Advanced sorting technologies for Food Waste

Technology compilation & Innovative Solution in Germany

IEA Bioenergy: Task 36

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Preface

This report explores advances in sorting technologies for food waste aimed at enhancing material recovery and reducing the waste management's climate impact; and provides insight into the German's food waste landscape and presents an innovative solution in the country. The purpose of the Task 36 reports is to showcase examples from which countries can get inspiration and support in implementing solutions in the waste/resource management and Waste-to-Energy sector that would facilitate their transition towards circularity.

The technologies and solutions presented in this compilation were selected due to their relevance in the field of waste sorting technologies. However, IEA Bioenergy Task 36 does not endorse any commercial products that may be mentioned on this report.

IEA Bioenergy Task 36, working on the topic 'Material and Energy Valorisation of Waste in a Circular Economy', seeks to raise public awareness of sustainable energy generation from biomass residues and waste fractions including MSW as well as to increase technical information dissemination. As outlined in the 3-year work programme, Task 36 seeks to understand what role energy from waste and material recycling can have in a circular economy and identify technical and non-technical barriers and opportunities needed to achieve this vision.

See http://task36.ieabioenergy.com/ for links to the work performed by IEA Bioenergy Task 36.

Summary

With over 1.05 billion tons of food waste generated annually worldwide, contributing 8-10% of global greenhouse gas emissions, effective sorting technologies are critical for environmental sustainability and resource recovery. Germany generates approximately 10.9 million tons of food waste per year, representing 18.5% of the EU's total. This contributes to 4% of national greenhouse gas emissions and causes economic losses of around 30 billion euros annually. With the EU's mandatory food waste sorting policy in force since 2024, advanced sorting technologies are essential for meeting the Sustainable Development Goal, SDG, 12.3 goal of halving per capita food waste by 2030.

The report provides an overview of the food waste sorting technologies available in the market from mechanical systems to artificial intelligence (AI) applications. Mechanical sorting employs shredders, vibrating screens, and magnetic separators but demonstrates lower efficiency in removing lightweight plastics and multilayer packaging. Optical and sensor-based systems utilize near-infrared spectroscopy and high-resolution cameras to differentiate organic materials from contaminants with high precision. Artificial intelligence-based systems achieve sorting accuracies exceeding 90% through deep learning algorithms and real-time classification. Advanced detection technologies including X-ray inspection, hyperspectral imaging, and metal detection provide complementary capabilities for quality assurance. Integration with Industry 4.0 infrastructures enables connectivity with enterprise systems, supporting cloud-based monitoring, traceability, and predictive maintenance. Real-time processing systems achieve sorting accuracies up to 99.9% with throughput capacities of several tons per hour.

In addition, this report highlights the food waste sector in Germany by presenting ReFood, a practical implementation at an industrial scale. Operating 12 anaerobic digestion facilities across Europe, ReFood processes up to 160,000 tonnes of food waste annually per facility using sophisticated mechanical separation systems. The Trossingen facility in Germany features dual processing lines for packaged and unpackaged waste streams. With nearly 100% material recovery rates, ReFood converts food waste into renewable energy, biomethane, and biofertilizer.

Advanced sorting technologies enable the circular economy by integrating mechanical, optical, AI-based, and detection systems with digital infrastructures to achieve high recovery rates while addressing the global challenge of food waste.

Background

Food waste (FW) remains a pressing global challenge with environmental, economic, and societal impacts. Food waste is a major global concern, with over 1.05 billion tons wasted annually and contributing up to 8-10% of global greenhouse gas emissions (UNEP, 2024). Economic evaluation of food waste demonstrates that the losses caused sum up to a value of $1 trillion in market value, which is equivalent to the occupation of nearly 30% of the world's agricultural land (UNEP, 2024).

Germany, as one of the countries with the highest population in the EU, plays a central role in shaping the EU food waste management system. Its large consumer base makes it one of the largest food markets in Europe, including food demand and food waste generation. This demographic weight translates into a significant environmental footprint and a major responsibility for achieving EU sustainability goals, especially in the food industry. The country plays a crucial role in policy development, including food safety, environmental regulation, and innovation within the EU. Germany's efforts to reduce food waste not only have a domestic impact but also a broader influence across Europe. Germany’s leadership is critical to the EU's commitment to Sustainable Development Goal 12.3, which aims to halve per capita FW by 2030.

A key aspect that frames the overall food waste management system, yet is often overlooked, is source separation at the household level. Germany has a long-established system of waste separation that includes dedicated collection streams for residual waste, packaging, paper, glass, and, importantly, biowaste. In principle, all households are required to separate kitchen and garden waste into a biowaste container (Biotonne), which forms the primary input for composting and anaerobic digestion processes. However, in practice, performance of household source separation shows considerable variation.

According to the most recent nationwide assessment, around 63% of German households have access to a Biotonne, while many remaining municipalities rely on bring-systems or do not offer separate biowaste collection at all (NABU, 2024). As a result, a substantial share of organic waste still enters the residual waste stream: municipal solid waste (MSW) sorting analyses show that approximately 39% of the residual household waste in Germany consists of biowaste that should have been separately collected (UBA, 2023). Even where separate biowaste systems are available, impurity levels remain a challenge. Before targeted improvement campaigns, contamination rates of up to 14% non-organic impurities were reported; after interventions, they stabilised between 1–5%, depending on the region (Angouria-Tsorochidou et al., 2023).

A similar situation exists across Europe. Recent assessments by Zero Waste Europe and the Bio-based Industries Consortium indicate that only 26% of food waste is effectively captured through separate collection systems in the EU, meaning that around 74% of food waste still ends up mixed with residual waste and is subsequently incinerated or landfilled rather than recovered (ZeroWasteEurope 2024). When considering the broader biowaste stream (including garden waste), the EU-wide separate collection rate remains at approximately 46%, further illustrating the large unrealised potential of household-level source separation.

Recognising the limitations of current separation practices is essential for contextualising the potential of advanced sorting technologies. These technologies can substantially improve the quality of organic waste streams by removing contaminants and enhancing material purity. They also help recover wrong sorted organic fractions from mixed waste streams. Thus, their deployment creates a dual environmental benefit:

1. Non-organic material is separated and recycled, preventing the need for virgin resources, while the remaining organic fraction can be directed to different valorisation pathways such as composting, anaerobic digestion (for biogas and fertiliser), nutrient extraction or other solutions that help reduce food wastage.

2. The material that is recovered escapes from polluting the organic residues or products of the treated food waste, meaning that non-organic impurities such as plastics or metals are removed early in the process and therefore cannot contaminate the organic fraction, which results in cleaner organic outputs and higher-quality end products.

This report presents a comprehensive overview of advanced food waste sorting technologies within the waste management industry, aimed at enhancing material recovery and reducing the sector's climate impact. It later shifts focus to Germany, offering insights into the country's food waste landscape by highlighting key statistics and exploring innovative strategies for food waste reduction and management through the application of cutting-edge sorting technologies.

This report is part of a complementary series of publications by Task 36. The first highlights the key role of advanced sorting technologies in accelerating the transition of the waste management sector toward a more circular economy (IEA Bioenergy: Task 36 (1), 2024). The second emphasizes the importance of reducing food waste and improving the recovery of unavoidable food waste for bioenergy production (IEA Bioenergy: Task 36 (2), 2024). Several national case studies (Sweden, Italy and Norway) are also presented by Task 36.

Classification of Food Waste Sorting Technologies

Advanced food waste sorting technologies play a crucial role in both increasing the quality and recovery of organic waste for material and energy valorization and, in some cases, reducing avoidable food wastage earlier in the supply chain (e.g., in canteens, restaurants, or retail). Most sorting technologies used in the waste management and energy sectors are designed to separate food waste from packaging, inert matter, and other contaminants, thereby preparing a clean organic fraction suitable for composting, anaerobic digestion (biogas and digestate), nutrient extraction, or other valorization routes. In parallel, emerging digital and sensor-based systems used at the production or consumption stage can help identify edible food before disposal, enabling food-waste prevention.

These sorting technologies are essential for improving the efficiency of food waste management and for supporting circular economy practices. In the EU, mandatory source-separation of food waste has been in force since 2024, underlining the urgency and relevance of high-quality food waste sorting for sustainable resource recovery.

Technological developments are advancing rapidly, incorporating optical sensors, hyperspectral imaging, artificial intelligence, robotics, and smart monitoring systems. These innovations enhance the precision and automation of sorting processes; they improve safety and reduce contamination levels. Thereby, they are increasing the value of both the recovered organic fraction and recyclable non-organic materials.

Table 1 provides an overview of various technologies for sorting organic waste. It serves to compare different approaches to the separation and processing of organic residues and to facilitate the selection of appropriate technologies.

Table 1: Overview of waste sorting technologies for organic waste

Technology	Capacity /Throughput	CAPEX (Investment)	OPEX (Operating Costs)	Technical specifications	Advantages	Limitation
,	Medium (hundreds of kg/hr, depends on shredder size)	Low to Medium (basic equipment, relatively low cost)	Medium (high wear & tear due to shredding/grinding, maintenance-intensive)	Shredders, grinders, vibrating screens, rotary drums, magnetic separators	Economical, simple, widely available	Low sorting accuracy, complex material handling, high maintenance
Optical & Sensor-Based Systems	High (tons/hr, depending on line design)	High (advanced sensors, lasers, cameras)	Medium (requires calibration, cleaning of sensors)	NIR spectroscopy, camera arrays, laser scanning, LED illumination	High accuracy (color, shape, material detection), non-contact, scalable	Sensitive to moisture/contamination, high initial cost
AI-Based Sorting Systems	Very High (tons/hr with real-time classification)	High (AI hardware, deep learning infrastructure)	Medium to High (training data, software updates, computing power)	Deep learning neural networks, computer vision, real-time image processing	Accuracy >90%, continuous self-learning, reduces contamination	Data-intensive, requires skilled operation, expensive setup
Advanced Detection Technologies (X-ray, Hyperspectral, Metal Detection)	High (depending on technology and product type)	Very High (specialized imaging equipment, shielding for X-ray)	Medium (energy use, calibration, operator training)	X-ray imaging, hyperspectral cameras (>100 wavelength bands), electromagnetic detectors	Detects internal defects, density differences, chemical composition, sub-metals	Very expensive, requires controlled environment, slower than optical systems

Technology	Capacity /Throughput	CAPEX (Investment)	OPEX (Operating Costs)	Technical specifications	Advantages	Limitation
System Integration & Operational Performance	Very High (multi-line, fully automated)	Very High (Industry 4.0 integration, IoT, MES/ERP links)	Medium to High (data storage, cloud, IT support)	ERP/MES connectivity, real-time processing, predictive maintenance, batch tracking	Full traceability, remote diagnostics, predictive analytics, highest quality assurance	Complexity, very high investment, requires digital infrastructure and IT expertise

MECHANICAL SORTING SYSTEMS

Mechanical sorting systems are primarily used in the waste management and bioenergy sector to improve the purity and recovery of food waste, and their design is tailored to the specific composition of organic waste streams. Unlike general household residual waste, food waste typically contains a high share of plastic films and trays from ready meals, multilayer packaging, paper and cardboard food containers, glass jars (e.g., yogurt, sauces, olives, pickled products), and various metal components such as aluminum lids or steel cans. It can also contain biomedical contaminants (e.g., broken thermometers or metal cutlery in canteens), foreign objects (e.g., stones, shells, bones), and inert material from preprocessing.

Mechanical sorting relies on a sequence of physical operations designed to separate the edible and inedible organic fraction from these specific contaminants. In the first step, shredders and grinders break open food packaging and homogenize the waste stream. Shredders reduce bulky items such as plastic trays from ready meals, cardboard from bakery goods, composite beverage cartons, and even glass jars containing food residues. Grinders further reduce particle size to ensure a uniform mixture for subsequent sorting stages.

After comminution, vibrating screens and rotary drum sieves (trommels) enable size-based separation. Vibrating screens allow smaller food waste particles — such as fragmented fruits, vegetables, cooked meal residues, or dairy products — to pass through, while they retain larger packaging fragments. Trommels use rotation, centrifugal forces, and gravity to separate items like broken glass pieces from olive jars, large plastic film clumps, or shells from seafood-processing waste.

To address metallic contaminants, magnetic separators remove ferrous metals commonly found in steel food cans or cooking utensils accidentally mixed into commercial kitchen waste. Eddy current separators extract non-ferrous metals, such as aluminum lids from yogurt cups, beverage cans, or foil packaging from confectionery products. Removing these materials ensures that the organic fraction entering composting, anaerobic digestion, or nutrient-recovery systems is clean and safe, while also allowing valuable metals to be recycled and reducing the extraction of virgin resources.

Performance characteristics:

Mechanical sorting systems, while economically favorable, typically show lower efficiency in removing material-based contaminants compared to advanced chemical or optical technologies. In this context, contaminants refer specifically to inorganic materials unintentionally mixed with food waste, such as small plastic fragments (e.g., film from ready-meal packaging), paper and cardboard pieces, multilayer packaging, metals (aluminum lids, steel can fragments), or small broken glass pieces from food jars.

These systems do not address chemical contaminants such as heavy metals or residues from food processing.

Because food waste streams often contain a complex mixture of packaging and food residues, multiple mechanical steps are required, which can reduce accuracy and increase operational costs. The removal of lightweight plastics, thin films, or complex multilayer packaging remains particularly challenging, leading to higher residual contamination in the final organic fraction.

Components:

- Shredders and grinders for opening food packaging and homogenizing mixed food waste streams (e.g., shredded vegetable waste mixed with plastic meal trays).

- Vibrating screens for high-frequency particle size separation, enabling finer food residues (e.g., chopped fruits, cooked food particles) to pass through while retaining larger packaging.

- Rotary drum sieves (trommels) for continuous classification using centrifugal and gravitational forces, effective for separating broken glass fragments, shells, or large packaging pieces.

- Magnetic separators (permanent or electromagnetic) for extracting ferrous metals such as steel can fragments or metal cutlery accidentally discarded in canteens; optional eddy current separators for non-ferrous metals like aluminum lids or foil.

- Ballistic separators to distinguish between light, flexible films (e.g., salad bags, cling film) and rigid plastics (e.g., yogurt cups, condiment containers), improving plastic separation efficiency.

Applications:

- Separation of plastics, multilayer packaging, and other inorganics from food waste.

- Removal of ferrous and non-ferrous metallic contaminants to improve downstream purity.

- Standardization of particle size to enable more efficient anaerobic digestion, composting, or other bioconversion processes.

OPTICAL AND SENSOR-BASED SYSTEMS

Performance characteristics:

Optical and sensor-based sorting systems use advanced imaging and spectroscopy to distinguish food waste from inorganic contaminants such as plastics, metals, glass, paper, or multilayer packaging. Technologies like near-infrared (NIR) spectroscopy detect characteristic absorption patterns to differentiate organic matter (e.g., fruit, vegetables, cooked meal residues) from polymers or composite materials. High-resolution visual recognition systems (RGB and hyperspectral cameras) support classification based on color, brightness, and contrast, enabling detection of visible packaging such as colored plastics or paper labels.

Laser scanners add information on particle geometry and surface texture, which is crucial for detecting materials that are difficult to classify with NIR alone (e.g., black plastics, dark-colored multilayer films).

Because these systems often combine multiple sensors—NIR, RGB, hyperspectral imaging, and laser triangulation—they can evaluate material composition, shape, size, and color simultaneously, providing very high accuracy even in heterogeneous food waste streams.

However, moisture, sticky food residues, or surface contamination may interfere with spectral readings and reduce accuracy. Moreover, optical systems require high initial investments, specialized maintenance, and controlled illumination conditions. This makes them highly efficient for large industrial facilities, but less accessible for smaller waste treatment plants.

Components:

- Near-infrared (NIR) spectroscopy sensors for detecting material composition, such as identifying specific plastic polymers, paper fibers, or organic residues.

- High-resolution camera arrays (RGB / hyperspectral) for visual-based classification through color, brightness, and contrast.

- Laser scanning modules for detecting surface properties and geometric features, particularly useful for black plastics or materials with low NIR reflectance.

- LED illumination systems to ensure uniform lighting, reduce shadows, and stabilize detection quality under varying environmental conditions.

Applications:

- High-precision separation of plastics, composite packaging, paper/cardboard, and glass fragments from mixed food waste streams.
- Quality control and identification of contaminants in pre-treated food waste prior to anaerobic digestion, composting, or nutrient-recovery processes.
- Sorting of food waste from supermarkets, food processing facilities, and household collection systems to ensure high-purity organic fractions.
- Detection of specific problematic materials (e.g., black plastics, multilayer films, coated paper) that cannot be reliably separated with mechanical systems.

ARTIFICIAL INTELLIGENCE-BASED SORTING SYSTEMS

Performance characteristics:

AI-based sorting systems represent the most advanced category of food waste sorting technologies, offering unparalleled precision in identifying and separating food residues, packaging materials, and inorganic contaminants. Using deep learning and computer vision, they can detect subtle differences in shape, texture, color, and material composition, including items partially covered with food residues or contaminated packaging that traditional optical systems struggle to classify.

The underlying machine learning models are trained on extensive datasets containing annotated images of food items, food waste fractions (e.g., vegetable scraps, cooked food residues, dairy waste), and diverse packaging materials. With continued exposure to new materials and contamination patterns, these systems self-improve over time through adaptive learning, without requiring hardware replacement.

A major strength is their capacity for real-time image processing, making classification decisions within milliseconds and enabling seamless operation in high-throughput environments. With purity and accuracy rates commonly exceeding 90%, AI-based sorting systems significantly reduce contamination in food waste streams and improve the efficiency of downstream processes such as anaerobic digestion, composting, or packaging recycling.

Components:

- Deep learning neural networks, primarily convolutional neural networks (CNNs), for extracting features and classifying food waste and packaging.
- Computer vision algorithms capable of identifying color, shape, surface texture, defects, and mixed-material components.
- High-speed imaging systems (RGB, hyperspectral, or multispectral cameras) for generating precise, high-resolution visual datasets.
- Real-time processing units combining GPUs/edge computing modules to ensure millisecond-level decision-making.

- Machine learning pattern-recognition modules enabling continuous model updates as new waste items or packaging types appear in the stream.

Applications:

- High-precision separation of food waste from complex packaging materials in household, commercial, and industrial food waste streams.
- Detection and removal of contaminated or partially obscured packaging (e.g., film-wrapped produce, sauce-covered trays, yogurt cups with residue).
- Classification of challenging materials such as flexible packaging, black plastics, multilayer films, and composite containers.
- Quality control in pre-sorted food waste prior to anaerobic digestion, composting, biorefineries, or nutrient recovery processes.
- Automated sorting in high-throughput facilities such as food processing plants, supermarket waste-preprocessing lines, and large-scale recycling centers.

Advanced Detection Technologies

X-RAY INSPECTION SYSTEMS

Performance characteristics:

X-ray inspection systems are essential tools in modern food quality, safety, and waste-stream purification. Unlike optical or mechanical methods, X-ray technology enables density-based detection, making it possible to identify contaminants that are invisible on the surface. This allows the reliable identification of inorganic foreign materials such as glass, metal, stones, bone fragments, and rigid plastic even when they are embedded in packaged products or mixed food-waste streams.

Modern X-ray units use multi-energy X-ray spectroscopy, which exposes materials to different X-ray energy levels to achieve more accurate material differentiation. Combined with advanced image-processing algorithms and machine-learning models, these systems can also detect internal product defects (e.g., voids, cracks), incorrect fill levels, or mass irregularities while reducing false positives.

With high detection accuracy and robustness, X-ray systems are particularly valuable in situations where conventional technologies reach their limits, such as in complex, contaminated, or fully packaged food waste streams.

Components:

- High-resolution X-ray emitters and detectors for generating and capturing density-contrast images.
- Multi-energy spectroscopy modules enabling material distinction across different X-ray energy levels.
- Automated image-processing software for analyzing density variations, particle structures, and potential foreign bodies.
- Machine-learning-based defect classification models for automated detection and evaluation of anomalies.

- Material-handling systems (conveyors, positioning units) that integrate X-ray inspection into continuous food-processing or food-waste-sorting lines.

Applications:

- Detection of inorganic foreign materials in food waste streams, such as glass from jars, metal fragments, stones, shells, or bone pieces.

- Quality and safety inspection of packaged and unpackaged foods, including identification of contaminants in cans, pouches, jars, trays, or plastic containers.

- Density-based material separation when optical, NIR, or mechanical systems fail to distinguish contaminants.

- Identification of internal defects such as voids, cracks, incomplete filling, or structural deviations in packaged products.

- Ensuring high-purity organic fractions for anaerobic digestion, composting, nutrient recovery, or other bioconversion processes in food-waste management.

HYPERSPECTRAL IMAGING (HIS)

Performance characteristics:

Hyperspectral imaging (HSI) is one of the most advanced optical detection technologies used in the food sector, providing deep chemical and structural insights into products. By capturing 100–250 narrow wavelength bands across the visible, NIR, and SWIR (short wave infrared) ranges, HSI produces unique spectral fingerprints that reveal the chemical composition of a material such as moisture, protein, sugar, or fat content.

In food inspection, HSI detects internal defects (e.g., bruising, rot, spoilage, freezer burn) that are invisible to conventional RGB cameras. It also enables molecular-level contamination detection, such as mold growth, mycotoxin presence, or foreign organic residues, and does so non-destructively and in real time, making it suitable for continuous processing lines.

In the context of material recovery and food-waste reduction, HSI plays a critical role by enabling:

• High-precision sorting of organic vs. non-organic materials, improving purity of recovered streams (e.g., clean biowaste for AD/composting).

• Early identification of spoiled or degraded food components, which prevents cross-contamination of otherwise recoverable organic fractions.

• Quality-based differentiation of food grades, allowing edible products to be redirected for consumption or secondary markets instead of being discarded.

This makes HSI a key enabler for maximizing the value of the organic fraction and reducing unnecessary food losses.

Components:

- Hyperspectral cameras capturing 100–250 spectral bands (VIS–NIR–SWIR).
- Illumination systems optimized for uniform spectral reflectance (typically halogen or LED).
- Real-time spectral analysis software that interprets chemical signatures and material classes.
- Machine-learning and chemometric models for classification, anomaly detection, and chemical composition prediction.
- Material-handling and conveyor integration for continuous, high-throughput inspection.

Applications:

- Material recovery in waste streams: distinguishing organic food residues from packaging, plastics, or other non-organic contaminants to improve purity of the organic fraction for composting, anaerobic digestion, or nutrient extraction.
- Food-waste reduction: identifying edible-quality materials versus spoiled or unsafe products, enabling re-routing to consumption, processing, or valorization instead of disposal.
- Internal defect detection: identifying bruising, rot, or structural defects invisible to surface inspection.
- Chemical and nutritional analysis: quantifying moisture, protein, fat, sugar, or other components for quality grading and process optimization.
- Contamination detection: identifying mold, mycotoxins, and other chemical contaminants at a molecular level.

METAL DETECTION SYSTEMS

Performance characteristics:

Metal detection systems are foundational technologies in food safety control, used extensively across meat, dairy, bakery, and packaged food production. They operate by generating electromagnetic fields and detecting any disturbance caused by metallic particles within or around the food product. Modern systems identify ferrous, non-ferrous, and stainless-steel contaminants, even when deeply embedded in products or packaging.

High-performance detectors employ multi-frequency scanning, enabling accurate detection across diverse food matrices—including products with high moisture or salt content, which traditionally interfere with single-frequency systems. Sensitivity thresholds allow detection of metal fragments as small as 0.3–0.5 mm, ensuring compliance with global food safety frameworks such as HACCP, IFS, and ISO 22000.

Because metal contaminants are identified at an early stage, individual items can be removed before entering downstream processing or packaging. This prevents unnecessary disposal of entire product batches, supports resource-efficient production, and reduces waste generated from safety-related recalls.

Components:

- Electromagnetic field generator that creates the detection zone.
- Signal receivers that identify disturbances caused by metallic particles.

- Multi-frequency processing units for enhanced accuracy across different food types.
- Automated rejection systems (air-jet, belt stop, pusher) that remove contaminated items from the line.
- Interface and monitoring software for calibration, sensitivity adjustment, and HACCP documentation.

Applications:

- Food-waste reduction: early removal of contaminated individual items prevents entire product batches from being discarded during quality checks or consumer recalls, significantly reducing waste along the supply chain.
- Enhanced product safety: reliable detection of ferrous, non-ferrous, and stainless-steel fragments ensures consumer protection and compliance with safety regulations.
- Quality assurance in high-throughput environments: suitable for fast conveyor lines without slowing production, maintaining efficiency while safeguarding product integrity.
- Prevention of downstream equipment damage: eliminating metal fragments protects shredders, slicers, and filling machines, avoiding maintenance downtime and additional material losses.
- Complementary integration with other systems: often used alongside X-ray inspection to create a comprehensive hazard detection strategy (metal + non-metal contaminants).

System Integration and Operational Performance

REAL-TIME PROCESSING SYSTEMS

Performance characteristics:

Real-time processing systems in modern food sorting and inspection technologies operate with millisecond-level reaction times, enabling immediate detection and removal of defective or contaminated products. High-performance multi-sensor setup combining optical, spectral, and AI-driven detection—synchronize identification and actuation so precisely that only the targeted product is removed, reducing false rejects and limiting avoidable food waste.

Advanced commercial systems such as the TOMRA 5C demonstrate sorting accuracies of up to 99.9% and throughput capacities of several tons per hour, supporting continuous industrial-scale operation (TOMRA, 2021; Brosnan & Sun, 2020). While primarily designed for controlled food processing environments, similar concepts are increasingly explored for centralized waste pre-treatment systems to separate food waste from residual household waste. Direct installation in truck-collected mixed waste streams remains technically challenging due to moisture, compaction, and heterogeneity, but ongoing research focuses on adapting real-time sorting units for municipal waste recovery facilities.

Components:

- High-speed optical, multispectral, or hyperspectral camera units.
- Real-time signal processing hardware with millisecond decision capability.
- Synchronization modules to align detection data with actuator timing.
- High-speed ejection mechanisms (air jets, pushers, paddles, diverter arms).

Applications:

- Pneumatic air jets for lightweight products (nuts, grains, confectionery).
- Mechanical pushers or flaps for heavier packaged items (meat, frozen food).
- Diverter arms for fragile goods (glass containers, baked products).
- Deflector paddles for free-falling material flows (cereals, nuts).
- Use food manufacturing to maintain product quality and minimize waste.
- Emerging application in centralized waste sorting to recover food waste from mixed residual streams prior to anaerobic digestion or composting.

AI ENHANCEMENT AND AUTOMATION

Performance characteristics:

Modern quality-control systems increasingly incorporate AI to enhance defect detection and ensure continuous monitoring. AI-enhanced sorting machines combine multisensory inputs such as optical cameras, hyperspectral imaging, and X-ray detection, with deep-learning algorithms to classify complex irregularities, including subtle discolorations, mold spots, or packaging defects.

Systems such as TOMRA LUCAi™ apply deep neural networks to analyze millions of data points in real time, continuously improving classification accuracy and enabling adaptive threshold settings as raw material quality fluctuates (TOMRA 2025). They additionally support predictive maintenance by identifying early signs of equipment wear.

An important performance benefit is the automatic logging of every rejected product. Each item can be linked to metadata such as timestamp, rejection cause, and associated image data, thereby supporting batch-level traceability and documentation.

Components:

AI-based evaluation and sorting systems rely on a coordinated combination of hardware and software components, including:

- Multisensor acquisition units (RGB cameras, hyperspectral sensors, X-ray detectors) for detailed structural and material assessment.
- Deep-learning models capable of extracting intricate features—color, shape, texture, density—to achieve precise classification.
- Logging and data-management modules that store images, metadata, and event histories for later traceability analysis.
- Edge and cloud infrastructures that enable continuous model training, version updates, and integration into smart logistics architectures.

Applications:

AI-enhanced sorting and inspection systems are used extensively in food-processing environments requiring real-time defect detection and high consistency. Automated classification increases process reliability, while adaptive decision rules compensate for fluctuations in incoming raw materials.

The comprehensive data captured by these systems aligns well with modern traceability frameworks that integrate IoT monitoring, cloud-based supervision, and blockchain-enabled event logging. Such systems provide time-stamped product histories and support smart food-logistics concepts (Wattanakul et al., 2018).

In practice, these technologies enable:

- Continuous learning through ongoing algorithm training.
- Recognition of complex defect patterns across multiple feature dimensions.
- Predictive maintenance informed by sensor data.
- Automated image and metadata logging for end-to-end traceability.

Practical Example: Winnow

A relevant practical example of AI application in the food sector is provided by Winnow Solutions, a company specializing in technological tools for reducing food waste. Its flagship system, Winnow Vision, uses computer vision and AI-based image recognition to automatically identify and record discarded food items in commercial kitchens. An overhead camera and integrated scale capture both visual and weight data, eliminating the need for manual documentation.

The insights generated by Winnow Vision enable kitchen operators to detect avoidable waste—such as overproduction, spoilage, or oversized portions—and adjust procurement and preparation routines accordingly. Organisations using the system commonly report significant reductions in food waste and related costs. By enabling continuous monitoring and data-driven decision-making, Winnow Vision supports more efficient resource use and contributes to greater consistency and safety in food handling. This example illustrates how AI-driven monitoring can make food-service operations more sustainable while reducing unnecessary losses across the supply chain. (Source: https://www.winnowsolutions.com/de/)

INDUSTRY 4.0 INTEGRATION

Performance characteristics:

Industry 4.0 integration enables sorting and inspection systems to function as fully connected elements within digital production environments rather than as isolated units. Through standardized interfaces, these systems achieve seamless data exchange with Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES), ensuring smooth coordination between operational processes and higher-level management functions.

Cloud-based platforms allow real-time remote monitoring, offering globally accessible dashboards that display performance indicators and system status. Rejected products can be automatically logged with image data, timestamps, and defect classifications, supporting compliance with quality and safety standards such as ISO 22000 and HACCP (Aung & Chang, 2014). The resulting digital traceability enhances food safety assurance and accelerates recall procedures.

Furthermore, AI-driven predictive analytics enable autonomous optimization of process parameters, reducing downtime and stabilizing throughput. In this way, sorting systems evolve into active contributors to efficiency, transparency, and quality improvement in smart manufacturing environments (Verdouw et al., 2016).

Components:

Industry 4.0-enabled sorting and inspection solutions typically incorporate:

- Interoperability modules for ERP and MES connectivity, facilitating bidirectional data exchange.
- Cloud and edge computing architectures that support remote data access, performance visualizations, and secure data storage.

- Integrated logging and traceability tools capable of capturing images, timestamps, defect categories, and batch information.
- AI-enabled diagnostic systems for predictive maintenance, anomaly detection, and autonomous parameter adjustment.

Applications:

In practice, these systems are deployed across food-processing lines to enhance operational transparency, improve safety, and streamline decision-making. Continuous data integration allows managers to monitor equipment performance, track defective items, and maintain regulatory compliance.

Traceability functions support rapid and targeted product recalls, while predictive analytics reduce unplanned downtime and stabilize production flows. As a result, Industry 4.0–enabled sorting systems help create manufacturing environments where accuracy, efficiency, and safety are optimized simultaneously.

Food waste in Germany

Germany generates approximately 10.9 million tons of food waste per year (BMEL, 2019) and represents approximately 18.5% of the EU's food waste. The biggest share of food waste (59%) in Germany is generated from households, followed by restaurants and food services (17%), processing and manufacturing industries (15%), retail and distribution sectors (7%), and primary production (2%). This sectoral distribution highlights the importance of required changes in consumer behaviour as well as the necessity in application of applying appropriate upstream and downstream solutions to achieve effective reduction.

The most frequently dumped food types in Germany are fruits and vegetables, followed by bakery products (especially bread), prepared meals and leftovers, dairy products, meat and sausages, and liquids such as milk and juices (BMEL, 2019), as shown in Figure 1. This trend is due to overbuying, spoilage, short shelf lives, and confusion over expiration labels (Herzberg et al., 2020).

Food waste contributes up to 4% of Germany's national greenhouse gas emissions (BMEL, 2019). The quantity of food waste generated every year has significant environmental burdens, responsible for between 14 to 20% of total environmental impacts, depending on the impact category (global warming potential, land use, water use, etc.) as reported by Jepsen et al. (2016). Halving food waste generation by 2030 could avoid over 6 million tons of CO_2eq emissions annually in Germany (BMEL, 2019). The water footprint created by food waste represents about 20% of Germany's total agricultural water use and roughly one-fifth of total household water consumption (Jepsen et al., 2016). The economic impacts of food waste are also significant. Calculations showed that avoidable food waste causes economic losses of around 30 billion euros annually in Germany (BMEL, 2019).

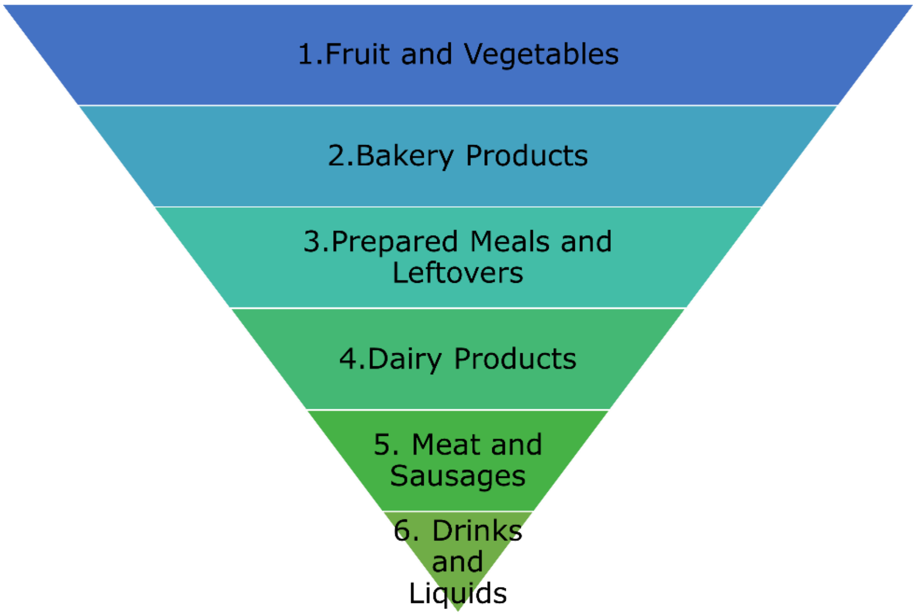

Figure 1: Hierarchy of most frequently wasted food types in Germany, data from (BMEL, 2019)

Innovative applied solution: The ReFood case

Name: ReFood GmbH & Co. KG

Type of facility: Anaerobic digestion and recycling plant for food waste

Owner/Operator: Saria Group (part of the Rethmann Group, Germany)

Location: 12 operating plants across Europe with presence in Germany, France and the UK:

- Germany: 5 operational plants supported by a network of 14 logistics centres collecting waste from 60,000 points across the country
- UK: 3 facilities (Doncaster, Widnes, Dagenham)
- France: 4 facilities

Capacity: Each plant processes thousands of tonnes annually (e.g., Doncaster facility up to ~160,000 tonnes per year)

History: ReFood is an international company with a 30-year history, originating from Saria's German operations. The German facilities served as the model for international expansion, with the UK operations launched in 2011 based on proven German technology and operational expertise. The German network remains the largest, demonstrating the maturity and sophistication of Saria's food waste management approach.

Investment: Around 20 € million per site (varies depending on scale)

WASTE STREAMS

Type of waste streams handled: Food waste from supermarkets, restaurants, food manufacturers and households

Waste composition: Biodegradable organic waste, including packaged food waste (meat, dairy, bakery, vegetables, cooked meals)

TECHNOLOGY DETAILS

Brief description of the process: ReFood collects segregated food waste and transports it to its facilities. After depackaging and preprocessing, waste is fed into anaerobic digesters where microorganisms break it down, generating biogas. The biogas is upgraded to produce renewable electricity, heat, or biomethane for injection into the grid. The digestate residue is treated and used as an organic biofertilizer for agriculture.

List of key technological components

- Depackaging equipment

- Pre-treatment and homogenisation systems

- Anaerobic digesters

- Biogas upgrading and CHP (Combined Heat & Power) units

- Digestate processing systems

Sorting and depackaging technologies: ReFood facilities employ sophisticated sorting and depackaging systems to handle the challenge of separating organic material from packaging:

Depackaging Systems

- Advanced mechanical separation using counter-rotating screw augers with serrated edges
- Hammermill-based systems with punch-plate screens for efficient separation
- Modern centrifuge-based separation technology
- Bag opening and shredding equipment for preliminary processing

Process Flow

- Incoming packaged food waste undergoes initial sorting and bag opening
- Material enters depackaging units where mechanical action separates organic content from packaging
- Organic slurry is extracted and prepared for anaerobic digestion
- Packaging materials (plastics, metals, cardboard) are separated into clean reject streams
- Reject materials are recovered for recycling where possible

ReFood facility in Trossingen, Germany: In response to evolving German regulations requiring strict separation of packaged and unpackaged food waste throughout the entire processing chain, ReFood opened an innovative facility in Trossingen in June 2020. This plant features two separate processing lines that handle packaged and unpackaged waste streams independently from collection through to final processing, representing a proactive response to regulatory developments.

Performance Characteristics

- High purity of organic pulp produced (minimal contamination)
- Clean separation of reject streams for improved recycling
- Reduced energy consumption compared to older technologies
- Smaller footprint and lower water usage
- Higher reliability with fewer moving parts requiring maintenance

Innovative features

- Ability to handle packaged food waste efficiently
- Zero-waste approach (energy + fertiliser recovery)
- Integration of food collection logistics with processing
- Contribution to circular economy (farm-to-fork-to-farm loop)
- Advanced dual-stream processing (German facilities) for regulatory compliance

The novelty of this plant relies primarily in the closed-loop valorisation of food waste into renewable energy and fertiliser, with German facilities pioneering approaches to regulatory compliance and processing efficiency.

Deployment environment

ReFood plants are typically located near urban centres with high food waste generation and good transport access. German facilities benefit from extensive logistics networks with collection points distributed nationwide.

Integration with existing waste treatment plants: Complements recycling and landfill diversion strategies, reduces strain on municipal waste facilities.

Performance metrics

Sorting efficiency: High (automated depackaging ensures minimal contamination in organic fraction and clean separation of recyclable packaging materials).

Throughput: Up to 160,000 tonnes per year per facility

Technical challenges during operation: Managing contamination, such as plastics, metals or other unwanted materials in incoming waste, odour control, and consistent biogas yield.

Flexibility of the system: Can process a wide variety of food waste, including packaged products; newer German facilities can handle separate streams of packaged and unpackaged waste.

Recovered materials/products

Type of material recovered: Biogas (electricity, heat, or biomethane) and biofertilizer (liquid digestate).

What are these materials used for? Renewable electricity and heat for homes and businesses; green biomethane for grid injection or vehicle fuel; nutrient-rich biofertilizer for agriculture.

About by-products/reject fraction: Minimal; packaging and non-organic residues are separated and recycled where possible.

Environmental impact

Material recovery rates: Nearly 100% of organic material recycled into energy or fertiliser.

About energy: Facilities produce enough renewable energy to power tens of thousands of homes per year.

Climate impact & emissions: Significant CO_2 emissions savings by diverting food waste from landfill; reduction in methane release from uncontrolled decomposition; displacement of fossil fuels and chemical fertilisers.

Societal impact

Job creation: Each facility supports dozens of direct jobs and many more indirectly in logistics and agriculture. The German network with its 14 logistics centres provides extensive employment across the collection and processing chain.

Community involvement: ReFood works with local businesses, councils, and farmers to ensure a closed-loop, sustainable system. They also provide educational outreach on food waste reduction. The German operations collect from 60,000 points nationwide, demonstrating extensive integration with commercial and municipal partners. They also provide educational outreach on food waste reduction.

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