized in a feature taxonomy that links each target group to practical indicators. It covers color/spectral, shape/size (morphometric), texture/surface-defect, and internal/chemical signatures, and also accounts for how cues are observed (surface vs. volumetric; static vs. dynamic) and how they are used in decisions (primary, auxiliary, indicator). This framework makes commercial solutions easier to compare and helps justify sensor and spectral-channel selection for a given crop and impurity profile.

Conclusion. Optical Grain Sorting Machines are a strategically important final-stage technology for quality and safety assurance in grain processing, and the proposed multidimensional classification provides a practical basis for selecting sensor modalities, machine design, and control settings according to the crop, defect types, and target performance indicators.

ISSN: 2409-4951 (Online), 2310-1008(Print)

Introduction

The problem of grain cleaning

During harvesting, transportation, and primary processing, grain lots inevitably contain impurities and a fraction of defective kernels that enter the stream together with the base crop. Even after preliminary cleaning, some problematic material remains because it is physically similar to sound grain or because defects are not visible in bulk handling (Pascale et al., 2022).

This is critical because residual impurities and defective kernels reduce commercial quality, increase wear and maintenance of processing equipment, and, most importantly, can compromise safety when fungal infection and mycotoxin contamination are present even at low levels. As a result, the risk is not limited to downgraded product grade but may extend to exceeding regulatory limits for hazardous compounds (Femenias et al., 2022; Freitag et al., 2022; Kos et al., 2023; McMullin et al., 2015).

Conventional mechanical cleaning is highly effective for removing impurities that differ markedly in size, density, or aerodynamic properties, yet it cannot reliably separate kernels and inclusions that closely match the base crop in mass and geometry, nor can it assess internal or early-stage defects (Abdullayev and Huseynzade, 2025). Therefore, more selective approaches based on optical features (color, texture, fluorescence, and spectral response) are required to detect and remove subtle defects and hazardous contaminants that remain beyond the resolution of purely mechanical separation (Ageh et al., 2025).

Advantages of optical sorting methods

Optical sorting belongs to a group of methods that operate not on the integral mass-geometric characteristics of kernels, but on their optical and morphological features (Abdullayev and Huseynzade, 2025; Yang et al., 2025). Unlike conventional mechanical cleaning-where the decision to remove a particle is based on its size, density, or aerodynamic properties-optical sorters analyze color, brightness, spectral reflectance, surface texture, and grain shape in real time (Abdullayev and Huseynzade, 2025; Feng et al., 2019; Zhu et al., 2021). This enables the detection and removal of problematic kernels that are virtually indistinguishable from sound grain in terms of mass and geometric parameters, yet exhibit characteristic visual or spectral differences (discoloration, darkening, localized spots, signs of micromycete infection) (Femenias et al., 2022; Feng et al., 2019; Kecskes-Nagy et al., 2016).

A key advantage of optical methods is their high selectivity toward specific groups of impurities and defective kernels (Abdullayev and Huseynzade, 2025; Yang et al., 2025). Depending on the configuration of illumination sources and sensors, the machine can respond to changes in the visible range, the near-infrared (NIR) region (Abdullayev and Huseynzade, 2024), the ultraviolet region, as well as to fluorescence and other specific optical effects, including polarization-dependent reflectance, differences in angular scattering, the specular component (gloss), and effects associated with translucency and surface microstructure (Feng et al., 2019; Masilamani et al., 2020). This enables the targeted removal of kernels with an elevated risk of mycotoxicosis, sprouted kernels, kernels with a darkened germ, as well as specific types of plant, mineral, or artificial contaminants that differ in color or spectral signature but are not always detectable at the mechanical cleaning stage (Carmack et al., 2019; Femenias et al., 2022; Graves et al., 1998; Jia et al., 2020; Kecskes-Nagy et al., 2016; Pearson et al., 2009).

Another important advantage is the inherent “kernel-by-kernel” decision-making paradigm. Each kernel or particle within the optical system’s field of view is analyzed individually, and the rejection decision is made based on a selected set of features and predefined thresholds (Feng et

ISSN: 2409-4951 (Online), 2310-1008(Print)

al., 2019; Yang et al., 2025; Zhu et al., 2021). In practice, this not only reduces the proportion of undesirable components in the target product, but also enables more precise control of sound-grain losses by adjusting the trade-off between cleaning intensity and acceptable losses (Carmack et al., 2019; Kecskes-Nagy et al., 2016). Optical sorters often support multiple sorting modes (e.g., "main product - reject - rework"), enabling flexible redistribution of streams according to the requirements of a given process (Abdullayev and Huseynzade, 2025; Yang et al., 2025).

A major advantage of modern optical systems is their programmability and adaptability (Abdullayev and Huseynzade, 2025; Maier et al., 2024). Changing the crop, target product, or end-quality requirements typically does not require equipment replacement, but rather adjustment of software settings, such as color- or spectrum-based sensitivity regions, trigger thresholds, and masks for analyzing specific kernel areas. This significantly reduces line changeover time when switching between crops (e.g., wheat-barley-maize-rice) and allows the same hardware platform to be used across a wide range of processing tasks (Abdullayev and Huseynzade, 2025; Zareiforoush et al., 2015).

From a resource-efficiency perspective, optical sorting provides additional opportunities to improve the efficiency of raw material utilization (Maier et al., 2024). First, it enables reductions in losses of sound grain by more precisely removing impurities and defective kernels that were previously separated together with a portion of the good fraction by coarse mechanical methods (Cujbescu et al., 2023; Kautzman et al., 2015). Second, reducing the content of problematic kernels in a batch at early stages of the process chain helps avoid unproductive costs associated with further processing of off-spec raw material and decreases the load on cleaning facilities and finished-product quality control systems (Delwiche et al., 2005; Dowell et al., 2002). Third, the ability to selectively separate specific fractions (e.g., severely infected or discolored kernels) creates potential for their dedicated utilization or disposal in the safest manner (Abdullayev and Huseynzade, 2025; Carmack et al., 2019; Yang et al., 2025).

Finally, modern optical sorters integrate naturally into the concept of digitalization in food technologies. Most industrial machines are equipped with tools for recording sorting statistics, transmitting data to supervisory control systems, and enabling remote monitoring and configuration (Abdullayev and Huseynzade, 2025; Rakipov et al., 2025). This transforms optical sorting not only into a tool for the physical cleaning of grain, but also into a real-time source of information on raw material quality, which should be taken into account when developing integrated resource-saving grain-processing technologies (Abdullayev and Huseynzade, 2025; Rakipov et al., 2025).

The aim of this review is to synthesize the physical principles and contemporary technical solutions of optical grain sorting and to develop generalized classifications of Optical Grain Sorting Machines and the optical features used to discriminate kernels from impurities. The study integrates scientific literature with evidence from industrial equipment and proposes an original multidimensional framework derived from the analysis of commercial sorter models.

Materials and methods

Approach to structuring the literature review

The review was conducted in a staged manner and included: searching for scientific sources, initial screening against formal criteria, in-depth content assessment, systematization and synthesis of the retrieved data, and the development of a classification of optical grain sorting machines. The search and selection strategy was designed in accordance with recommendations for scoping and systematic reviews reported by M. D. J. Peters and A. Carrera-Rivera (Carrera-

ISSN: 2409-4951 (Online), 2310-1008(Print)

Rivera et al., 2022; Peters et al., 2021), with adaptation to the applied engineering specificity of optical grain sorting.

The literature search was performed using keywords and their combinations in Ukrainian and English across bibliographic and full-text databases, including Web of Science, Scopus, Google Scholar, as well as other available electronic resources. Search queries were structured to cover the key directions of the review: (1) the design, architecture, and operating principles of optical grain sorters (including the feeding unit, inspection zone, and rejection system); (2) sensing and illumination systems and optical/spectral inspection approaches; (3) optical features of impurities and kernel defects; and (4) algorithmic data-analysis methods - image processing, spectral analysis, machine learning, and deep learning - for automated recognition of objects in grain streams.

The formal criteria for the initial screening included the publication type (original research articles and reviews), thematic relevance to sorting in grain streams, absence of duplicates, and availability of the full text (open access or via institutional resources). During the in-depth assessment, priority was given to studies that concurrently reported experimental results (sorting performance/quality metrics), described the equipment design and operating principle, and detailed the features and methods used to discriminate grain kernels, impurities, and defective components.

The primary body of sources was limited to the period 2010-2025, which captures the current state of development of optical systems and data-analysis algorithms for sorting tasks. Publications published before 2010 were included when they were foundational to specific aspects of the topic (in particular, historical background and the evolution of optical sorters) and lacked fully comparable, more recent counterparts. To broaden the set of relevant sources, the reference lists of the selected publications were also screened, which enabled the identification of additional studies and reduced the risk of missing important work.

Approach to developing a generalized classification of machines

The development of a generalized classification of optical grain sorting machines and optical features was conducted as a separate stage of the study, grounded in the compiled body of literature. The underlying assumption was that no single criterion (e.g., spectral range alone or conveying system type alone) can fully capture the diversity of design and functional solutions; therefore, the classification was designed to be multidimensional. For each machine model, a combination of attributes was analyzed, including sorting type (color-based; color-and-shape; color-and-spectral properties), the feeding method and grain-stream formation, the level of automation, the intended application, the operating spectral range and sensor type, and the target crops. The key grouping criteria and the concept of the generalized classification were previously presented and discussed in conference papers (Galka and Sharan, 2025a, 2025b).

In the first stage, models were grouped according to similar design and operational characteristics, identifying "prototype" machine configurations (chute-fed, belt-based, and hybrid; mono- and multispectral; laboratory and industrial, etc.). In the second stage, a "cross-cutting" analysis was performed to determine how consistently the same models were assigned to the same groups under different criteria and to identify the attributes that proved most informative for characterizing differences between equipment classes. As a result, several complementary dimensions of the classification were established: sorting type; design features and stream-handling approach; level of automation; application focus; optical-system characteristics; and orientation toward specific cereal crops.

A similar approach was applied to the classification of optical features. Based on descriptions in scientific publications and technical documentation, the features used to discriminate grain

ISSN: 2409-4951 (Online), 2310-1008(Print)

kernels and impurities were first grouped into broad categories according to their physical nature (color-spectral, morphometric, textural, surface-defect features, and internal/chemical features). The classification was then refined by considering the observation modality (surface vs. volumetric; static vs. motion-dependent) and the role of each feature in decision-making (primary, auxiliary, or indicative). The final classifications of machines and features represent an authorial proposal that synthesizes the available evidence and provides a structured framework for further research and for practical selection of optical sorters.

Results and discussion

Historical aspects of the development of optical grain sorting machines

Before the advent of mechanized cleaning systems, impurities and defective kernels were removed predominantly by manual picking, which was associated with high labor intensity and subjective quality assessment (Xu et al., 2024; Yang et al., 2025). The earliest attempts to mechanize the conditioning of grain mass relied exclusively on mechanical and pneumatic principles (Olkhovskyi and Dudarev, 2021). In industrial practice, fan-based and screen (sieve) separators gradually became established, combining the effects of gravity, air flows, and geometric separation on sieves (Aliev, 2020; Olkhovskyi and Dudarev, 2021). Subsequently, these devices evolved into multi-stage grain-cleaning units incorporating vibrating sieves, adjustable aspiration, and gravity tables (Kharchenko et al., 2024). However, even advanced mechanical process schemes retained a fundamental limitation: they could not reliably remove impurities and defective kernels similar in size and mass to the main fraction, which motivated a shift toward alternative physical sorting principles, including optical methods (Abdullayev and Huseynzade, 2025; Carmack et al., 2019; Kozłowski et al., 2024; Maier et al., 2024; Pascale et al., 2022; Yang et al., 2025).

Early attempts to exploit optical properties of materials in food technologies involved simple photoelectric devices capable of distinguishing only the presence or absence of an object or coarse color differences (He et al., n.d.; Inamdar and Suresh, 2014). In the 1930s-1940s, industrial machines emerged that employed selective color-based recognition for sorting seeds, peas, and legumes; during this period, the first photoelectric sorters with vacuum-tube components and rudimentary threshold-trigger circuits were described in Europe and North America (Yang et al., 2025). Such solutions include early photoelectric sorters developed in the 1930s, in which individual particles sequentially passed through the inspection zone of a photoelectric sensor and the resulting signal actuated a reject mechanism, as well as early UK serial machines developed by Gunson's SORTEX (founded in 1947), such as the G1 electronic separator used for sorting peas and beans, which laid the groundwork for later grain-sorting machines (Abdullayev and Huseynzade, 2025). Although their throughput and reliability were limited, these developments laid the groundwork for the subsequent advancement of machine "vision" in post-harvest grain processing (Abdullayev and Huseynzade, 2025; Maier et al., 2024).

Further technological progress in the 1950s-1960s was associated with the emergence of more sensitive photoelectric sensors, improvements in illumination systems, and a transition from purely laboratory setups to industrial continuous-operation separators (Pasikatan and Dowell, 2001; Yang et al., 2025). Manufacturers began the mass production of color sorters for rice, coffee, and legumes, and subsequently for cereal grains (Abdullayev and Huseynzade, 2025). This period was characterized by the use of narrow-band optical filters and multiple photoelectric sensors tuned to monitor specific spectral bands, enabling, for example, the separation of darkened or discolored kernels from the bulk grain stream (Pasikatan and Dowell, 2001). Nevertheless, the

ISSN: 2409-4951 (Online), 2310-1008(Print)

systems remained single-channel or dual-channel, and the analysis was limited to an integral signal from a small area of the kernel surface (Pasikatan and Dowell, 2001; Yang et al., 2025).

Already at the early stages of optical sorting technology development, specific tasks were formulated specifically for cereal grains (Maier et al., 2024; Pasikatan and Dowell, 2001). A classic example is the removal of ergot from rye seed, where conventional mechanical methods proved inefficient due to the similar size and mass of kernels and sclerotia, whereas differences in coloration enabled reliable separation of these components based on optical features (Pasikatan and Dowell, 2001). Another important direction was the sorting of seed by germination capacity and the degree of disease infestation, while in breeding practice, color traits (e.g., red- and green-kernel forms of wheat and other crops) were used for automated selection of desirable genotypes (Carmack et al., 2019; Cujbescu et al., 2023).

A defining stage in the development of modern optical grain sorting systems was the 1980s-1990s, when advances in microelectronics, the introduction of digital array cameras, and the widespread adoption of digital image-processing methods enabled the creation of high-throughput and reliable machines with automated grain quality assessment (Abdullayev and Huseynzade, 2025; Yang et al., 2025). It became possible to analyze not only the mean brightness level, but also the spatial distribution of color, as well as the shape and orientation of kernels (Pearson, 2010; Pearson et al., 2012; Xie et al., 2004). During this period, a specialized class of machines emerged for sorting wheat, maize, barley, rice, and oilseed crops (Abdullayev and Huseynzade, 2025; Yang et al., 2025). Multichannel systems combining the visible and near-infrared ranges were introduced, enabling assessment of surface condition and, to some extent, the internal structure of kernels (Haff et al., 2013; Pearson et al., 2013a; Peiris and Dowell, 2010).

At the beginning of the 21st century, optical sorting technology gained new momentum due to advances in high-speed processors, LED illumination sources, and digital image-processing algorithms (Ageh et al., 2025; Maier et al., 2024). Commercially available multi- and hyperspectral systems emerged, capable of recording the reflectance or transmittance spectrum of each particle across numerous narrow wavelength bands (Ageh et al., 2025; Femenias et al., 2022; Haff et al., 2013; Li et al., 2022). This substantially expanded the ability to sort based on latent defects, signs of microbiological infection, changes in chemical composition, and related factors, particularly when combined with machine-learning and deep-learning methods (Femenias et al., 2022; Min and Cho, 2015). During the same period, "intelligent" grain sorters entered the market, integrating multiple sensor modalities (RGB, NIR, UV, fluorescence) and supporting adaptive tuning of rejection criteria tailored to specific crops and processing objectives (Armstrong et al., 2016; Maier et al., 2024).

The accumulation of these technical solutions has led to the emergence of modern approaches to classifying optical grain sorting machines by sensor type, the number and spectral range of channels, and the image-analysis algorithms implemented. Thus, the historical development of optical grain sorting machines can be viewed as a transition from simple photoelectric devices to complex multichannel machine-vision systems. Each stage of this evolution was accompanied by broader spectral capabilities, higher spatial resolution, and increasingly sophisticated image-analysis algorithms, which gradually transformed optical sorting into a key tool within resource-efficient technologies for grain cleaning and preparation for processing.

Typical design and operating principle of optical grain sorting machines

The operating principle of optical grain sorting machines can be described as implementing a "kernel-by-kernel" strategy: each particle passing through the inspection zone is captured by optical sensors, the acquired image or spectral response is analyzed in real time, and the control

ISSN: 2409-4951 (Online), 2310-1008(Print)

system then compares the measured feature set against predefined quality criteria to issue a reject or accept command (Dowell et al., 2007; Pearson, 2009, 2010; Pearson et al., 2013a).

A typical optical grain sorter comprises a set of functional subsystems that ensure the successive stages of the process. In general, the machine includes: (1) a feeding system for forming a stable monolayer or controlled grain stream (Kleinhans et al., 2022; Nordell, 1997); (2) an optical module (illumination and acquisition sensors) (Bühler AG, 2016a; Maier et al., 2024); (3) an image-processing and decision-making unit (feature extraction, classification, and synchronization) (Abdullayev and Huseynzade, 2025; Maier et al., 2024); (4) a rejection system and the routing of trajectories/channels for fraction discharge (predominantly pneumatic) (Bühler AG, 2016a, n.d.; Satake Corporation, n.d.); (5) systems for cleaning the optics and working assemblies, diagnostics, and maintenance (Bühler AG, 2016a, 2016d; Satake Corporation, n.d.); (6) a control system and operator interface for setting operating modes, monitoring parameters, and integrating the machine into the processing line (Bühler AG, 2016a; Folgado et al., 2024; TOMRA Sorting, n.d.).

Table 1 summarizes these subsystems, their primary functions, key parameters that govern sorting performance, and typical operational issues. Importantly, overall efficiency is determined not only by the optical module and classification algorithm, but also by the stability of grain-stream formation and the timing accuracy of the rejection actuation, which jointly define the achievable selectivity and product loss.

Table 1

Optical grain sorting machines subsystems

Subsystem	Main function	Adjustable parameters
Feeding	Forms a stable monolayer grain stream with minimal overlap and predictable motion	Feed rate; vibration frequency & amplitude; chute angle; belt speed; stream thickness and uniformity across width
Optical	Illumination and optical information capture	Wavelength (RGB/NIR/UV); illumination intensity/stability; camera resolution; exposure; optics alignment; background/contrast
Image-processing and decision making	Extracts features, classifies accept/reject, and synchronizes decision with actuation	Feature set; decision thresholds; model type (rules/ML/DL); processing latency; trigger alignment; sampling rate
Rejection system and fraction routing	Removes detected objects and directs fractions into separate channels	Air pressure; valve opening time; nozzle pitch; activation window; geometry of chutes/hoppers; number of fractions
Maintenance	Keeps optics and assemblies functional; supports self-checks and planned maintenance	Observed parameters; wiper cycles; cleaning schedule; diagnostics coverage; event logs; logs throttling
Control and Operator Interface	Coordinates subsystems, sets modes/recipes, monitors parameters, and integrates into the processing line	Operating modes/recipes; interlocks; communications with upstream/downstream equipment; logging & traceability; remote diagnostics (if available)

Each subsystem is described in detail below.

ISSN: 2409-4951 (Online), 2310-1008(Print)

Feeding and grain-stream formation system. The feeding system is responsible for conveying grain from the receiving hopper to the optical inspection zone and for establishing a particle-motion regime in which each kernel is maximally accessible for sensor observation (Abdullayev and Huseynzade, 2025; Nordell, 1997). A typical feed path includes a loading hopper, a metering device (gate, feeder, or screw), one or more vibratory or belt feeders, distribution chutes, and a working surface (a chute or belt conveyor) (Nordell, 1997). The primary function of this assembly is to transform a chaotic granular flow into an ordered monolayer or quasi-monolayer with minimal particle overlap (Nordell, 1997).

In chute-fed (gravity) machines, grain leaving the vibratory feeder moves along an inclined surface, where the combined action of vibration and gravity forms a thin, spatially extended stream (Pearson, 2010). Chute geometry, inclination angle, and vibration frequency and amplitude are selected to ensure a uniform stream density and to reduce the likelihood of kernels agglomerating into clusters (Nordell, 1997; Tan et al., 2020). A generalized schematic diagram of the chute-type grain sorting machine is shown in Figure 1.

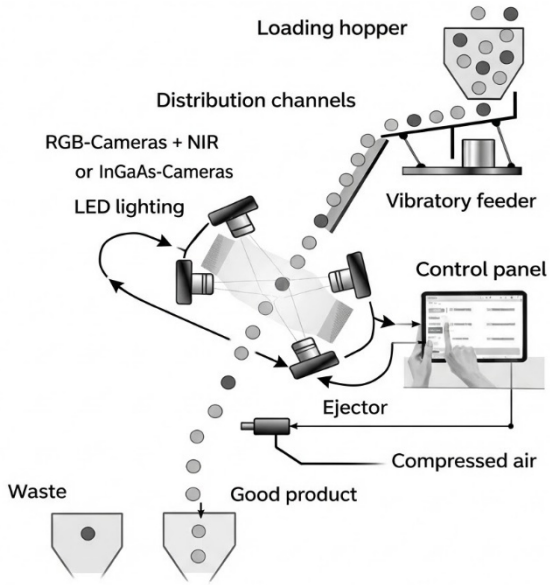

Figure 1. Generalized schematic diagram of the chute-type grain sorting machine

In belt-type machines, the flow is formed on a moving conveyor belt: kernels are arranged into a single layer on a horizontal or slightly inclined surface and then, together with the belt, enter the optical inspection zone (Wallace, 1984). This approach improves the positional stability of particles; however, it requires a more complex mechanical assembly and additional maintenance of the conveyor system (Wallace, 1984). A generalized schematic diagram of the belt-type grain sorting machine is shown in Figure 2.

The key parameters characterizing the performance of the feed system are the uniformity of grain distribution across the flow cross-section, the layer thickness, the particle velocity, and the temporal stability of these indicators (Nordell, 1997; Tan et al., 2020). An excessive layer thickness causes kernels to overlap and leads to loss of information from the lower layers, whereas an overly low flow density reduces the machine's throughput (Dowell et al., 2006; Pearson, 2010; Pearson et al., 2012). Therefore, manufacturers typically provide feed adjustment options by changing the position of gates in the hopper, tuning the vibration

ISSN: 2409-4951 (Online), 2310-1008(Print)

frequency of the feeders, adjusting the chute inclination angle, or varying the belt speed (Nordell, 1997; Tan et al., 2020). In some modern machines, automatic load-control systems are used: based on sensor signals, they regulate the material feed, maintaining an optimal layer thickness for the selected sorting mode (Abdullayev and Huseynzade, 2025; Maier et al., 2024; Pearson et al., 2012).

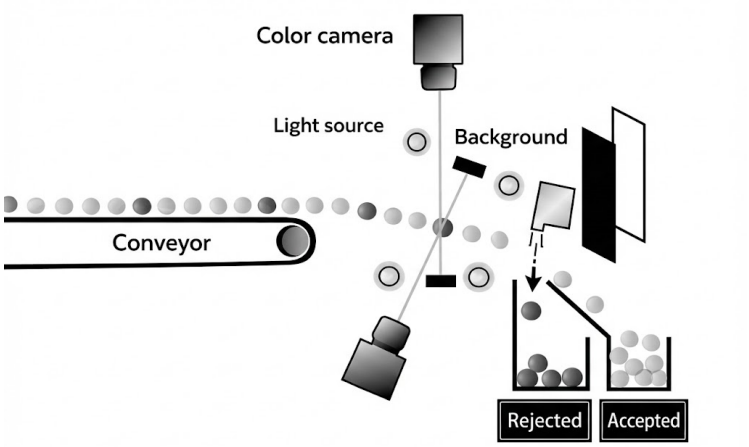

Figure 2. Generalized schematic diagram of the belt-type grain sorting machine

The performance of the feed system directly affects sorting results: a non-uniform flow, local accumulations, or variations in particle velocity complicate optical analysis, increase positioning errors of individual kernels, and reduce the triggering accuracy of reject air nozzles (Tan et al., 2020).

Optical module: illumination and detectors. The optical module of an optical sorter consists of an illumination system and one or more radiation receivers (cameras or other optical sensors) that generate an image or a spectral response for each individual kernel (Abdullayev and Huseynzade, 2025; Ageh et al., 2025). The main task of this subsystem is to ensure stable, reproducible observation conditions under which optical features (color, brightness, spectral reflectance, and surface texture) are maximally contrasted against the background illumination and minimally distorted by external factors (Delwiche, 2008; Haff et al., 2013). The design of the optical module determines the wavelength ranges used for analysis, the spatial resolution at which images are acquired, and how reliably the system can distinguish small defects and subtle differences between kernels (Pearson, 2009; Pearson et al., 2012).

Illumination systems in industrial sorters are predominantly based on light-emitting diode (LED) sources, which provide high intensity stability, low heat generation, and the ability to produce both broadband and narrowband radiation in the visible, near-infrared (NIR), and ultraviolet (UV) ranges (D'Souza et al., 2015; Finardi et al., 2021; Pearson et al., 2013a). In early designs, halogen or xenon lamps with optical filters were used; however, they are gradually being replaced by LED systems due to their longer service life, better spectral controllability, and easier integration with control electronics (Ageh et al., 2025; Delwiche, 2008). The illumination geometry (top, bottom, or angled lighting; combinations of diffuse and

ISSN: 2409-4951 (Online), 2310-1008(Print)

directional light) is selected to reduce specular reflections from smooth surfaces, enhance the contrast of hull defects, and, when required, enable a transillumination mode to assess the internal condition of kernels (Cataltepe et al., 2004b; Wang et al., 2005). To stabilize illumination characteristics, diffusing screens, polarization filters, and optical elements that homogenize the illumination field are often used (Ageh et al., 2025).

Signal acquisition is performed using line-scan or area-scan cameras, sometimes in combination with other sensor types (e.g., NIR detectors or UV receivers) (Ageh et al., 2025; Pearson et al., 2013a; Yao et al., 2023). Line-scan cameras are typically oriented across the flow, and the image is formed by sequentially capturing individual lines as the grain moves; this approach is well suited to chute-type machines with high flow velocities (Ageh et al., 2025; Pearson, 2010). Area-scan cameras are more commonly used in belt sorters, where the motion trajectory is more predictable and each kernel remains in the field of view for a longer time (Ageh et al., 2025; Wallace, 1984). The spatial resolution of the cameras must be sufficient to reliably detect small surface defects and analyze kernel shape, while accounting for the trade-off between detail level and the data volume that must be processed in real time (Ageh et al., 2025; Maier et al., 2024).

In terms of spectral characteristics, optical modules may be single-channel (monochrome) systems with a set of filters, three-channel RGB systems, or multichannel multispectral and hyperspectral cameras (Ageh et al., 2025; Haff et al., 2013; Nansen et al., 2008). RGB systems enable color analysis in three basic channels, which is sufficient for most sorting tasks based on discoloration, darkening, varietal differences, or the degree of surface cleanliness of the grain (Ageh et al., 2025; Pearson et al., 2012). Adding an NIR channel extends the capability to detect internal defects, hidden damage, and differences in chemical composition, since near-infrared reflectance spectra are sensitive to moisture, protein, and fat content, as well as to certain components of cell walls (Dowell et al., 2006; Haff et al., 2013; Jiang, 2020; Siesler et al., 2002). UV and fluorescence channels are used to detect kernels affected by certain micromycete species or foreign impurities that exhibit characteristic fluorescent properties (Ageh et al., 2025; Graves et al., 1998; Min and Cho, 2015; Pearson et al., 2009). Hyperspectral systems, which record dozens to hundreds of narrow spectral bands, are still found mainly in research settings (Nansen et al., 2008; Vejarano et al., 2017; Zhou et al., 2021).

To reduce the impact of random factors (illumination instability, changes in optical contamination, and aging of light sources), optical modules are typically equipped with calibration means: the use of “white” and “black” reference standards, correction of field-of-view non-uniformity, and regular verification of sensor sensitivity (Ageh et al., 2025; Li et al., 2022). Many machines include automated calibration procedures that are initiated when the crop type is changed or after maintenance (Ageh et al., 2025). An important design feature is also whether inspection is performed from one or both sides of the flow: in some sorters, kernels are captured only from the exposed side, whereas other models use dual-side inspection with two rows of cameras, reducing the likelihood of missing defects localized on the opposite surface (Kozłowski et al., 2024; Pearson et al., 2008).

The coordinated operation of the illumination system and sensors determines the quality of the primary data on which all subsequent image-processing algorithms are based. Therefore, developers of optical sorters pay particular attention to selecting spectral ranges, illumination geometry, camera type, and resolution, thereby building into the optical module the potential to implement more advanced analysis and classification methods in downstream system blocks (Abdullayev and Huseynzade, 2025; Yang et al., 2025).

Image-processing and decision-making unit. The image-processing and decision-making unit is the “digital core” of an optical sorter: here, raw data from cameras or other

ISSN: 2409-4951 (Online), 2310-1008(Print)

sensors are transformed into a set of features suitable for classification, and based on these features, a decision is made to reject or accept each individual kernel (Ageh et al., 2025; Maier et al., 2024; Yang et al., 2025). In a typical system architecture, the processing pipeline includes: primary signal processing (normalization, noise filtering, correction for field-of-view non-uniformity), segmentation (separating objects from the background), extraction of informative features (color, spectral, morphometric, textural, and defect-related features), object classification, and generation of control signals for the rejection system (Ageh et al., 2025; Min and Cho, 2015).

At the primary image-processing stage, the main tasks are to compensate for illumination variations, suppress sensor dark noise, and correct non-uniformities in the optical system (Ageh et al., 2025; Feng et al., 2019). For this purpose, various brightness normalization methods are used, including "white" and "black" reference corrections and high-frequency noise filtering (Feng et al., 2019; Gonzalez and Woods, 2017). At the segmentation stage, kernels are separated from the background (e.g., the belt or chute), often using thresholding methods in intensity or color spaces, as well as simple morphological operations to separate touching objects (Gonzalez and Woods, 2017; Pearson et al., 2012). The result is a set of binary masks or contours that define which pixels belong to a specific particle, enabling the transition from the "image" level to the level of "individual objects" (Abbasgholipour et al., 2010; Gonzalez and Woods, 2017).

Feature extraction involves computing, for each kernel, a set of parameters that describe its condition and its deviation from the "reference" product (Haff et al., 2013; Pearson, 2010; Yorulmaz et al., 2011). These parameters include color statistics in different color models (RGB, HSV, etc.), spectral reflectance measures in specific bands, geometric characteristics (area, length, width, aspect ratio, roundness), texture indices (homogeneity, contrast, entropy), as well as local features related to the presence of spots, cracks, darkened regions, and similar defects (Armstrong et al., 2015; Cataltepe et al., 2004b; Pearson, 2010; Pearson et al., 2013a). In many industrial machines, users are given the ability to configure "sensitivity zones"-specific regions of the image for which features are computed (e.g., the germ area or the central part of the endosperm), allowing the system to be finely adapted to the characteristics of a particular crop (Femenias et al., 2022; Haff et al., 2013; Yorulmaz et al., 2011).

Kernel classification is typically implemented by comparing the extracted feature set with predefined thresholds or models corresponding to the classes "acceptable grain," "reject," and sometimes "reprocess" (material requiring additional processing) (Pasikatan and Dowell, 2003; Pearson et al., 2012). In the simplest cases, threshold-based algorithms and rule-based approaches are applied: if the value of a certain indicator (e.g., relative brightness in the "green" channel or fluorescence intensity) falls outside the permissible range, the kernel is assigned to the reject fraction (Yao et al., 2023). More advanced systems use multidimensional threshold regions constructed in feature space or classical machine-learning methods (linear/logistic regression, decision trees, support vector machines, simple neural networks), which better account for interrelationships among different features (Kozłowski et al., 2024; Majumdar and Jayas, 2000a; Santiago et al., 2024).

Modern high-throughput sorters increasingly integrate deep-learning elements for grain image analysis, particularly convolutional neural networks (CNNs) that operate directly on the image or its patches and automatically learn internal feature representations (Hidayat et al., 2023; Santiago et al., 2024). In this case, the image-processing unit includes not only standard preprocessing and segmentation stages but also inference modules of a trained neural network that outputs the probabilities of a kernel belonging to a given class (Fezzai et al., 2023; Zhu et al., 2021). Based on these probabilities, the control system makes the final decision, often with

ISSN: 2409-4951 (Online), 2310-1008(Print)

the option to fine-tune decision thresholds to balance cleaning performance against losses of marketable product (Yang et al., 2025; Yellanki, 2025).

From a technical standpoint, the image-processing and decision-making unit is implemented using embedded industrial controllers, single-board computers, or specialized FPGA/ASIC-based modules, enabling real-time processing of large data streams (Gyaneshwar and Nidamanuri, 2020; Pearson, 2009; VSB Engineering College, India et al., 2020). Strict latency requirements arise because only a very short time elapses between image acquisition and the moment a kernel reaches the actuation zone of the reject nozzle. Therefore, the computational algorithms must be not only sufficiently accurate but also strictly time-deterministic in execution (Pearson, 2009, 2010). To coordinate operation with the actuators, the control system generates a sequence of pulses synchronized with the positions of kernels in the flow, as discussed in more detail in the next subsection.

Rejection system. The rejection system provides the physical separation of the grain stream into the target product and rejects in accordance with the decisions generated by the image-processing unit (Haff et al., 2013; Pearson, 2010; Pearson et al., 2012). In most modern optical grain sorters, pneumatic rejection systems based on compressed-air nozzles are used; short air pulses deflect undesirable particles from the main trajectory (Pearson, 2010; Pearson et al., 2012; Tan et al., 2020). The nozzle arrangement geometry, their number, spacing, and valve opening time are selected with regard to grain velocity and the distance from the optical inspection zone to the rejection zone, in order to maximize jet accuracy on the target kernel and minimize the impact on neighboring particles (Pearson, 2010; Tan et al., 2020).

In chute-type sorters, after passing through the optical analysis zone, the grain follows a ballistic trajectory, and the nozzles are positioned in the lower part of the path so that a compressed-air pulse alters the trajectory of an unwanted particle, diverting it into a separate collection channel (Haff et al., 2013; Pearson, 2010). A key parameter in this case is the delay time between image acquisition and nozzle actuation: it must precisely match the time required for a kernel to travel from the “inspection line” to the “rejection line” (Pearson, 2009, 2010; Tan et al., 2020). To achieve this, the control system uses calibrated flow-velocity values and, in some cases, additional position sensors or synchronization with the camera frame rate (Ageh et al., 2025; Nordell, 1997). Mismatch in these parameters leads to misses (unwanted kernels not being rejected) or excessive removal of good product (Pearson et al., 2012; Tan et al., 2020).

In belt sorters, the rejection zone is typically located near the end of the conveyor belt, where the kernels separate from the belt and enter free flight (Wallace, 1984). The nozzles are oriented to deflect unwanted particles in the vertical or horizontal plane, creating separate trajectories for the main product, rejects, and, if required, an intermediate fraction (reprocess) (Haff et al., 2013; Pearson, 2010). The belt configuration enables better control over the initial motion conditions of particles (speed and direction), which improves rejection accuracy; however, it requires coordinating the pneumatic system with conveyor kinematics and implementing more complex solutions to protect the nozzles from dust and product contamination (Nordell, 1997; Tan et al., 2020; Wallace, 1984).

The operation of the rejection system involves a number of operational trade-offs. Increasing air pressure and pulse duration improves the likelihood of removing unwanted kernels, but it also raises the risk of entraining neighboring, potentially marketable kernels and increases energy consumption (Delwiche et al., 2005; Inamdar and Suresh, 2014; Tan et al., 2020). Conversely, overly short or weak pulses reduce the cleaning efficiency. Therefore, manufacturers provide the ability to adjust pressure, valve opening time, and the nozzle activation “window” depending on the crop, sorting mode, and the desired balance between cleaning performance and losses of the main product (Abdullayev and Huseynzade, 2025;

ISSN: 2409-4951 (Online), 2310-1008(Print)

Pearson, 2010; Tan et al., 2020). In some models, adaptive modes are implemented, where rejection parameters are adjusted based on actuation statistics or feedback from quality-control systems (Kleinhans et al., 2022).

Product trajectories downstream of the rejection zone are arranged using receiving hoppers, chutes, and diverter valves that ensure separate collection of the main product, rejects, and, where applicable, reprocess material (Haff et al., 2013; Nordell, 1997; Wallace, 1984). The receiving channels are designed to minimize cross-contamination of fractions due to ricochets, re-mixing, and secondary dust generation (Nordell, 1997). The quality of flow separation at this stage is no less important than nozzle actuation accuracy, since poor channel geometry can partially negate the advantages of high-precision optical and pneumatic sorting (Nordell, 1997). Overall, the rejection system, together with properly organized product trajectories, determines the final purity of the fractions, the losses of marketable grain, and the energy intensity of the process (Delwiche et al., 2005; Pearson et al., 2012).

Maintenance system. Cleaning systems in optical sorters combine passive and active measures: seals, protective enclosures, and optimized aerodynamics reduce dust deposition on optical components, while compressed-air blow-off, brush/wiper mechanisms, and in some cases washing with drying provide regular cleaning (Bühler AG, 2016a, 2016d); The cleaning modes may be fixed or set by the operator depending on operating conditions and the dust content of the product (Bühler AG, 2016a). In parallel, built-in diagnostics monitor illumination intensity, temperature/humidity, air pressure, nozzle operation, and the state of the electronics, generate warnings for deviations, and often perform self-tests of key modules during startup (Bühler AG, 2016a, 2016d, 2016b).

Service maintenance is supported through the operator interface, which displays event logs, sorting statistics, nozzle actuation counts, operating hours, and other indicators important for planning scheduled maintenance (Bühler AG, 2016a, 2016d). Some manufacturers provide the option of remote access to the machine for diagnostics, software updates, and optimization of settings for specific operating conditions (Bühler AG, 2016b).

Control system and operator interface. The control system coordinates the operation of all units of the optical sorter-from grain feeding and the optical module to the pneumatic rejection system and service subsystems-and synchronizes them with the rest of the processing line equipment (Bühler AG, 2016a; Pearson et al., 2012). Typically, it includes an industrial controller or embedded computer, input/output modules for sensors and actuators, an operator interface (panel/touchscreen or remote access), and communication means for external systems (SCADA, MES) (Bühler AG, 2016a, 2016b; Folgado et al., 2024). Through the control system, operating modes, sorting parameters, acceptance thresholds for optical features, and the logic of interaction with the processing line are configured (e.g., stopping the feed when the allowable reject level is exceeded) (Bühler AG, 2016a; Satake Corporation, n.d.). The operator interface is typically implemented as a graphical menu with “recipes” for different crops and products, specifying color/spectral-response ranges, defect sensitivity, the trade-off between cleaning efficiency and losses of marketable grain, nozzle parameters, and more; the operator can adjust thresholds, enable/disable features, and perform calibration using reference samples (Bühler AG, 2016a). In advanced systems, additional guidance and visualizations are provided-examples of classified kernels and statistical distributions of key features-which simplifies tuning without requiring in-depth knowledge of optical metrology (Bühler AG, 2016a; Satake Corporation, n.d.).

In an integrated processing line, the optical sorter operates as a node within automated production control: it receives signals on the status of upstream and downstream equipment

ISSN: 2409-4951 (Online), 2310-1008(Print)

(hoppers, screw conveyors, bucket elevators, mills, mixers) and transmits data on its own status, throughput, reject fraction, and alarm/warning events (Bühler AG, 2016a; Satake Corporation, n.d.). Via industrial protocols (Modbus, Profibus, Profinet, EtherNet/IP, etc.), its control system is connected to the plant network, enabling scenarios such as automatic feed reduction or shutdown, flow diversion, starting backup lines in the event of a failure, and collecting historical data for analysis (Bühler AG, 2016b; Rakipov et al., 2025). A separate, important aspect is the informational potential: in real time, the machine "sees" grain quality and can serve as a source of operational data on batch-to-batch variability, temporal changes, the appearance of atypical impurities, or signs of contamination (Bühler AG, 2016a; Wang et al., 2013). Integrating these data into monitoring systems enables more flexible management of raw-material flows (e.g., diverting high-risk batches to separate processing or blending) and rapid response to deviations related to suppliers, storage, or weather factors, transforming the sorter from a "local cleaning device" into an active element of the digital infrastructure that supports resource efficiency and stable finished-product quality (Rakipov et al., 2025).

Objects of optical sorting and types of impurities in grain streams.

Objects and impurity classes targeted by optical sorters. Optical sorters do not operate on a "continuous" grain mass but on individual objects passing through the inspection zone: kernels of the base crop, foreign particles, and defective elements of various origins (Maier et al., 2024; Pearson, 2010). For grain processing, it is important not only to reduce the overall impurity content, but also to selectively remove those components that most strongly affect safety, technological properties, and the market quality of the product (Kecskes-Nagy et al., 2016), therefore, it is advisable to use a detailed classification rather than a simple division into "grain" and "impurities". Optical methods make it possible to detect kernels and impurities that are difficult or impossible to reliably separate by mechanical means due to their similarity to the main fraction in size, mass, or density (Aviara et al., 2022; Maier et al., 2024), but that differ in optical, spectral, or morphological characteristics.. In practice, the following groups of objects for optical sorting are typically distinguished: defective and damaged kernels of the base crop; plant impurities (weed seeds, kernels of other crops, and plant residues); mineral impurities; artificial (technogenic) impurities; and biological impurities and manifestations of microbiological contamination - this grouping is then used as a basis for describing optical features and configuring sorting algorithms. (Graves et al., 1998; Jia et al., 2020; Pasikatan and Dowell, 2001).

Defective and damaged kernels of the base crop. Defective and damaged kernels include grains that belong to the base crop (wheat, maize/corn, rice, etc.) but exhibit deviations from the normal morphological or physiological state (Kozłowski et al., 2024; Majumdar and Jayas, 2000a). These may include kernels with hull cracks, shriveled and underdeveloped kernels, as well as heavily broken or mechanically damaged grains incurred during harvesting, transportation, or drying (Kozłowski et al., 2024; Khaeim et al., 2019; Pascale et al., 2022). A separate group comprises sprouted kernels, as well as kernels with visible signs of mold infection (changes in hull color, localized spots, mycelial growth) (Carmack et al., 2019; Guerra and Cuevas, 2024; Jia et al., 2020; Pearson et al., 2013b; Yorulmaz et al., 2011) or discoloration and darkening of the germ (Armstrong et al., 2015; Pearson et al., 2009).

The presence of such kernels impairs the technological properties of the raw material (flour yield and quality, vitreousness, and the stability of baking properties) (Baasandorj et al., 2015; Cha et al., 2025), and, in cases of mycological infection, may compromise safety due to the risk of mycotoxins (Pascale et al., 2022; Pearson et al., 2004). Because defective kernels often differ

ISSN: 2409-4951 (Online), 2310-1008(Print)

only slightly from sound kernels in mass and size, mechanical cleaning is relatively ineffective; in contrast, optical sorters identify them based on changes in color/texture and local defects, and in some cases by spectral or fluorescent signatures (Caporaso et al., 2018; Kecskes-Nagy et al., 2016).

Plant impurities. Plant impurities include foreign inclusions of plant origin that are not part of the target crop: weed seeds, kernels of other crops (e.g., rye in wheat or sorghum in corn), fragments of stems and leaves, glumes/husk scales, parts of corn husks, straw fragments, and similar materials (Aliev, 2020); Some of these impurities differ substantially from grain in size and density and can be removed by mechanical separators, whereas impurities with similar mass-geometric parameters often remain after conventional cleaning. They reduce raw-material uniformity, complicate cleaning/drying/milling operations, and may increase crude fiber content and introduce undesirable flavor and aroma components into the final product (Aliev, 2020; Inamdar and Suresh, 2014). From the perspective of optical inspection, such impurities often exhibit characteristic differences in shape (elongated, flattened, with specific "awns" or needle-like structures), color, and surface gloss. This enables selective removal of weed seeds and kernels of other crops based on color/spectral and morphometric features, especially when a high level of varietal purity is required (Abdullayev and Huseynzade, 2025; Kozłowski et al., 2024; Majumdar and Jayas, 2000a, 2000b).

Mineral impurities. Mineral impurities are inorganic solid particles that enter the grain mass during harvesting, transportation, and storage (stones, soil clods, sand, fragments of glass or slag, ferromagnetic inclusions, etc.); a substantial portion of them is removed by destoners, gravity tables, and magnetic separators (Graves et al., 1998; Reddy, 2010), however, small or atypically shaped particles may remain in the stream and pose a risk to both equipment and consumers (Kecskes-Nagy et al., 2016; Reddy, 2010). For optical systems, these impurities typically differ from kernels in shape, surface texture, and optical properties (hue, matte/glossy appearance, and a different reflection/absorption behavior in the visible and NIR ranges). Therefore, optical sorting can complement mechanical cleaning stages by removing residual stones and soil clods (Abdullayev and Huseynzade, 2025; Feng et al., 2019; Liu et al., 2022), which is particularly important for high-quality food products with strictly regulated levels of hard inclusions.

Artificial (technogenic) impurities. Artificial (technogenic) impurities are foreign objects of industrial or household origin that enter grain streams during harvesting, transportation, or storage (fragments of plastic parts and packaging materials, rubber, textiles, paper, small metal elements, cables, as well as fine polymer particles that are increasingly regarded as microplastics) (Chen et al., 2025); due to sizes comparable to kernels or a "favorable" shape, they can pass through sieve and pneumatic systems and are not always reliably removed by mechanical methods (Graves et al., 1998). At the same time, their optical properties typically differ substantially from those of grain (color, gloss, reflectance behavior in the visible and NIR ranges, and texture), so optical sorters can effectively detect and remove such objects (Abdullayev and Huseynzade, 2025); This is especially true for polymers which, despite their wide range of colors, exhibit characteristic spectral "fingerprints" in the infrared region, making the use of combined visible and NIR channels advantageous for their detection (Masilamani et al., 2020; Stuart, 2004).

Biological impurities and microbiological contamination. Biological impurities include both macroscopic objects (whole insects, larvae, pupae, body fragments, and excreta) and

ISSN: 2409-4951 (Online), 2310-1008(Print)

manifestations of microbiological contamination associated with the growth of molds and bacteria on the grain surface. Some of these occur as separate impurities (insect bodies, mycelial clumps), while others manifest through changes in kernel appearance (darkening, spots, deposits, shifts in hull hue), effectively moving them into the group of defective kernels but with a different etiology (Somiahnadar, 2003; Stathas et al., 2023; Vejarano et al., 2017). Microbiological contamination is particularly hazardous due to the risk of mycotoxin accumulation, which often shows no pronounced visual signs at early stages. However, studies indicate that infected kernels may exhibit specific changes in color-spectral characteristics and fluorescence response, making the use of optical systems in the UV and NIR ranges promising (Jia et al., 2020; Min and Cho, 2015); some industrial solutions already claim a reduction in the proportion of potentially contaminated kernels by combining visible, NIR, and fluorescence channels (Pearson et al., 2009; Yao et al., 2023).

Optical features. From a computer-science perspective, an optical grain sorter can be regarded as a system that solves a multiclass classification problem for objects in a stream (e.g., marketable grain, impurities, defective kernels, etc.) based on visual/spectral observation data (Aznan et al., 2021; Yang et al., 2025). Several methodological approaches are used to implement such classification: (a) algorithmic computer-vision and image-processing methods with explicit extraction of semantically meaningful structures (segmentation, morphological analysis, decision rules) (Aviara et al., 2022; Majumdar and Jayas, 2000a); (b) classical machine learning using relatively simple models (linear classifiers, decision trees, ensembles, etc.) that operate on precomputed features (Cataltepe et al., 2004a); (c) deep-learning methods in which feature representations and the classification rule are largely learned jointly from data (in particular, convolutional neural networks and their variants) (Fezzai et al., 2023; Hidayat et al., 2023; Zhu et al., 2021).

Unlike deep learning, the first two approaches typically require a feature-engineering stage-that is, an explicit definition of an informative feature vector describing the object, on the basis of which the class assignment decision is made (Majumdar and Jayas, 2000a, b; Yorulmaz et al., 2011). It is therefore advisable to present a provisional classification of such features, since it may be practically useful for readers when configuring optical sorting parameters. In this subsection, optical features are conventionally divided into several groups: color-spectral, morphometric, textural, surface-defect features, as well as internal and chemical features

Color-spectral features. Color-spectral features are fundamental for most optical sorters (Ageh et al., 2025; Li et al., 2022). They describe the intensity of reflected or transmitted light in one or more wavelength ranges (visible, near-infrared, ultraviolet), as well as the relationships among these ranges (Caporaso et al., 2018; Li et al., 2022). In the simplest case, these are brightness values in the three RGB channels or coordinates in another color space (e.g., HSV, Lab) that characterize the hue, saturation, and lightness of the grain surface (Ageh et al., 2025; Carmack et al., 2020; Pearson et al., 2012). These features allow the detection of discolored, darkened, yellow, chalky, or locally stained kernels, characteristic in particular of rice, wheat, and corn (Cha et al., 2025; Sairi and Mustaffha, 2020).

In more advanced systems, not only three-color analysis is used, but also measurements of intensity in specific portions of the visible and near-infrared spectrum (Caporaso et al., 2018; Cha et al., 2025; Dowell et al., 2006). The set of such measurements forms a spectral “fingerprint” of a kernel, which may be characteristic of a particular variety, degree of maturity, moisture or protein content, as well as mold infection (Dowell et al., 2006; Femenias et al., 2022; Jia et al., 2020; Wesley et al., 2008). In multispectral and hyperspectral systems, spectral features include dozens to hundreds of channels, enabling more fine-grained recognition

ISSN: 2409-4951 (Online), 2310-1008(Print)

models but requiring more sophisticated analysis algorithms and dimensionality-reduction techniques (Caporaso et al., 2018; Cataltepe et al., 2007; Feng et al., 2019; Gyaneshwar and Nidamanuri, 2020).

For certain tasks, relative spectral measures are important: ratios of intensities across different channels and indices analogous to well-known "vegetation indices" in remote sensing, but adapted to grain and impurities (Li et al., 2022; Pasikatan and Dowell, 2004; Pearson et al., 2004; Zhou et al., 2021). Such indices are less sensitive to changes in absolute illumination brightness and allow the specifics of surface microstructure to be accounted for more effectively (Caporaso et al., 2018).

Morphometric features (shape, size, and proportions). Morphometric features describe the geometric properties of kernels and impurities derived from their projection in the image plane (Aviara et al., 2022; Majumdar and Jayas, 2000a, b). Typical parameters include object area, the length and width of the minimum bounding rectangle, the ratio of maximum to minimum dimensions, degree of roundness or elongation, compactness, eccentricity, and similar measures. More complex shape descriptors may also be used, for example those based on contours or elliptical approximations (Aviara et al., 2022; Majumdar and Jayas, 2000b).

These features are particularly important for separating kernels of the base crop from plant impurities (weed seeds, kernels of other crops), as well as for identifying fractions that are unacceptable in terms of shape or size, such as chipped, fragmented, or excessively small kernels (Maier et al., 2024; Majumdar and Jayas, 2000a). For example, the seeds of many weeds have a more elongated shape, characteristic "spines" (awns), or asymmetric contours, which can be effectively captured by aspect-ratio measures and compactness indicators (Majumdar and Jayas, 2000a, b). In seed production, morphometric features help improve varietal purity by separating characteristically shaped kernels from atypical ones (Abdullayev and Huseynzade, 2025; Maier et al., 2024).

Some morphometric indicators are related to mass-geometric characteristics traditionally used in mechanical systems; however, in optical sorting they are obtained directly from images and can be combined with color-spectral and textural features, improving the overall discriminative power of the system (Ageh et al., 2025; Feng et al., 2019; Majumdar and Jayas, 2000a, b).

Surface texture features. Texture features describe the spatial non-uniformity of brightness or color on the kernel surface-that is, the character of "graininess," roughness, the presence of small inclusions, striping, or other regular or random structures (Carmack et al., 2020; Majumdar and Jayas, 2000b). In practice, they are assessed using statistical measures (variance, entropy, coefficient of variation), features computed from the gray-level co-occurrence matrix (GLCM), local binary patterns, and other texture-analysis methods adapted to the hardware constraints of an industrial system (Cataltepe et al., 2004a; Majumdar and Jayas, 2000b).

Texture features are particularly useful for detecting surface damage that is not always accompanied by a sharp change in average color but alters the hull microrelief-for example, corrosion-like spots, mold foci, erosive damage, or traces of insect pest activity (Jia et al., 2020; Majumdar and Jayas, 2000b; Min and Cho, 2015). In rice, for example, texture characteristics can be used to distinguish chalky kernels from more translucent ones (Majumdar and Jayas, 2000b; Sairi and Mustaffha, 2020), in wheat, they can be used to identify kernels with a disrupted endosperm structure (Cha et al., 2025; Majumdar and Jayas, 2000b).

ISSN: 2409-4951 (Online), 2310-1008(Print)

In combined algorithms, texture features are often used as auxiliary cues that refine decisions made based on color and shape: if the color matches the reference but the texture differs substantially, the kernel may be classified as defective or problematic for a specific product type (Ageh et al., 2025; Aviara et al., 2022; Majumdar and Jayas, 2000b).

Surface defects and damage features. Surface-defect features focus on local changes in the hull appearance: cracks, chips, dents, spots, localized darkening or discoloration, and areas with altered gloss (Chengqian et al., 2025; Kozłowski et al., 2024; Pearson et al., 2012). Unlike global color or texture measures, these features are tied to specific surface regions and require segmentation of the defective areas (Aviara et al., 2022; Chengqian et al., 2025; Guerra Ibarra and Cuevas, 2024). To extract them, local thresholding methods, edge operators, morphological operations, as well as analysis of brightness and texture gradients within small windows are used (Aviara et al., 2022; Guerra Ibarra and Cuevas, 2024; Majumdar and Jayas, 2000b).

These features are critical for tasks where the presence or absence of specific defects matters more than the overall kernel color-for example, hull or endosperm cracks, insect nibbling marks, pinpoint mold lesions, or localized scorching/darkening due to overheating (Cataltepe et al., 2004b, 2004a; Chengqian et al., 2025). In some cases, local defects determine the technological suitability of grain (e.g., in groats production or seed material preparation), so sorting algorithms are designed to detect such regions even when average color indicators remain within normal limits (Liu et al., 2022; Rahman and Cho, 2016).

Modern systems that use deep-learning methods can automatically learn features of surface defects from image analysis without explicit defect-region segmentation; however, from the standpoint of interpretability and fine tuning, it is often useful for the operator to be able to visualize and control these local parameters (Fezzai et al., 2023; Zhu et al., 2021).

Internal and chemical features (NIR spectra, translucency, fluorescence). Internal and chemical features are associated with kernel characteristics that cannot be fully described by surface color or texture but manifest through spectral response in the NIR region, changes in translucency, transmittance indicators, or fluorescent properties (Caporaso et al., 2018; Femenias et al., 2022; Min and Cho, 2015). In the near-infrared range, reflectance and transmittance spectra are sensitive to moisture, protein, fat, starch content, and certain secondary metabolites, enabling indirect assessment of maturity, damage, and microbiological infection of grain (Caporaso et al., 2018; Dowell et al., 2006; Femenias et al., 2022; Masilamani et al., 2020).

Fluorescence features arise when grain is irradiated with ultraviolet light and the resulting secondary emission is recorded in a different wavelength range (Min and Cho, 2015; Yao et al., 2023). Certain mycotoxins and metabolites of molds exhibit characteristic fluorescence bands, which were used in laboratory practice even before industrial sorters became widespread (Min and Cho, 2015). Integrating UV and fluorescence channels into industrial machines enables selective removal of kernels with an elevated risk of mycotoxicosis, although the precise relationship between visible fluorescence and toxin levels remains a complex scientific problem (Femenias et al., 2022; Min and Cho, 2015; Pearson et al., 2009).

These features are particularly promising for applications where safety and functional-technological properties are more critical than visual appearance (e.g., production of infant foods, dietetic products, and specialized feeds) (Femenias et al., 2022). At the same time, their use requires calibration and validation for specific crops and under particular growing and storage conditions, making such systems more complex to implement (Caporaso et al., 2018; Masilamani et al., 2020; Min and Cho, 2015).

ISSN: 2409-4951 (Online), 2310-1008(Print)

Summary and implications

A generalized classification scheme for optical grain sorting machines. Optical grain sorting has progressed from early photoelectric separators to multichannel machine-vision systems that combine several spectral ranges, high-speed imaging, and specialized decision algorithms. The historical perspective indicates that each development stage -from vacuum-tube circuitry to digital systems and deep learning was driven not only by hardware advances but also by evolving views on which objects and discriminative cues should be detected in the grain stream.

Based on an analysis of industrial models of optical grain sorters described in the literature and in manufacturers' technical documentation, a generalized classification of optical grain sorting machines was developed. The baseline version of this generalized classification scheme was presented for expert discussion in the conference paper "Classification of Optical Grain Separators" (Galka and Sharan, 2025a, 2025b). Unlike traditional approaches that focus primarily on a single criterion (e.g., spectral range or the type of conveying system), the proposed classification considers machines simultaneously in terms of sorting purpose, design features, automation level, application focus, crop specificity, and optical-system characteristics. This approach better captures the real diversity of commercially available solutions and provides a convenient framework for comparing and selecting equipment for specific processing tasks.

Suggested Optical Grain Sorter Machines classification is depicted in the Figure 3.

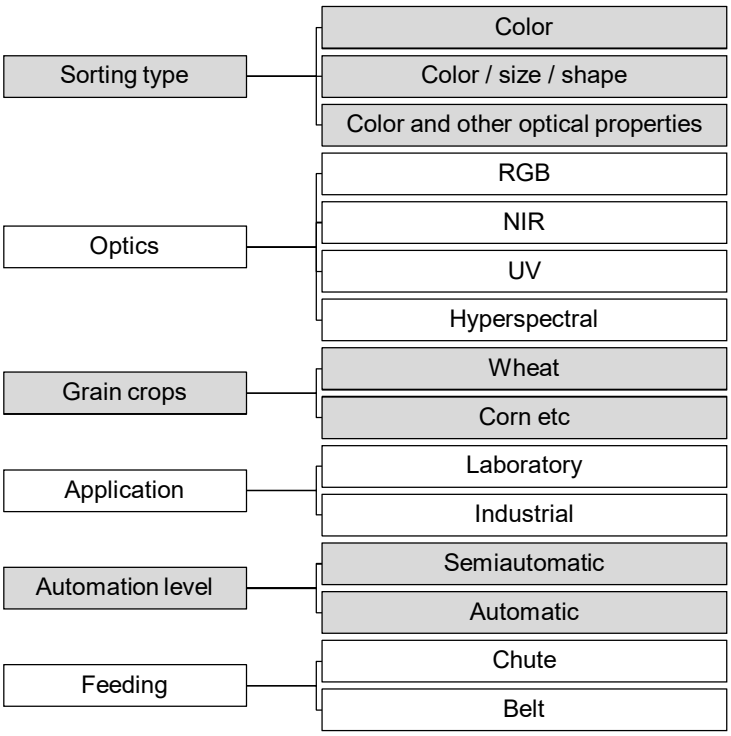

Figure 3. Optical grain sorting machines classification

ISSN: 2409-4951 (Online), 2310-1008(Print)

Following subsections discuss the main dimensions of this classification. The aim is not to "rigidly" assign each machine to a single class: most industrial sorters belong to several groups simultaneously (for example, an industrial belt-based NIR sorter for rice incorporating elements of deep learning). Rather, the classification is proposed as a generalized coordinate system in which a specific model can be positioned, alternative solutions compared, and the development of processing schemes incorporating optical sorting can be planned.

Classification by sorting type. Sorting type is the most intuitive dimension for users and reflects the features used for rejection decisions. Based on technical documentation, three groups are distinguished: (1) color sorters; (2) color + shape/size sorters; (3) color + other optical properties sorters.

(1) Color sorters operate primarily on color–spectral cues and detect discolored, darkened, or spotted kernels, impurities of contrasting color, and foreign particles whose hue differs from the base material. They are typical entry-level solutions for wheat, corn, and barley, aimed at improving appearance and partially removing defective kernels.

(2) Color + shape/size sorters complement color analysis with morphometric control (length, width, aspect ratio, roundness), improving selectivity for weed seeds, kernels of other crops, and fractions atypical in size or shape. They are common where varietal purity or narrow size fractions are required (e.g., seed production).

(3) Color + other optical properties sorters additionally use cues such as NIR reflectance, translucency, gloss, and fluorescence, enabling detection of internal defects, early mycological infection, changes in chemical composition, and specific artificial contaminants. These machines are most relevant for applications with elevated safety requirements and for maintaining stable functional and technological properties of grain raw materials.

Classification by feeding type. This dimension captures how grain is fed and conveyed through the inspection zone. Four groups are distinguished: chute (gravity) sorters, belt sorters, pneumatic-transport machines, and hybrid systems.

Chute sorters form a thin stream on inclined vibrating chutes; grain moves by gravity through the inspection zone. They are structurally simple and high-throughput for basic cleaning, but kernel positional stability is limited, placing higher demands on optical and ejector timing.

Belt sorters spread grain in a single layer on a horizontal or slightly inclined conveyor before optical analysis. This improves control of trajectories and orientation and supports more advanced shape/texture analysis, at the cost of higher mechanical complexity and conveyor maintenance.

Pneumatic and hybrid systems convey grain in airflow channels or combine multiple feeding principles along the pathway. They enable adaptation for fragile, heat-sensitive, or heavily contaminated products.

Classification by automation and intelligent control. Three provisional groups are distinguished: semi-automatic, automatic, and intelligent (smart) optical sorters.

Semi-automatic machines rely on operator-driven setup and monitoring: crop changes, thresholds, and modes are adjusted manually, and visualization tools are limited. They are typical for small enterprises, laboratories, or earlier equipment generations.

Automatic sorters maintain preset parameters, offer crop-specific "recipe" interfaces, and support automated calibration. The operator sets overall targets (e.g., reject fraction or cleaning level), while the system controls feeding, rejection, and basic diagnostics.

ISSN: 2409-4951 (Online), 2310-1008(Print)

Intelligent (smart) sorters add self-tuning and adaptive thresholds, ML/DL-based image analysis, and expanded data logging/communication. They can adapt to raw-material variability, recommend settings, and in some cases refine models from accumulated data, aligning optical sorting with plant digital infrastructure.

Classification by application. By application focus, optical sorters can be divided into laboratory and industrial systems.

Laboratory machines have low throughput and simplified feeding, but typically offer flexible access to raw outputs (images, spectra). They support research, algorithm development, calibration of industrial settings, and detailed inspection of specific batches; in some cases, they serve as prototypes for industrial designs.

Industrial sorters are built for continuous, high-throughput operation within processing lines and include advanced diagnostics and service features. They prioritize reliability, energy efficiency, and operator-oriented interfaces, and in production they function not only as cleaning equipment but also as real-time "quality sensors."

Classification by grain crops (sorting objects). Product catalogs indicate that many optical sorters are offered as crop- or product-specific (e.g., wheat, corn, rice, seeds, groats, compound feed), alongside universal machines that cover diverse bulk foods through flexible software "recipes."

For wheat and other bread cereals, settings typically target defective or infected kernels, weed seeds, and plant/mineral impurities that reduce flour quality and safety. For corn, emphasis is often placed on detecting kernels potentially affected by toxigenic fungi and removing husk/cob fragments and damaged ear pieces.

For rice, key targets depend on husked vs. unhusked material and include yellow, chalky, discolored, and chipped kernels that strongly affect grade and appearance. Seed sorters prioritize varietal purity, kernel integrity, and absence of mechanical damage, usually applying stricter thresholds.

Universal sorters can process multiple crops and even other bulk products (nuts, legumes, dried fruits), but require careful recipe reconfiguration and sometimes mechanical adjustments (e.g., chutes/feeding). In practice, sorting-object classification helps match machine capabilities to the specific needs of an enterprise.

Classification by optical system. This technically central dimension reflects the spectral range and sensor type. Five groups are distinguished: RGB, NIR, UV/fluorescence, multispectral, and hyperspectral systems.

RGB sorters operate in the visible range (three channels) and primarily evaluate surface color and brightness, enabling rejection of discolored or clearly defective kernels and impurities that differ in color.

NIR systems extend sensing beyond the visible range and add information linked to internal structure and chemical composition, supporting detection of subtler differences associated with moisture, infection, and maturity.

UV/fluorescence systems target materials with characteristic fluorescence, including certain molds and organic contaminants.

Multispectral and hyperspectral systems capture responses in dozens to hundreds of narrow bands, enabling more precise recognition of grain condition and impurities, but they are more common in research or highly specialized industrial use due to cost and data-processing complexity.

ISSN: 2409-4951 (Online), 2310-1008(Print)

This classification is also important for ML/DL-based recognition because the selected spectral channels determine which features can be extracted and how effectively hidden defects and hazardous impurities can be detected.

Integration of optical sorting machines into grain processing lines. Optical sorting should be regarded as the final, "fine" stage of grain cleaning, rather than as a universal replacement for traditional mechanical and pneumatic equipment (Kharchenko et al., 2024; Yang et al., 2025). In a typical process flow, optical sorters are installed downstream of the pre-cleaning and main-cleaning equipment train (screen separators, aspirators, destoners, gravity tables, etc.), once most coarse, light, and heavy impurities have already been removed from the stream, along with a substantial portion of plant and mineral inclusions (Kharchenko et al., 2024; Pascale et al., 2022). This is because excessive contamination of the grain mass with nonstandard particles, dust, and fine fractions compromises feed stability, complicates the operation of the optical module, and increases the load on the rejection system (Bühler AG, 2016a; Kleinhans et al., 2022).

Optical sorters are typically selected for a specific raw material and its characteristic impurity profile: wheat, rice, corn, seed material, or groats each require different machine configurations, illumination modes, sets of optical features, and software "recipes" (Ageh et al., 2025; Yang et al., 2025). In practice, this means that when designing a processing line, the equipment manufacturer and the customer agree not only on throughput, but also on the target tasks (which specific defective kernels and foreign materials should be removed, to what extent, and according to which visual criteria) (Ageh et al., 2025). A substantial proportion of machines are delivered with factory presets for common crops, but for industrial operation additional parameter tuning to specific grain lots and the plant's requirements is almost always carried out (Bühler AG, 2016a, 2016b; Yang et al., 2025). In this sense, an optical sorter is not a "standard separator," but a tool that is configured to the customer's needs (Ageh et al., 2025; Bühler AG, 2016a).

From the standpoint of plant layout, optical sorters are demanding in terms of operating conditions. Most industrial models are designed for installation in enclosed facilities with controlled ranges of temperature, relative humidity, and airborne dust levels (Bühler AG, 2016a, 2016b). Excessive dust, condensation, abrupt temperature fluctuations, or drafts can contaminate optical surfaces, destabilize illumination, increase the rate of false triggers, and raise maintenance demands (Bühler AG, 2016a, 2016d). Therefore, when integrating a sorter, a local aspiration hood, isolation from external influences, and accessible process space for scheduled cleaning and service are often provided (Bühler AG, 2016d, 2016c). Installing machines outdoors-without protection from weather conditions and vibration-is generally unacceptable (Bühler AG, 2016b, 2016c).

A separate practical requirement is the sensitivity of optical sorters to vibrations and impact loads (Bühler AG, 2016b, 2016c). Any loss of stability in the positioning of cameras, illumination sources, and feed-system components directly affects image quality, kernel positioning accuracy, and synchronization with the rejection system (Pearson, 2009; Pearson et al., 2012). Therefore, when integrating the machine into the production environment, it is necessary to account for existing vibration sources (bucket elevators, crushers, large fans) and, where needed, use vibration-isolating mounts, damping elements, and a rational equipment layout (Bühler AG, 2016b, 2016c). Improper placement of the sorter relative to vibrating machines can negate the benefits of even a well-tuned optical system (Bühler AG, 2016b).

In summary, integrating optical sorters into grain-cleaning schemes requires: (1) ensuring a sufficient level of preliminary mechanical cleaning; (2) selecting and configuring

ISSN: 2409-4951 (Online), 2310-1008(Print)

the machine for the specific crop and impurity spectrum; (3) providing appropriate indoor operating conditions; and (4) accounting for the sensitivity of the optical and mechanical modules to vibration. Only when these prerequisites are met can optical sorting realize its potential as a "precision" stage for selectively removing problematic kernels and foreign materials at the end of the process chain.

Conclusions

The review demonstrates that optical grain sorting technology has evolved from simple photoelectric devices to advanced machine-vision systems integrating multiple spectral ranges, high-speed cameras, and specialized image-processing algorithms. Each stage of development from vacuum-tube circuits to digital platforms and deep learning has been driven not only by advances in hardware, but also by changing concepts of target objects and relevant features in the grain stream. Based on a systematic analysis of industrial equipment, a multidimensional classification of optical grain sorters is proposed, accounting for sorting mode, design features, automation level, application focus, crop specificity, and optical-system characteristics, enabling consistent comparison of machines and clearer requirements for process-line design. In addition, optical sorting features are structured by physical nature, observation modality, and decision-making role, linking sorter types to impurity classes and recognition strategies. Practical analysis shows that optical sorters function most effectively as a final, fine-cleaning stage following mechanical and pneumatic separation, provided that adequate upstream cleaning, proper machine selection, and stable operating conditions are ensured. Future developments are expected to focus on wider adoption of multi- and hyperspectral systems, deep learning, and deeper integration of sorters into digital production infrastructures, while further research should assess their technological and resource efficiency and promote standardization of feature sets and testing protocols.

References

Abbasgholipour M., Omid M., Keyhani A., Mohtasebi S. (2010), Sorting raisins by machine vision system, *Modern Applied Science*, 4(2), pp. 49–60, https://doi.org/10.5539/mas.v4n2p49

Abdullayev H., Huseynzade E. (2024), Infrared imaging analysis as non-destructive maintenance of food processing equipment, *Journal of Materials and Engineering*, 2(4), pp. 315–322, https://doi.org/10.61552/JME.2024.04.009

Abdullayev H., Huseynzade E. (2025), Automated optical sorting machines for food industry, *Journal of Engineering, Management and Information Technology*, 3(2), pp. 135–140, https://doi.org/10.61552/JEMIT.2025.02.007

Ageh O.M., Hashim N., Shamsudin R., Che Man H., Mohd Ali M., Onwude D.I., Dasore A. (2025), Optical imaging for food grain quality evaluation – recent advances and future perspectives, *International Journal of Agricultural Sustainability*, 23(1), 2569166, https://doi.org/10.1080/14735903.2025.2569166

Aliev E.B. (2020), *Mechanical and technological foundations of precision separation of seeds of agricultural crops, Doctor of Sciences Thesis*, Dnipro State Agrarian and Economic University, Dnipro, Ukraine.

ISSN: 2409-4951 (Online), 2310-1008(Print)

Armstrong P.R., Maghirang E.B., Pearson T.C. (2015), Detecting and segregating black tip-damaged wheat kernels using visible and near-infrared spectroscopy, *Cereal Chemistry*, 92(4), pp. 358–363, https://doi.org/10.1094/CCHEM-09-14-0201-R

Armstrong R.P., Maghirang B.E., Yaptenco F.K., Pearson C.T. (2016), Visible and near-infrared instruments for detection and quantification of individual sprouted wheat kernels, *Transactions of the ASABE*, 59(6), pp. 1517–1527, https://doi.org/10.13031/trans.59.11566

Aviara N.A., Adesanya A.A., Iyilade I.J., Olorunsola E.O., Oyeniyi S.K. (2022), Application of image analysis in food grain quality inspection and evaluation during bulk storage, *Arid Zone Journal of Engineering, Technology and Environment*, 18(4), pp. 693–706, Available at: https://azojete.com.ng/index.php/azojete/article/view/681

Aznan A., Gonzalez Viejo C., Pang A., Fuentes S. (2021), Computer vision and machine learning analysis of commercial rice grains: a potential digital approach for consumer perception studies, *Sensors*, 21(19), 6354, https://doi.org/10.3390/s21196354

Baasandorj T., Ohm J., Simsek S. (2015), Effect of dark, hard, and vitreous kernel content on protein molecular weight distribution and on milling and breadmaking quality characteristics for hard spring wheat samples from diverse growing regions, *Cereal Chemistry*, 92(6), pp. 570–577, https://doi.org/10.1094/CCHEM-12-14-0249-R

Bühler AG (2016a), *SORTEX A ColorVision/MultiVision: Operator's Manual*, Internal technical documentation (PDF), Bühler AG, Uzwil, Switzerland.

Bühler AG (2016b), *SORTEX A ColorVision/MultiVision: Preinstallation Checklist*, Internal technical documentation (PDF), Bühler AG, Uzwil, Switzerland.

Bühler AG (2016c), *SORTEX A ColorVision/MultiVision: Preparation of the Machine*, Internal technical documentation (PDF), Bühler AG, Uzwil, Switzerland.

Bühler AG (2016d), *SORTEX A ColorVision/MultiVision: Supervisor & Maintenance*, Internal technical documentation (PDF), Bühler AG, Uzwil, Switzerland.

Caporaso N., Whitworth M.B., Fisk I.D. (2018), Near-infrared spectroscopy and hyperspectral imaging for non-destructive quality assessment of cereal grains, *Applied Spectroscopy Reviews*, 53(8), pp. 667–687, https://doi.org/10.1080/05704928.2018.1425214

Carmack W.J., Clark A., Dong Y., Brown-Guedira G., Van Sanford D. (2020), Optical sorter-based selection effectively identifies soft red winter wheat breeding lines with Fhb1 and enhances FHB resistance in lines with and without Fhb1, *Frontiers in Plant Science*, 11, 1318, https://doi.org/10.3389/fpls.2020.01318

Carmack W.J., Clark A.J., Dong Y., Van Sanford D.A. (2019), Mass selection for reduced deoxynivalenol concentration using an optical sorter in SRW wheat, *Agronomy*, 9(12), 816, https://doi.org/10.3390/agronomy9120816

Carrera-Rivera A., Ochoa W., Larrinaga F., Lasa G. (2022), How to conduct a systematic literature review: a quick guide for computer science research, *MethodsX*, 9, Article 101895, https://doi.org/10.1016/j.mex.2022.101895

Cataltepe Z., Cetin E., Pearson T. (2004a), Identification of insect-damaged wheat kernels using transmittance images, *2004 International Conference on Image Processing (ICIP 2004)*, IEEE, Singapore, pp. 2917–2920, https://doi.org/10.1109/ICIP.2004.1421724.

Cataltepe Z., Genc H., Pearson T. (2007), A PCA/ICA-based feature selection method and its application for corn fungi detection, *Proceedings of EUSIPCO 2007 (European*

ISSN: 2409-4951 (Online), 2310-1008(Print)

Signal Processing Conference), IEEE Document ID: 7098948, Available at: https://hdl.handle.net/11527/49346

Cataltepe Z., Pearson T., Cetin E. (2004b), Fast insect damage detection in wheat kernels using transmittance images, *2004 IEEE International Joint Conference on Neural Networks (IJCNN 2004)*, IEEE, Budapest, Hungary, pp. 1343–1346, https://doi.org/10.1109/IJCNN.2004.1380142.

Cha J.K., Park H., Kwon Y., Lee S.M. (2025), Enhancing wheat quality through color sorting: a novel approach for classifying kernels based on vitreousness, *Frontiers in Plant Science*, 16, 1534621, https://doi.org/10.3389/fpls.2025.1534621

Chen Z., Carter L.J., Banwart S.A., Kay P. (2025), Environmental levels of microplastics disrupt growth and stress pathways in edible crops via species-specific mechanisms, *Frontiers in Plant Science*, 16, 1670247, https://doi.org/10.3389/fpls.2025.1670247

Chengqian J., Gong C., Zhichang C., Man C., TengXiang Y., Yinyan S., Xiaobin G. (2025), Detection method of broken grains and impurities in harvested soybeans using feature wavelength selection and MobileNetV4-Unet-SGCPNet hybrid network, *Smart Agricultural Technology*, 101749, https://doi.org/10.1016/j.atech.2025.101749

Cujbescu D., Nenciu F., Persu C., Găgeanu I., Gabriel G., Vlăduț N.V., Matache M., Voicea I., Pruteanu A., Bularda M., et al. (2023), Evaluation of an optical sorter effectiveness in separating maize seeds intended for sowing, *Applied Sciences*, 13(15), 8892, https://doi.org/10.3390/app13158892

Delwiche S.R. (2008), High-speed bichromatic inspection of wheat kernels for mold and color class using high-power pulsed LEDs, *Sensing and Instrumentation for Food Quality and Safety*, 2(2), pp. 103–110, https://doi.org/10.1007/s11694-008-9037-1

Delwiche S.R., Pearson T.C., Brabec D.L. (2005), High-speed optical sorting of soft wheat for reduction of deoxynivalenol, *Plant Disease*, 89(11), pp. 1214–1219, https://doi.org/10.1094/PD-89-1214

Dowell F.E., Baenziger P.S., Maghirang E.B. (2007), Automated single kernel sorting for enhancing grain quality in breeding lines, *2007 ASABE Annual International Meeting*, Minneapolis, Minnesota, USA, 17–20 June 2007, Paper No. 073059, American Society of Agricultural and Biological Engineers (ASABE), https://doi.org/10.13031/2013.23179

Dowell F.E., Boratynski T.N., Ykema R.E., Dowdy A.K., Staten R.T. (2002), Use of optical sorting to detect wheat kernels infected with *Tilletia indica*, *Plant Disease*, 86(9), pp. 1011–1013, https://doi.org/10.1094/PDIS.2002.86.9.1011

Dowell F.E., Maghirang E.B., Graybosch R.A., Baenziger P.S., Baltensperger D.D., Hansen L.E. (2006), An automated near-infrared system for selecting individual kernels based on specific quality characteristics, *Cereal Chemistry*, 83(5), pp. 537–543, https://doi.org/10.1094/CC-83-0537

D'Souza C., Yuk H., Khoo G., Zhou W. (2015), Application of light-emitting diodes in food production, postharvest preservation, and microbiological food safety, *Comprehensive Reviews in Food Science and Food Safety*, 14(6), pp. 719–740, https://doi.org/10.1111/1541-4337.12155

Femenias A., Gatius F., Ramos A.J., Teixido-Orries I., Marín S. (2022), Hyperspectral imaging for the classification of individual cereal kernels according to fungal and mycotoxins contamination: a review, *Food Research International*, 155, 111102, https://doi.org/10.1016/j.foodres.2022.111102

ISSN: 2409-4951 (Online), 2310-1008(Print)

Feng L., Zhu S., Liu F., He Y., Bao Y., Zhang C. (2019), Hyperspectral imaging for seed quality and safety inspection: a review, *Plant Methods*, 15(1), Article 91, https://doi.org/10.1186/s13007-019-0476-y

Fezzai O., Taibeche A., Karima R. (2023), Deep learning for product quality inspection: state of the art, *2023 IEEE 17th International Conference on Applied Computational Intelligence and Informatics (SACI)*, IEEE Record: 10156475, https://doi.org/10.1109/SACI57756.2023.10156475

Finardi S., Hoffmann T.G., Schmitz F.R.W., Bertoli S.L., Khayrullin M., Neverova O., Ponomarev E., Goncharov A., Kulmakova N., Dotsenko E., et al. (2021), Comprehensive study of light-emitting diodes (LEDs) and ultraviolet-LED lights application in food quality and safety, *Journal of Pure and Applied Microbiology*, 15(3), pp. 1125–1135, https://doi.org/10.22207/JPAM.15.3.54

Folgado F.J., Calderón D., González I., Calderón A.J. (2024), Review of Industry 4.0 from the perspective of automation and supervision systems: definitions, architectures and recent trends, *Electronics*, 13(4), 782, https://doi.org/10.3390/electronics13040782

Freitag S., Sulyok M., Logan N., Elliott C.T., Krska R. (2022), The potential and applicability of infrared spectroscopic methods for the rapid screening and routine analysis of mycotoxins in food crops, *Comprehensive Reviews in Food Science and Food Safety*, 21(6), pp. 5199–5224, https://doi.org/10.1111/1541-4337.13054

Galka D.V., Sharan A.V. (2025a), Classification of optical grain separators, *Trends in lean manufacturing and food packaging: Proceedings of the 14th International Specialized Scientific and Practical Conference, National University of Food Technologies, Kyiv,* pp. 179–180

Galka D.V., Sharan A.V. (2025b), Classification of optical grain separators, *Proceedings of the 91st International Scientific Conference of Young Scientists and Students "Youth Scientific Achievements to the 21st Century Nutrition Problem Solution"*, National University of Food Technologies, Kyiv, pp. 115–116.

Gonzalez R.C., Woods R.E. (2018), *Digital Image Processing*, 4th ed. (Global Edition), Pearson, New York, NY, USA.

Graves M., Smith A., Batchelor B. (1998), Approaches to foreign body detection in foods, *Trends in Food Science & Technology*, 9(1), pp. 21–27, https://doi.org/10.1016/S0924-2244(97)00003-4

Guerra J.P., Cuevas F.J. (2024), Application of digital image processing techniques for agriculture: a review, In: *Digital Image Processing – Latest Advances and Applications*, IntechOpen, https://doi.org/10.5772/intechopen.1004767

Gyaneshwar D., Nidamanuri R. (2020), A real-time FPGA accelerated stream processing for hyperspectral image classification, *Geocarto International*, 37, pp. 1–18, https://doi.org/10.1080/10106049.2020.1713231.

Haff R.P., Pearson T.C., Maghirang E. (2013), A multispectral sorting device for isolating single wheat kernels with high protein content, *Journal of Food Measurement and Characterization*, 7(4), pp. 149–157, https://doi.org/10.1007/s11694-013-9150-7.

He L., Niu Z., Chen D. (2011), Research on development of color sorter using TRIZ, in: *IFIP Advances in Information and Communication Technology*, Vol. 370, Springer, Berlin, Heidelberg, pp. 271–279, https://doi.org/10.1007/978-3-642-27281-3_32

Hidayat S.S., Rahmawati D., Prabowo M.C.A., Triyono L., Putri F.T. (2023), Determining the rice seeds quality using convolutional neural network, *JOIV: International Journal on Informatics Visualization*, 7(2), p. 527, https://doi.org/10.30630/joiv.7.2.1175

ISSN: 2409-4951 (Online), 2310-1008(Print)

Inamdar A.A., Suresh D.S. (2014), Application of color sorter in wheat milling, *International Food Research Journal*, 21(6), pp. 2083–2089, Available at: http://www.ifrj.upm.edu.my/21%20(06)%202014/3%20IFRJ%2021%20(06)%202014%20Suresh%20621.pdf

Jia B., Wang W., Ni X.Z., Chu X., Yoon S.C., Lawrence K.C. (2020), Detection of mycotoxins and toxigenic fungi in cereal grains using vibrational spectroscopic techniques: a review, *World Mycotoxin Journal*, 13(2), pp. 163–178, https://doi.org/10.3920/WMJ2019.2510

Jiang G.L. (2020), Comparison and application of non-destructive NIR evaluations of seed protein and oil content in soybean breeding, *Agronomy*, 10(1), Article 77, https://doi.org/10.3390/agronomy10010077

Kautzman M.E., Wickstrom M.L., Scott T.A. (2015), The use of near infrared transmittance kernel sorting technology to salvage high quality grain from grain downgraded due to Fusarium damage, *Animal Nutrition*, 1(1), pp. 41–46, https://doi.org/10.1016/j.aninu.2015.02.007

Kecskes-Nagy E., Korzenszky P., Sembery P. (2016), The role of color sorting machine in reducing food safety risks, *Potravinarstvo Slovak Journal of Food Sciences*, 10(1), pp. 354–358, https://doi.org/10.5219/511

Kleinhans K., Küppers B., Hernández Parrodi J.C., Ragaert K., Dewulf J., De Meester S. (2022), Increase throughput and sorting quality with flowcontrol, *9th Sensor-Based Sorting & Control 2022 (SBSC 2022)*, Shaker Verlag, Aachen, Germany, pp. 85–98, https://doi.org/10.2370/9783844085464-85, ISBN: 978-3-8440-8546-4.

Kharchenko Ye.I., Sharan A.V., Yaniuk T.I., Suprun-Krestova O.Yu. (2024), *Innovatsii v zernovykh tekhnolohiiakh* [Innovations in grain technologies], Oldi+, Odesa.

Kos J., Anić M., Radić B., Zadravec M., Janić Hajnal E., Pleadin J. (2023), Climate change – a global threat resulting in increasing mycotoxin occurrence, *Foods*, 12(14), 2704, https://doi.org/10.3390/foods12142704

Kozłowski M., Szczypiński P.M., Reiner J., Lampa P., Mrzygłód M., Szturo K., Zapotoczny P. (2024), Identifying defects and varieties of malting barley kernels, *Scientific Reports*, 14(1), 22143, https://doi.org/10.1038/s41598-024-73683-3

Li L., Chen S., Deng M., Gao Z. (2022), Optical techniques in non-destructive detection of wheat quality: a review, *Grain & Oil Science and Technology*, 5(1), pp. 44–57, https://doi.org/10.1016/j.gaost.2021.12.001

Liu Y., Zhang J., Yuan H., Song M., Zhu Y., Cao W., Jiang X., Ni J. (2022), Non-destructive quality-detection techniques for cereal grains: a systematic review, *Agronomy*, 12(12), Article 3187, https://doi.org/10.3390/agronomy12123187

Khaeim H.M., Clark A., Pearson T., Van Sanford D. (2019), Methods of assessing Fusarium damage to wheat kernels, *Al-Qadisiyah Journal for Agriculture Sciences (QJAS)*, 9(2), pp. 297–308, https://doi.org/10.33794/qjas.Vol9.Iss2.91

Maier G., Gruna R., Längle T., Beyerer J. (2024), A survey of the state of the art in sensor-based sorting technology and research, *IEEE Access*, 12, pp. 6473–6493, https://doi.org/10.1109/ACCESS.2024.3350987

Majumdar S., Jayas D. (2000a), Classification of cereal grains using machine vision: I. Morphology models, *Transactions of the ASAE*, 43, pp. 1669–1675, https://doi.org/10.13031/2013.3107

Majumdar S., Jayas D. (2000b), Classification of cereal grains using machine vision: III. Texture models, *Transactions of the ASAE*, 43(6), pp. 1681–1687, https://doi.org/10.13031/2013.3068

ISSN: 2409-4951 (Online), 2310-1008(Print)

Masilamani P., Venkatesan S., Janaki P., Eevera T., Sundareswaran S., Rajkumar P. (2020), Role of near-infrared spectroscopy in seed quality evaluation: a review, *Agricultural Reviews*, Article R-1960, https://doi.org/10.18805/ag.R-1960

McMullin D., Mizaikoff B., Krska R. (2015), Advancements in IR spectroscopic approaches for the determination of fungal derived contaminations in food crops, *Analytical and Bioanalytical Chemistry*, 407(3), pp. 653–660, https://doi.org/10.1007/s00216-014-8145-5

Min H., Cho B.K. (2015), Spectroscopic techniques for nondestructive detection of fungi and mycotoxins in agricultural materials: a review, *Journal of Biosystems Engineering*, 40(1), pp. 67–77, https://doi.org/10.5307/JBE.2015.40.1.067

Nansen C., Kolomiets M., Gao X. (2008), Considerations regarding the use of hyperspectral imaging data in classifications of food products, exemplified by analysis of maize kernels, *Journal of Agricultural and Food Chemistry*, 56(9), pp. 2933–2938, https://doi.org/10.1021/jf073237o

Nordell L.K. (1997), Particle flow modeling: transfer chutes & other applications, *15th International Materials Handling Conference (BELTCON 9)*, Johannesburg, South Africa, 22–23 October 1997, Available at: https://cvdyn.com/wp-content/uploads/2020/01/Particle-Flow-Modeling.pdf

Olkhovskyi V., Dudarev I. (2021), Separation methods and separators of grain mass, *Agricultural Machines*, 47, pp. 102–112, https://doi.org/10.36910/acm.vi47.655

Pascale M., Logrieco A.F., Lippolis V., De Girolamo A., Cervellieri S. (2022), Industrial-scale cleaning solutions for the reduction of Fusarium toxins in maize, *Toxins*, 14(11), 728, https://doi.org/10.3390/toxins14110728

Pasikatan M., Dowell F. (2001), Sorting systems based on optical methods for detecting and removing seeds infested internally by insects or fungi: a review, *Applied Spectroscopy Reviews*, 36(4), pp. 399–416, https://doi.org/10.1081/ASR-100107719

Pasikatan M., Dowell F. (2003), Evaluation of a high-speed color sorter for segregation of red and white wheat, *Applied Engineering in Agriculture*, 19, pp. 71–76, https://doi.org/10.13031/2013.12725

Pasikatan M., Dowell F.E. (2004), High-speed NIR segregation of high- and low-protein single wheat seeds, *Cereal Chemistry*, 81(1), pp. 145–150, https://doi.org/10.1094/CCHEM.2004.81.1.145

Pearson T. (2009), Hardware-based image processing for high-speed inspection of grains, *Computers and Electronics in Agriculture*, 69(1), pp. 12–18, https://doi.org/10.1016/j.compag.2009.06.007

Pearson T. (2010), High-speed sorting of grains by color and surface texture, *Applied Engineering in Agriculture*, 26(3), pp. 499–505, https://doi.org/10.13031/2013.29948

Pearson T., Brabec D., Haley S. (2008), Color image based sorter for separating red and white wheat, *Sensing and Instrumentation for Food Quality and Safety*, 2(4), pp. 280–288, https://doi.org/10.1007/s11694-008-9062-0

Pearson T., Maghirang E., Dowell F. (2013a), A multispectral sorting device for wheat kernels, *American Journal of Agricultural Science and Technology*, 2, pp. 45–60, https://doi.org/10.7726/ajast.2013.1004

Pearson T., Moore D., Pearson J. (2012), A machine vision system for high speed sorting of small spots on grains, *Journal of Food Measurement and Characterization*, 6(1–4), pp. 27–34, https://doi.org/10.1007/s11694-012-9130-3

ISSN: 2409-4951 (Online), 2310-1008(Print)

Pearson T., Wicklow D., Bean S., Brabec D. (2013b), Sorting of fungal-damaged white sorghum, *American Journal of Agricultural Science and Technology*, 1(3), pp. 93–103, https://doi.org/10.7726/ajast.2013.1009

Pearson T.C., Wicklow D.T., Brabec D.L. (2009), Technical Note: Characteristics and Sorting of White Food Corn Contaminated with Mycotoxins, *Applied Engineering in Agriculture*, 26(1), pp. 109–113, https://doi.org/10.13031/2013.29463

Pearson T.C., Wicklow D.T., Pasikatan M.C. (2004), Reduction of aflatoxin and fumonisin contamination in yellow corn by high-speed dual-wavelength sorting, *Cereal Chemistry*, 81(4), pp. 490–498, https://doi.org/10.1094/CCHEM.2004.81.4.490

Peiris K.H.S., Dowell F.E. (2010), Single kernel NIR sorting to enhance quality of wheat breeding lines, *CST-SA–ICC International Grains Symposium: Quality and Safety of Grain Crops and Foods*, Gauteng, South Africa, 3–5 February 2010, University of Pretoria Conference Centre, University of Pretoria, *Proceedings of Papers*, pp. 16–21.

Peters M., Marnie C., Tricco A., Pollock D., Alexander L., Mcinerney P., Godfrey C., Khalil H. (2021), Updated methodological guidance for the conduct of scoping reviews, *JBI Evidence Implementation*, 19(1), pp. 3–10, https://doi.org/10.1097/XEB.0000000000000277

Rahman A., Cho B.K. (2016), Assessment of seed quality using non-destructive measurement techniques: a review, *Seed Science Research*, 26(4), pp. 285–305, https://doi.org/10.1017/S0960258516000234

Rakipov V., Gulyaev R., Yunusov R., Sultonov A., Rafikov D. (2025), Optical sorting methods and information technologies in the integrated system for improving the quality and traceability of bare sown cotton seeds, *Proceedings of SPIE – Optical and Computational Technologies for Measurements and Industrial Applications (OptiComp 2025)*, 13803, Article 1380302, Bukhara, Uzbekistan, https://doi.org/10.1117/12.3075464

Reddy R.N. (Ed.) (2010), *Agricultural process engineering*, Gene-Tech Books, New Delhi, India, ISBN: 978-8181921734 (ISBN-10: 8181921731).

Sairi S.A.M., Mustaffha S. (2020), Comparative study of three rice brands' quality through measuring broken rice percentage using Sortex A ColorVision (Buhler) optical sorters, *IOP Conference Series: Earth and Environmental Science*, 515, Article 012017, https://doi.org/10.1088/1755-1315/515/1/012017

Santiago P., Pascual R., Cumbe M., Macaso J., Villanueva F., Dioses I.A. (2024), Classification of rice grain varieties based on morphological features using image processing and machine learning techniques, *Proceedings of ICSGRC 2024*, https://doi.org/10.1109/ICSGRC62081.2024.10691272

Satake Corporation (n.d.), *Instruction Manual: Optical Sorter Satake SSM3001/SSM5001 (AMS/BM/DMS/AIS/BI/DIS)*, Internal technical documentation (PDF), Satake Corporation.

Siesler H.W., Ozaki Y., Kawata S., Heise H.M. (Eds.) (2002), *Near-Infrared Spectroscopy: Principles, Instruments, Applications*, Wiley-VCH Verlag GmbH, Weinheim.

Stathas I.G., Sakellaridis A.C., Papadelli M., Kapolos J., Papadimitriou K., Stathas G.J. (2023), The Effects of Insect Infestation on Stored Agricultural Products and the Quality of Food, *Foods*, 12(10), Article 2046, https://doi.org/10.3390/foods12102046

Stuart B.H. (2004), *Infrared Spectroscopy: Fundamentals and Applications*, John Wiley & Sons, Ltd.

ISSN: 2409-4951 (Online), 2310-1008(Print)

Tan Y.N., Thanh Son L., Quang Tuyen T., Huy Bich N., Truong Thinh N. (2020), Study of Design and Manufacture for One-Line Rice Color Sorting Machine, *Science & Technology Development Journal – Engineering and Technology*, 3(SI1), pp. SI71–SI79, https://doi.org/10.32508/stdjet.v3iSI1.724

Sujitha S., Augustia N. (2020), FPGA implementation of CALIB_IO, wave and clock generation modules for grain sorting machine, *ICTACT Journal on Microelectronics*, 5(4), pp. 854–860, https://doi.org/10.21917/ijme.2020.0147

TOMRA Sorting GmbH. (2016), AUTOSORT & FINDER: common user interface – user manual (UM-KO-0020-REV2.1-en, Rev. 2.1), TOMRA Sorting GmbH, Mülheim-Kärlich, Germany.

Vejarano R., Siche R., Tesfaye W. (2017), Evaluation of biological contaminants in foods by hyperspectral imaging: a review, *International Journal of Food Properties*, 20(Suppl 2), pp. 1264–1297, https://doi.org/10.1080/10942912.2017.1338729

Wallace B.W.H. (1984), Seed conveyors - comparison & contrasts, *Proceedings of the Short Course for Seedsmen*, Mississippi Agricultural and Forestry Experiment Station (MAFES), Mississippi State University, pp. 89–102, available at: https://scholarsjunction.msstate.edu/seedsmen-short-course/418

Wang F., Xi Z., Yang J., Yang X. (2013), Research progress of grain quality nondestructive testing methods, In: Li D., Chen Y. (Eds.), *Computer and Computing Technologies in Agriculture VI* (IFIP Advances in Information and Communication Technology, Vol. 393), Springer, Berlin, Heidelberg, pp. 255–262, https://doi.org/10.1007/978-3-642-36137-1_31

Wang N., Zhang N., Dowell F.E., Pearson T. (2005), Determining vitreousness of durum wheat using transmitted and reflected images, *Transactions of the ASAE*, 48(1), pp. 219–222, https://doi.org/10.13031/2013.17920

Wesley I.J., Osborne B.G., Larroque O., Bekes F. (2008), Measurement of the protein composition of single wheat kernels using near infrared spectroscopy, *Journal of Near Infrared Spectroscopy*, 16(6), pp. 505–516, https://doi.org/10.1255/jnirs.820

Xie F., Pearson T., Dowell F.E., Zhang N. (2004), Detecting vitreous wheat kernels using reflectance and transmittance image analysis, *Cereal Chemistry*, 81(5), pp. 594–597, https://doi.org/10.1094/CCHEM.2004.81.5.594

Xu S., Wang H., Liang X., Lu H. (2024), Research progress on methods for improving the stability of non-destructive testing of agricultural product quality, *Foods*, 13(23), 3917, https://doi.org/10.3390/foods13233917

Yang M., Shi Y., Song Q., Wei Z., Dun X., Wang Z., Wang Z., Qiu C.W., Zhang H., Cheng X. (2025), Optical sorting: past, present and future, *Light: Science & Applications*, 14(1), 103, https://doi.org/10.1038/s41377-024-01734-5

Yao H., Zhu F., Kincaid R., Hruska Z., Rajasekaran K. (2023), A low-cost, portable device for detecting and sorting aflatoxin-contaminated maize kernels, *Toxins*, 15(3), 197, https://doi.org/10.3390/toxins15030197

Yellanki V.S., Kavuri S., Anitha K., Lydia M.S., Srilakshmi N., Das M.N., Tripathy J. (2025), Grain quality testing using neural networks, *International Journal of Environmental Sciences*, 11(8), pp. 893–900, https://doi.org/10.64252/awrwt611

Yorulmaz O., Pearson T.C., Çetin A.E. (2011), Cepstrum based feature extraction method for fungus detection, In: Kim M.S., Tu S.-I. and Chao K. (Eds.), *Sensing for Agriculture and Food Quality and Safety III*, Proceedings of SPIE, 8027, 80270E, https://doi.org/10.1117/12.882406

ISSN: 2409-4951 (Online), 2310-1008(Print)

Zareiforoush H., Minaei S., Alizadeh M.R., Banakar A. (2015), Potential applications of computer vision in quality inspection of rice: a review, *Food Engineering Reviews*, 7, pp. 321–345, https://doi.org/10.1007/s12393-014-9101-z

Zhou Q., Huang W., Liang D., Tian X. (2021), Classification of aflatoxin B1 concentration of single maize kernel based on near-infrared hyperspectral imaging and feature selection, *Sensors*, 21(13), Article 4257, https://doi.org/10.3390/s21134257

Zhu L., Spachos P., Pensini E., Plataniotis K.N. (2021), Deep learning and machine vision for food processing: a survey, *Current Research in Food Science*, 4, pp. 233–249, https://doi.org/10.1016/j.crfs.2021.03.009

Author identifiers ORCID
Dmytro Galka 0009-0009-8877-1136
Andrii Sharan 0009-0000-7140-5038

Cite:

Ukr J Food Sci Style

Galka D., Sharan A. (2025), Optical grain sorting machines: review of principles of operation and classification, *Ukrainian Journal of Food Science*, 13(2), pp. 274–304, https://doi.org/10.24263/2310-1008-2025-13-2-12

APA Style

Galka, D., & Sharan, A. (2025). Optical grain sorting machines: review of principles of operation and classification. *Ukrainian Journal of Food Science, 13*(2), 274–304. https://doi.org/10.24263/2310-1008-2025-13-2-12

ISSN: 2409-4951 (Online), 2310-1008(Print)