Bulky Waste Detection

Kanadevia Inova AG (KVI) has released to the market the new product Bulky Waste Detection. It has been piloted for more than one year in two Swiss plants and KVI is actively advancing commercial discussions across the European and Middle East Waste-to-Energy (WtE) sector and continues to generate promising new opportunities. The Bulky Waste Detection is a flexible computer vision system that can be installed in new plants or as a retrofit. It monitors 24/7 the tipping of waste and warns the crane operator in real time if a bulky item has entered the bunker through a user-friendly interface. The user receives all the information needed to be able to decide and act, i.e. either shredding, removing or releasing the item depending on its potential problematic impact to plant operation.

The KVI Advanced Digitalization group has developed a Digital Product that aims at reducing blockages in WtE plants caused by bulky items that lead to plant shutdowns, which result in a reduction of plant availability and monetary losses. In addition, blockages occur often in the bottom ash extractor where the process of removal is hazardous, therefore this solution also minimizes Health and Safety risks.

The problem statement

WtE plants face operational challenges due to both minor and major blockages, with minor ones disrupting waste feed consistency and major ones potentially causing full plant shutdowns. These issues place significant responsibilities on crane operators, who cannot feasibly monitor every gate while a truck is tipping to identify problematic waste. The number of tipping gates can vary between 4 to more than 10 depending on the size of the plant, and typically in each gate there is one truck coming every three minutes. The variability of waste adds to the challenge, what causes issues in one plant may be harmless in another, making it essential for any solution to be flexible and adaptable across different waste profiles. Moreover, while extremely problematic waste is rare, its occurrence can lead to severe disruptions. Therefore, an effective solution must be both cost-efficient and broadly applicable, avoiding the need for extensive manual customization at each facility, and must be able to cope with very few, or even non-existing images of a problematic waste when deployed in a customer.

The approach

To be effective, a detection solution in WtE operations must identify bulky items immediately upon tipping, before the next truck arrives, providing timely insights for decision-making that support diverse bunker management strategies. Given the variability of waste and the limited availability of training images for problematic materials, the system must have a broad detection scope and prioritize sensitivity over precision; it is more critical to avoid missing problematic items than to eliminate false positives. Additionally, the solution must be designed with the operations team in mind, ensuring it delivers actionable information without overwhelming the user with excessive data or complexity.

To develop a practical and scalable waste detection solution for WtE operations, computer vision and machine learning technologies were selected, relying on cost-effective RGB cameras. These cameras are strategically installed in the bunker areas that offer a clear field of view of the tipping process, are positioned outside the crane's operational moving zone, and allow for installation without interrupting plant operations.

PRODUCT FEATURES

User Interface

The user interface (shown in **Figure 1**) provides actionable insights through an alarm view that enables immediate response, while also offering a historical overview via alarm log. The settings view of the interface supports various configurations to accommodate the operational differences across WtE plants, such as activation and deactivation of specific gates monitoring, configurable bulky waste size limits, and detection catalogue. Additionally, user feedback plays a critical role in monitoring prediction quality and continuously refining the model through targeted training.

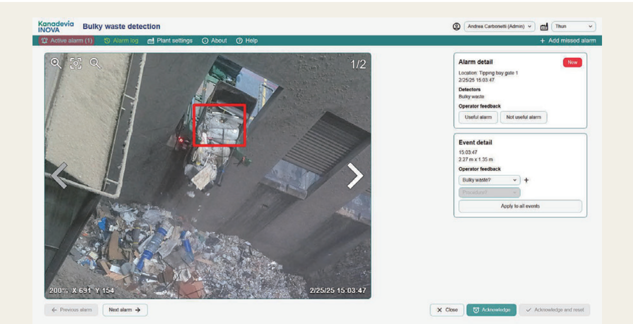

Figure 1　User interface of Bulky Waste Detection showing the detailed view of an alarm. Image with bounding box on the left, and alarm and event details on the right

Detection targets and model journey

The solution features two bulky waste models with two specific detection targets, that are configurable to provide a flexible solution that adapts to different waste and plant operation profiles.

Size Based Detector

This detector is built on a pipeline that includes a size-based segmentation step and an image classification step, that is able to distinguish large objects in the field of view of interest that are waste from those that are not waste. This is a general-purpose detector that can detect any type of waste above specific dimensions. This type of broad detection target allows for the adaptability of this solution to any type of waste profile, as the solution does not need to know exactly what are the specific problematic waste (which changes from plant to plant).

The Size Based Detector has been trained to detect standard bulky waste and elongated bulky waste. The figure below shows a 2D representation of Standard and Elongated Bulky Waste. Standard Bulky Waste is a type of waste where both major and minor axis are larger than a specified threshold, examples are mattresses, IBC containers, pallets, large rolls, tires, large pipes, etc. Elongated Bulky Waste is a type of waste where the minor axis is significantly smaller than the major axis, examples include palm trees, large pipes, large roles, etc. As thresholds vary from plant to plant, the user can configure them in the WebApp independently, and the solution will adjust automatically to provide only alarms for the objects that are above the configured threshold (L_{ST}, L_{minor}, L_{major}).

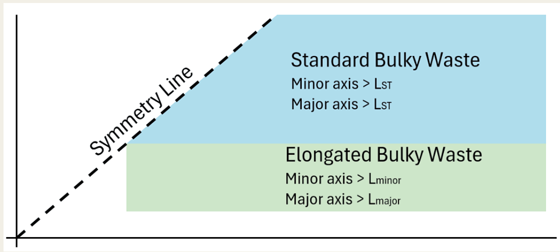

Figure 2　2D representation of Standard and Elongated Bulky Waste

Bulky Waste Object Detector

This is a standard object detector, trained to detect specific waste objects. Our experience has shown that one model with multiple detection targets provides better results than one model per detection target. We have a model that detects mattresses and IBC containers, and we plan to add more detection targets based on user feedback and requests.

Near real time detection

The very short latency time of the solutions allows the operation team on site to react quickly when a bulky item arrives at the tipping bay of the bunker and if needed start the chosen procedure before the item is covered by an incoming truck or is mixed within the bunker.

Secure and Reliable Architecture

Figure 3 shows a simplified system architecture of the solution. The solution consists of cameras and a server that are installed on site. The server is connected securely to the backend services that are hosted on the KVI private cloud network. A WebApp displays the user interface, which can be accessed from a chosen device (e.g. a laptop or tablet) on or off site with a network connection. The users receive a user account, which grants them access to data from their plant only. The KVI private network is monitored 24/7 for cybersecurity risks.

The server on site, has local storage where raw images are stored up to 30 days, which allows recovering images to investigate specific events further on specific time windows.

Among other things, back-end services monitor detection performance based on user feedback, are used to re-train models on demand if the performance degrades and are used to train and deploy new Bulky Waste Object Detector.

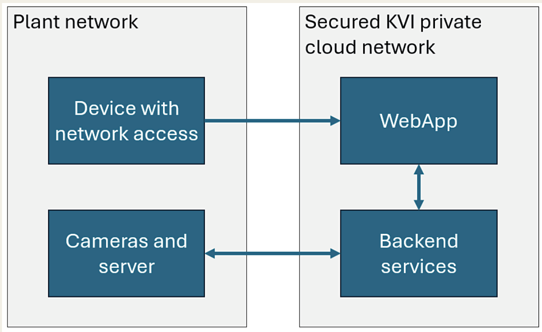

Figure 3　Simplified system architecture overview

Figure 4 shows a schematic of the camera position and mounting on the bunker, and **Figure 5** shows a photograph of the camera setup. The camera mounting set up is fixed with screws on a surface of the bunker that allows to point the field of view of the camera to the gates. The setup contains a roof to protect the camera and a rail to adjust the camera position.

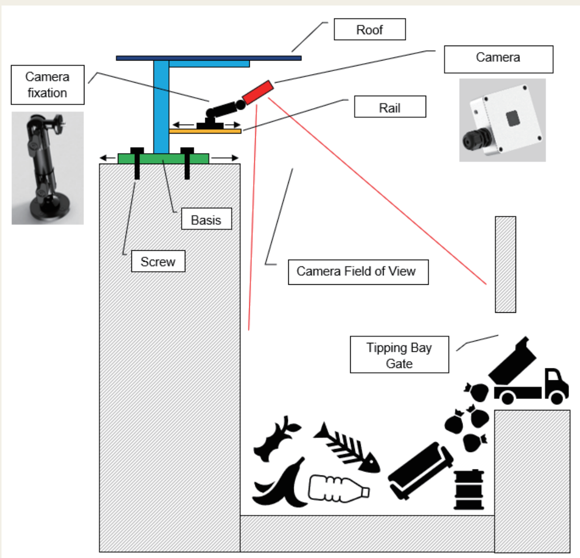

Figure 4　Schematic of the camera position with respect to the bunker wall and tipping gate

Figure 5　Photograph of the camera setup

Installation and Commissioning

Table 1 shows the end-to-end customer journey, including the installation and commissioning.

Table 1　End-to-end customer journey

Phase	Duration
Preparation and planning	2 months
Installation and commissioning	1 month
Customer onboarding	2 weeks
Hyper care	2 months
Support	Contract based

The solution allows for flexible installation while the plant is running, for both new and retrofit plants. Below is a short list of installation requirements:

- Internet connectivity on site
- Device with internet to access the interface
- Room for a server cabinet, climate controlled
- Adequate bunker lighting
- Bunker dust management

The models do not require substantial amounts of recorded images and lengthy training periods during commissioning, achieving satisfactory detection performance in only a few weeks.

■ IMPLEMENTATION

Multidisciplinary approach

Developing an effective solution for waste detection and management in WtE operations requires a multidisciplinary approach that integrates several key domains. UX Research and Design ensures the system is intuitive and aligns with the demanding workflows of crane operators, minimizing cognitive load while maximizing usability. Data Science plays a central role in building robust detection models that can handle waste variability and prioritize sensitivity to avoid missing critical items. To support scalability and adaptability, Software Architecture must provide a flexible and modular foundation, while Software Engineering ensures reliable implementation and integration with plant systems. Finally, MLOps (the engineering field of Machine Learning System Operations) is essential for maintaining and continuously improving machine learning models in production, enabling efficient deployment, monitoring, and updates across diverse plant environments. This (non-exhaustive) collaborative framework is vital to delivering a solution that is both technically sound and operationally practical.

Staged releases

An initial technology scouting exercise revealed that no suitable solutions were available on the market, requiring us to develop a custom solution from the ground up. Open-source image banks lack sufficient visual data of WtE bunkers, which is a niche domain, making it difficult to train models effectively. As a result, open-source pre-trained models perform poorly, and building an internal dataset became necessary. We began with large-scale releases to bootstrap a functional solution, then transitioned to smaller, iterative releases to incorporate customer feedback in the development cycle. **Table 2** provides an overview of the staged releases, including the main outcomes.

Table 2 Staged releases

Release	Outcome
Feasibility study	Data exploration, development of detection concept and pipeline with offline studies
Prototype	System development (transition to online system), validated core capabilities (standard bulky waste detection in real time), first iteration of user interface to collect user feedback
1.0.0.0	Industrialization (enhanced security, monitoring, operational tooling and processes), new user interface (improved user experience) and new notification concept
1.0.1.0	Technical enhancements of performance and monitoring
1.1.0.0	Ability to detect bulky waste with an elongated shape, improvements in precision reducing false alarms
1.2.0.0	Introduction of waste object detector

Validation

Validation vehicles

The solution (both prototype and subsequent releases) has been piloted in two Swiss plants over more than one year. The pilot phase has allowed for continuous testing and improvement of the solution online with direct feedback from end-users.

Prototype validation

Figures 6 and **7** show a two-month extract of validation data collected during the prototyping phase. The first figure shows the weekly precision of the detected events. During this phase, the solution achieved a satisfactory precision target, except for one data point. During this week, in Plant 2, there was an operation event in the bunker that caused a significant accumulation of dust in the camera that impacted the ability to monitor the bunker. It was extremely helpful during the pilot phase to experience such extreme events during normal operation, so that lessons learned can be transformed into operational concepts and mitigation measures to ensure satisfactory functioning of the solution.

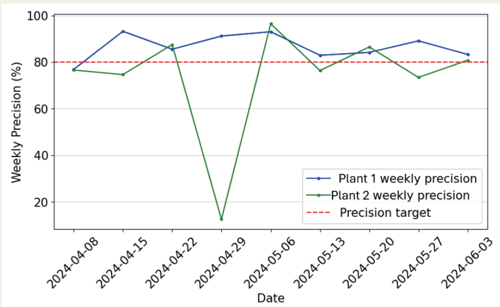

Figure 6 Weekly measured precision and target precision during 2-month period of pilot testing

The next figure shows the event detection latency time of the solution, wich is calculated as the time that an image with a detected event arrives at the user interface minus the time when that image was recorderd from the camera stream. The solution showed very early on very good latency results.

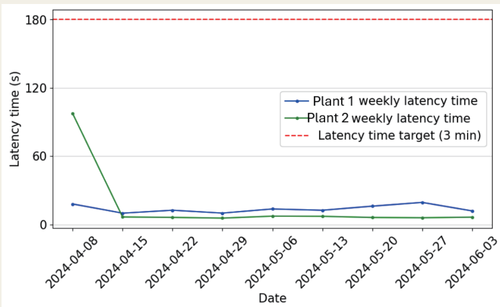

Figure 7 Event latency time during 2-month pilot testing

Validation for product introduction

Product validation is more than just achieving technical targets, but also engagement, satisfaction, value and commercial targets. For the scope of this article, the focus in this section will be technical and engagement. **Table 3** shows a summary of the validation metrics achieved at product introduction stage.

Table 3　Main validation metrics

Metric	Value
Detection precision	83 %
Sensitivity	100 %
Avg notification latency time	1.6 min
Avg operator response	2 h
Notification reduction	73 %

Adding to precision and sensitivity metrics, there are the following metrics:

- Avg notification latency time: the time when a notification arrives at the interface minus the time when a bulky waste is detected.
- Avg operator response: the time when a user processes a notification shown in the interface minus the time when that notification arrived at the interface
- Notification reduction concept: with release 1.0.0.0 the notification concept was improved and the number of notifications to the user was reduced by 73 %.

The operator response to an alarm by providing feedback on the content of alarm and what the operator did about the alarm. More specifically:

- the operator confirms that the alarm was acknowledged following the normal alarm philosophy in plant operation
- the operator provides feedback on whether that alarm is correct and useful
- the operator gives feedback about what was done about the detected bulky waste, if it was shredded, removed or if nothing was done

An average response time to an alarm of 2 h is a positive engagement metric, because it means that the operator is engaging with the UI as expected.

APPROACH AND FUTURE DEVELOPMENT

As the product enters a stabilization and growth phase, the next staged releases will focus on improving the MLOps maturity and extending the catalogue of object detectors. In addition, together with R&D from Kanadevia Corporation, we are exploring whether multimodal GenAI can be integrated effectively and whether it provides additional benefits.

The computer vision platform that is behind the backend services is an enabler for future capabilities beyond the detection of bulky waste. By extending the computer vision platform to monitor waste properties and expanding the monitoring area to the whole bunker, this platform can be an enabler of a smart autonomous bunker management system concept by providing real time observability of the incoming waste (tipping) and the waste in the mixing and stappling areas of the bunker. This observability can be of benefit to an advanced crane control system that considers waste properties in real time when making decisions on mixing, stappling and feeding.

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