Vision-based automated waste audits: a use case from the window manufacturing industry

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Abstract

Waste auditing is one of the tools used to quantify waste generation in construction processes, especially in industrialized building construction facilities that aim to reduce waste. These audits are organized following a regular schedule to monitor manufacturing activities with respect to the waste generated. However, the identification and quantification of waste through occasional audits of activities at any particular workstation remains a biased, manual, error-prone, and monotonous task. This paper proposes the automation of waste auditing in industrialized construction facilities, using as a case study a cutting station on a window manufacturing line. The waste generated during the cutting process is quantified using contour-based image processing algorithms, and the identification of the material is determined by optimized deep learning classification models. This approach allows the continuous acquisition of waste generation data at the workstation level and enables data-driven waste management decision-making that has the potential to support the reduction of waste in industrialized building construction facilities.

Keywords: construction waste; machine vision; deep learning; waste management; window manufacturing.

1. Introduction

The construction industry is, directly and indirectly, responsible for approximately 40% of all the natural resource consumption and waste generated each year in North America (Agamuthu, 2008). The Canadian construction industry generates about 27% of the total municipal solid landfill deposits in the form of construction and demolition wastes (Yeheyis et al., 2013). The consumption of these natural resources is contributing to the degradation of the environment on a large scale (Mercader-Moyano & Ramírez-de-Arellano-Agudo, 2013). Meanwhile, a reliable estimation of construction waste can help mitigate the impact of such waste at the project level. In other words, one cannot reduce what it cannot measure (Guerra et al., 2019). Prefabrication and offsite construction techniques have been identified as one way of reducing waste generation in the construction industry (Ajayi et al., 2015). By having a controlled manufacturing environment, waste reduction approaches can be effectively applied to monitor, control, and optimize waste reduction efforts during construction and fabrication processes (Banihashemi et al., 2017).

From a lean perspective, waste is anything in any manufacturing process that adds no value to the product from the customer's point of view. On a production line, it is inevitable that over time some parameters of the process deviate from optimal performance and generate material waste. Ultimately, this waste reduces the production efficiency and quality of the production processes (Psarommatis et al., 2020). Lower productivity eventually affects the profitability of the manufacturer, which, in turn, might be transferred to the customer in terms of higher product cost or lower quality, negatively impacting customer satisfaction. For offsite construction practitioners, quality and productivity are crucial factors for a successful business. Waste reduction is a sustainable policy for construction practitioners, especially in offsite construction, where the controlled environment and the repetitive nature of their processes facilitate the introduction of waste reduction actions that can be rapidly integrated and continuous.

Waste auditing, the first step in any waste reduction approach, aims to efficiently assess the magnitude and composition of the waste generated by the manufacturing processes, which can initiate a strategic plan to prevent, reduce, or utilize the specific waste under study. To be effective, waste audits must be done thoroughly in a systematic manner under the direction of a dedicated waste supervisor who has domain-specific experience and knowledge of waste audit procedures and rationale. Despite their benefits, waste audits are a labor-intensive and costly, albeit necessary, procedure for manufacturers. As an Industry 4.0 approach, smart automated waste auditing and reporting processes have been identified as one of the key areas to be researched that would enable zero-waste manufacturing and a more circular economy (Kerdlap et al., 2019). Although zero-waste manufacturing requires the integration of various technologies across the value chain, smart waste auditing and waste reduction planning are the first steps forward and represent the primary and initial challenges for waste generators, such as organizations operating in the offsite construction manufacturing industry.

For example, in the window manufacturing industry, waste audits are conducted to assess production process performance and to plan the recycling processes required for the waste materials, including aluminum and polyvinyl chloride (PVC). These waste audits are especially important as most of the manufacturing processes are high volume, and small changes in the performance may considerably affect the amount of material waste generated. For that reason, waste audits occur as often as twice per month, which can be considered an important effort when compared to, for example, the six-month mandatory waste audit schedule required by some provincial regulations in Canada (e.g., Ontario Regulation 102/94). On window production lines, waste is generated from three main sources: 1) the cutting stations where the stock length of glass or window frame material, i.e., aluminum or PVC, is cut to specified sizes generating waste (remaining material from the stock length and scrap from the cutting process); 2) deviations in the process parameters at automated stations on the production line, e.g., welding or corner cleaning, that generate non-remanufacturable defective parts; and, 3) non-conforming products that are separated during quality control inspections after manual operations, i.e., assembly of window hardware components or glass installation.

The present study proposes an automated waste auditing procedure using computer vision and deep learning technologies, which is then applied to audit the profile cutting station for unplasticized polyvinyl chloride (uPVC) windows. When a customer order is confirmed and a shop order is generated, cutting stations are the first stations in the production process sequence. Waste auditing at these upstream stations can capture the generation of waste before it propagates its inefficiencies downstream the production line. This paper is structured as follows: first, a literature review of current research trends around waste management and waste auditing is provided; then, the research methodology is presented. Next, the window manufacturing use case is reported, explaining current practice as a benchmark, the proposed vision-based model, and the algorithms used to acquire the data. Finally, the results are presented and discussed before ending with some conclusive remarks.

2. Literature Review

The increasing awareness regarding the construction industry's environmental impact from construction waste has led to the development of many research studies regarding waste management practices. Adverse impacts of waste generation in construction processes are multiple, including occupying a large amount of land space for waste landfilling (Poon et al., 2003), hazardous pollution (Esin & Cosgun, 2007), and continuous depletion of natural resources (Yuan & Shen, 2011). Although impractical and potentially unreachable, “zero-waste” has been the goal pursued by researchers for the past decade and has led to a well-established hierarchy for waste management methods comprising four levels (from less to more desirable): dispose, recycle, reuse, and reduce (Peng et al., 1997). While the three main strategies for waste management (recycle, reuse, and reduce) are the cornerstones of current practices, the reduction of waste is the desired end for any waste management approach.

Apart from minimizing material usage, waste reduction offers other major benefits: cost reduction associated with material transportation and with waste disposal and recycling, reduced emissions, and reduced material cost (Poon, 2007). Waste reduction is considered the most effective and efficient method available to minimize the impact of construction waste generation and alleviate many of the environmental problems associated with waste disposal. Although some recent examples of the merits of construction waste management can be found in, for example, Australia (Park & Tucker, 2017) or China (Huang et al., 2018), its practical application lacks a fundamental link between waste management practices and the factors that contribute to the generation of waste in the construction industry (Kabirifar et al., 2020). Another barrier to the adoption of effective strategies for waste reduction is the lack of timely and proper communication between the various actors who need to cooperate in implementing and executing such strategies; therefore, most stakeholders limit themselves to waste reduction actions within their own management cycle (Esa et al., 2017).

A potential waste reduction solution that has been increasingly advocated for by industry is prefabrication. Prefabrication is a strategy that brings the manufacture of structures or components to a location other than the construction site. Also known as offsite construction or industrialized construction, the products are generally manufactured in a specialized facility where various materials and a degree of automation can be used in a controlled environment (Ritter et al., 2020). In prefabrication, the positive impacts of waste reduction could be observed if the correct tools are used on the production lines to address potential waste (Tam et al., 2007). Among the tools available to address waste generation, waste audits (or waste inspections) have helped determine the effectiveness of process implementation by monitoring and analyzing the trends of waste generation. In construction and demolition industries, waste audits can be used to quantify waste flows, estimate recycling rates of common waste material, and examine the factors affecting secondary waste markets (Marcellus et al., 2013). Moreover, waste audits have been used to determine the impact of waste management execution in industrialized construction projects (Jaillon et al., 2009; Lu & Yuan, 2013).

Intelligent or automated waste audits that comprise hardware and software solutions can quantify waste, segregate waste, or assess waste reduction and diversion opportunities through recycling or reuse. Quantitative and accurate waste audits and waste estimation are essential requirements for effective construction waste management (Li et al., 2016). Current hardware research is primarily focused on the area of smart waste bins that automatically segregate waste by analyzing the material content and size through visual sensors, e.g., cameras and lasers (Wijaya et al., 2017), reducing disposal cost on-site. On the software side, online tools have been developed that carry out data analytics on waste management processes to review waste collection systems, existing waste management practices and costs, and current levels of on-site recycling and energy consumption (Yen Ting et al., 2017). These digital tools and technological advances are able to identify opportunities for improvement in waste management procedures. A clear reduction in material waste resulting from automated waste audits has been recently reported (Rašković et al., 2020). In construction, a commercial tool was developed by Building Research Establishment Ltd. called SMARTWaste that simplifies reporting for environmental compliance and management of construction waste during projects. Users have reported up to 40% waste reduction on-site using this platform (Kerdlap et al., 2019). More recently, a deep convolutional neural network (CNN) was used to classify typical construction wastes using digital photos of waste material disposed of in construction site bins, with a reported accuracy of approximately 94% (Davis et al., 2021). Waste audits (automated or not) provide, at best, a snapshot of the waste generated by a process for which waste management approaches may lead to plans to reduce waste in future projects. However, sporadic waste audits cannot accurately predict the impact of changes to the production line on waste generation. The benefit of industrialized construction is the repetitiveness of the manufacturing processes, which can facilitate the translation of waste management practices into measurable waste reduction. Systematic waste audits provide better insight into the relationship between process factors and waste generation and can optimize waste reduction efforts through the implementation of data-driven techniques and intelligent data analytics (Bilal et al., 2016).

In summary, many research studies have considered waste reduction as an optimization problem where design and process parameters could be analyzed to determine optimal strategies. These strategies follow well-known methodologies and have proven successful to reduce waste in manufacturing environments. To validate those strategies, waste audits are common to measure waste created. However, certain limitations of the current research solutions can be listed:

- Manual waste audits provide time-limited feedback on waste reduction strategies and cannot be used for long term assessments. As the development and validation of different waste reduction strategies is delayed, this reduces industrial facilities to achieve sustainability targets.

- Manufacturing processes are becoming more flexible, introducing new products and features quickly to satisfy client requirements. As those changes are introduced at the process level, waste generation increases its variability rendering previous waste audits outdated, requiring collecting new sets of data to quantify the new levels of waste being generated.

- Also, manual waste audits become more expensive to perform as labor costs increase pressuring industries to find alternative solutions to achieve “zero-waste”. This direct cost of waste audits impedes to scale up waste reduction strategies to support sustainability within manufacturing processes.

From this perspective, the development of continuous data acquisition systems that could automate the waste auditing process would benefit industrialized construction facilities by reducing labor costs, increasing the accuracy of data acquisition, providing continuous monitoring of waste-generating construction processes, and reducing the amount of time between implementation and determining the measurable impacts of the waste reduction policies. This paper aims to present this approach using as a case study a window manufacturing line at a production facility in Canada.

3. Methodology

The approach proposed herein adopts a data science research (DSR) methodology to quantify the waste generated during cutting operations on a window manufacturing line using computer vision techniques. The DSR methodology differs from other types of methodologies by aiming to develop an artifact: something that is useful and improves the problem that is identified and explained in the context of the research gap (Hevner et al., 2004). The process of developing an artifact consists of a rigorous procedure of identifying gaps in the literature and developing the artifact and its evaluation methods in a structured and replicable manner while clearly communicating its outputs. The artifact developed in this paper consists of a vision-based approach to automatically quantify waste generated and to enable continuous auditing of manufacturing operations in an industrialized construction facility. In possession of this artifact, it is possible to track the amount of waste generated in a process from a large sample of data without being restricted to a few examples collected during regular waste audits. This methodology has been previously applied, as equally successfully, in the development of vision-based approaches to, for example, track productivity (Martinez et al., 2021) or monitor safety (Fang et al., 2018) in the industrialized construction sector.

Overall, the approach presented in the present study aims to generate the information required to automatically populate a waste audit form using machine vision and enterprise resource platform (ERP) information. The proposed system captures a set of images after each cut is performed, enabling instantaneous identification of the profile being cut and quantification of the waste generated during that process using novel image processing techniques. An overview of the proposed approach is illustrated in Figure 1, and the details regarding its implementation are presented in the following sections.

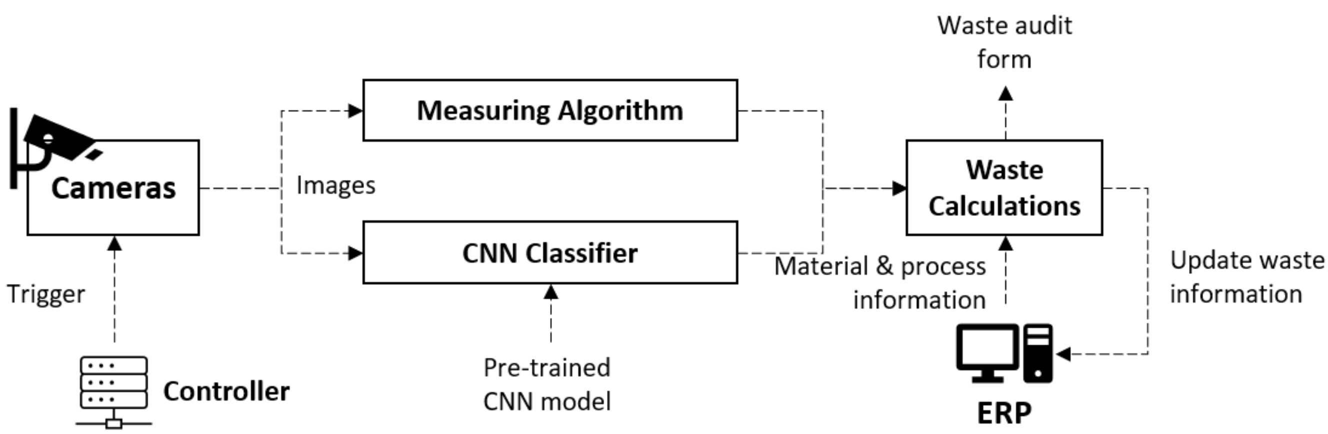


Figure 1. Proposed architecture for automated waste audits via deep learning and machine vision.

4. Case study: waste audit at a uPVC window profile cutting station

Current waste audit practice

Presently, bi-weekly manual waste audits (MWAs) are conducted by production supervisors at the unplasticized polyvinyl chloride (uPVC) window manufacturing cutting station under study in order to assess the manufacturing processes in terms of material waste generation. The results will feed back into an ERP system to adjust production costs and improve production practices (Jituri et al., 2018). In addition, the results of the MWAs represent a benchmark against which the proposed framework in the present study is evaluated.

For the purpose of data collection, the steps required to complete an MWA are followed to conduct 21 waste audits in a uPVC window manufacturing facility over a period of four weeks. The experiments are carried out during normal work shifts with as few interruptions to production operations as possible. A standard operating procedure (SOP) is developed and refined to accommodate the working conditions of the cutting stations where the MWAs are completed. Each experiment took approximately 3 hours, on average, to complete, which is considered a long time.

The first step of the MWA procedure is to populate the waste audit form with identification information such as the date and time when the audit is conducted, the raw material profile number and length, and the station at which the profile is to be cut. The following steps are then carried out to quantify the total length of material waste for a sample production run:

1. Ensure that the material processed at the station that day matches the material to be audited.
2. Measure the raw material profile length ($l_{profile}$). Profile lengths vary between 14 and 21 feet and depend on the supplier and profile type.
3. Determine the number of windows to audit based on the sequence of windows to be cut during the audited shift.
4. Based on the number of windows in production, determine the number of cut profiles ($N_{profiles}$) needed to produce all windows in the batch, as estimated by Equation (1):

$$N_{profiles} = 2 + \frac{1}{l_{profile}} \times \sum_{i=1}^{n} x_i \tag{1}$$

   where (x_i) is the length of a single-window part, (n) is the total number of parts to be cut in the batch, and two extra pieces are added to account for the waste on both profile extremes.

5. Collect all the material waste in the current audit batch in a designated recycling bin.
6. Based on the collected material, calculate the actual length used to manufacture the designated window batch according to the Equations (2)–(4):

$$l_{used} = l_{pulled} - l_{leftover} \tag{2}$$

$$l_{pulled} = N_{profiles} * l_{profile} \tag{3}$$

$$l_{leftover} = \sum_{i=1}^{k} y_k \tag{4}$$

   where (l_{pulled}) is the total length of the profiles uploaded, ($l_{leftover}$) is the total length of material leftover after the audit is complete, (k) is the total number of leftover pieces, and (y_k) is the length of each piece.

7. Obtain the material lengths required for the window manufacturing ($l_{required}$) from the central production database. The windows in the batch to be audited are extracted from the daily production reports.
8. Calculate the wasted material length as shown in Equation (5):

$$l_{waste} = l_{pulled} - l_{leftover} - l_{required} \tag{5}$$

9. Finally, calculate the percentage of waste material by length according to Equation (6):

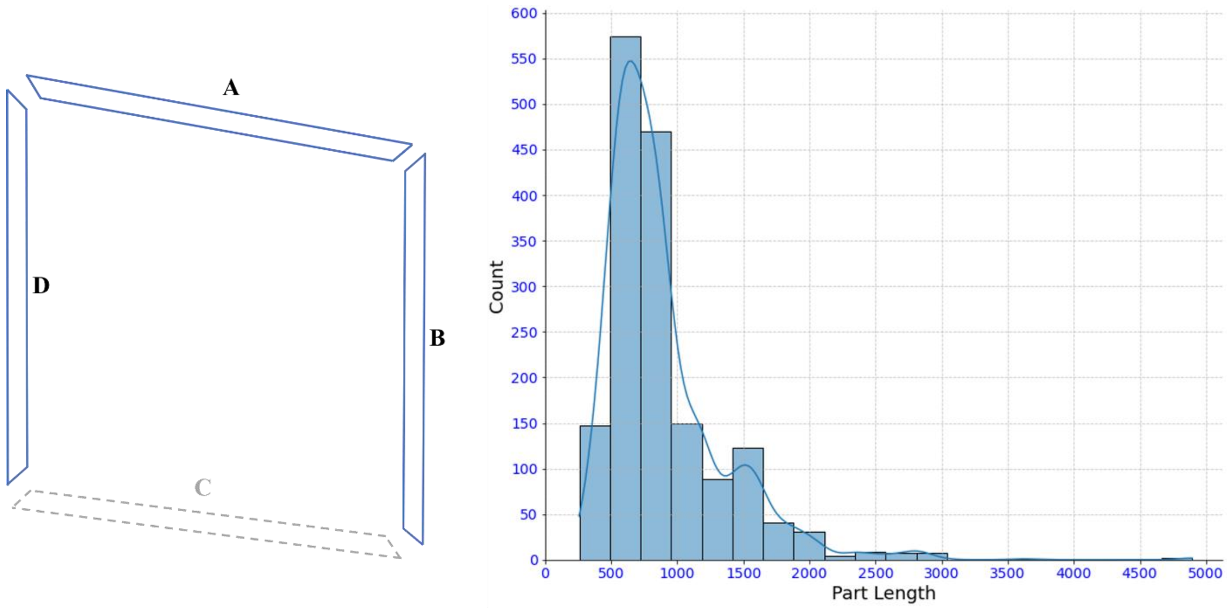
$$\%_{waste} = \frac{l_{waste}}{l_{pulled}} \tag{6}$$

One motivation for the current study is to reduce the time it takes to conduct a waste audit by implementing an automated system to complete waste audits more frequently at the cutting stations with minimal interruption to the production work. It is worth noting that each MWA is performed on a single-window profile; however, the cutting stations where the audit is being performed can accommodate several profile types during the same work shift. Table 1 shows a simplified synthetic example of one MWA form. The form is divided into three sections: 1) audit preparation and identification, 2) data collection from the enterprise resource platform (ERP) system and the ongoing floor operations, 3) waste calculations based on the equations above.

Table 1. Example of a manual waste audit form.

1) Audit Preparation			
Date of audit	2019-12-16	Start and end time	12:03 PM to 12:58 PM
Production line	Line ID #2	Material ID code	402867
2) Data Collection			
Raw material profile length	16 ft	# Profiles pulled	15
Number of parts to be cut	69	Required length (BOM)	189 ft (57,607 mm)
3) Waste Calculation			
Total leftover length	11,010 mm	Total pulled length	73,152 mm
Total waste length	4,535 mm	Waste percentage	6.2 %

Window frames are typically composed of a minimum of four profiles (see Figure 2.a). Each window is composed of three pieces of the same profile type, and the fourth piece is of a slightly different profile that must accommodate weeping holes for water drainage. The lengths of the parts range from approximately 300 mm to 4,900 mm. To benchmark the current waste audit results, an MWA is performed for the cutting station at which the highest volume of cuts are performed per hour. Figure 2.b shows the quantitative distribution of the profile lengths in the MWA, with mean and median values of 890 mm and 760 mm, respectively.



(a) (b)

Figure 2. (a) Schematic of the typical window parts, (b) Distribution of window part lengths obtained during the MWA experiment.

Data acquisition system

This subsection presents the proposed vision-based model developed to obtain the necessary visual data to identify and measure window profile waste from cutting stations. The aim of this system is to extract the information necessary to complete the waste audit forms. The system is developed around a *Ferracci Machines* cut-off saw (model TR-A5 45GA), and Figure 3 illustrates a schematic of the proposed vision-based system as applied to the aforementioned machine.

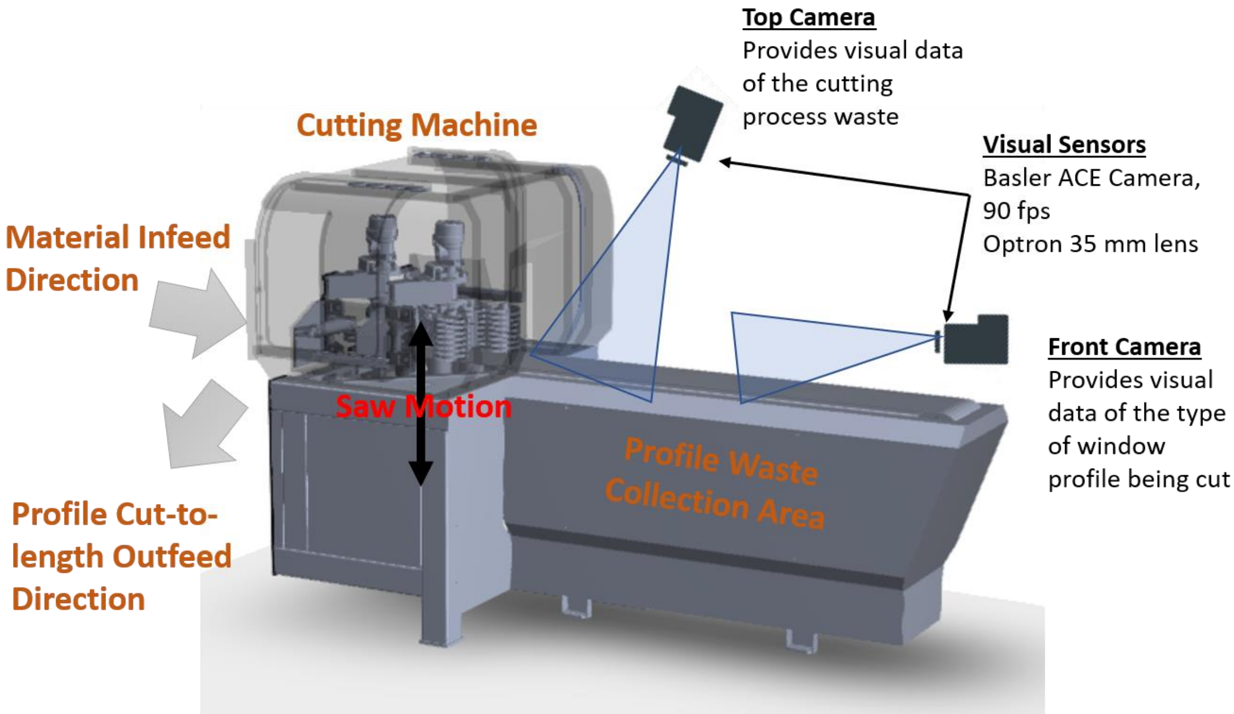


Figure 3. Schematic model of the vision-based system at the cutting station under study.

The window profiles made of raw uPVC material are manually introduced by the operator into the double head cutting machine, which can take up to four profiles at one time. The operator aligns the profile against the guides that keep the profile in position when cut by the saw. The operator manually inputs the required cut length into the computer numerical control (CNC) machine. The cutting machine automatically adjusts, leaving any excess material beyond the saw cutting line. The operator then proceeds to start the automated cutting process, after which the cut-to-length profile is manually removed. The excess waste material is automatically pushed out of the machine area towards the profile waste collection area, where the proposed vision system captures the images that are used to identify the excess profile material and measure the dimensions of the cut profiles in the waste area.

The proposed system provides real-time data acquisition regarding the cutting operations as they occur. In order to automatically populate the MRW form, the system must identify the profile type being cut and the length of profile waste resulting from each cut. Once this data is obtained, the rest of the necessary information is inferred using the available ERP information and is calculated using Equations (1) through (6) as presented above. The following subsections detail the processes employed to extract this information from the images obtained using the visual sensors.

Profile identification

By processing the visual data obtained using optical sensors, the present study proposes a supervised learning approach, such as deep learning, to identify the type of window frame profile that is currently being audited. While extensive industrial defect detection methods, such as feature selection, can provide comprehensive results, such solutions remain limited to the characteristics and features of the final product. Thus, if a new feature is introduced in the product, a new set of problems may arise (Weimer et al., 2016). In window manufacturing, profiles are updated and changed frequently; thus, an easily updatable and robust process is required that does not rely on pre-defined profile features.

In contrast to manually engineered image processing solutions, supervised machine learning approaches, such as deep learning, may be used to overcome the limitations inherent in manually redefining the features for each new inspection problem in a reactive fashion. The complexity of identifying window profiles is due to the size of the geometrical features that differentiate one from another. In other words, the transverse section of each profile is of a clearly different shape. As wasted profiles are obtained from a cutting process, the profile cross-section is clearly visible, and the geometrical features are identifiable.

The present study investigates the use of convolutional neural networks (CNNs) to extract those geometrical features and classify the cut profiles by type based on initial search parameters. This approach is a popular and successful approach in the construction sector, being employed to classify objects with small features such as screws on steel frames (Martinez et al., 2020b) or cracks in concrete surfaces (Cha et al., 2018).

To develop a supervised deep learning model, a database is created that contains visual data of the target window frame profiles. The selected profiles are chosen based on production volume and variability in shapes. The dataset used in this study contains 1,752 unique images of four different profile types. The images are manually labeled and have a resolution of 1,446 × 2,316 pixels. Images are of a single profile, captured in different lighting conditions and orientations. A total of 377, 438, 478, and 459 images are used from profiles “402867”, “420697”, “402861”, and “479200” respectively. Details on the profile type used in this study are shown in Figure 4. A collection of random sample images from the dataset are shown in Figure 5.

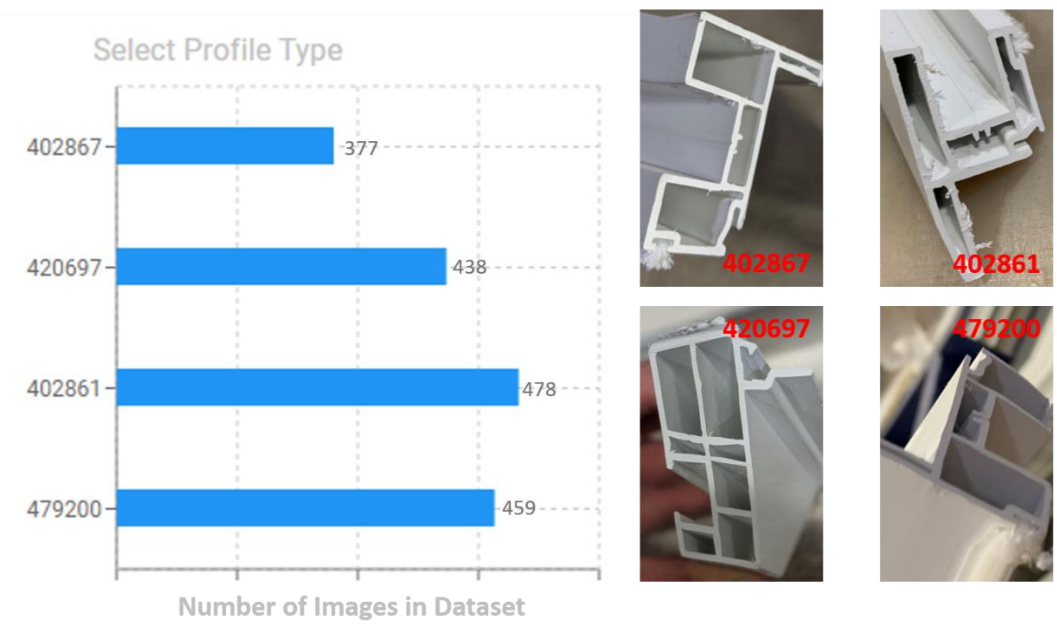


Figure 4. Left: bar chart with the number of images per window profile type in the developed dataset. Right: a sample image for each profile type in the developed dataset.

Figure 5. Sample images from the dataset used for training and validation of the CNN models.

To identify window profile types using CNNs, several common and easily accessible architectures are investigated in order to compare them to determine which performs best. In this study, VGG16, VGG19, Xception (MobileNet), DNET169, ResNet50, ResNet101, Inception v3, and AlexNet are tested. As the classification problem itself is simple enough, transfer learning is used to reduce training time and motivate ease of replication. Transfer learning, it should be noted, has proven to be effective in reducing computational demand and in providing accurate trained models even with small datasets (Han et al., 2018). For that reason, all the neural networks have been pre-trained with the COCO dataset and the main convolutional base remains frozen and only the final layers (SoftMax classification layers) for each model are retrained for the purpose of window profile type identification.

To generate valid training and validation datasets, images are randomly selected from the labeled images such that each type of label—for each type of window profile—represents a minimum of 15% of all the images contained in the validation set. The remaining images are used for training the neural networks. Hence, the training and validation datasets contained 1227 and 525 images, respectively. Both training and validation are performed using Keras and TensorFlow libraries within a Python environment.

The environment in which the neural networks were trained had important computational limitations. As such, the fine tuning of the model hyperparameters aims to maximize classification accuracy while aiming to reduce the computational power required to train and validate the models. Therefore, certain limitations are introduced during the training phase: all the following model architectures are trained using stochastic gradient descent with momentum optimizer, starting with a momentum of 0.9, and a batch size of 32. The hyperparameters analyzed are the number of epochs and the initial learning rate. Note that, the learning rate is set to decrease by a factor of 10 if the learning process stagnates and validation loss has not decreased by more than 0.0001 after 5 epochs, reducing the computational time needed to analyze the training process.

The first hyperparameter to be fine-tuned is the learning rate, as it has the least amount of flexibility when using pre-trained models. The learning has to be decreased from its initial learning rate (by default, 0.1 for the COCO dataset), as only an adjustment of the weights is required. Therefore, an empirical approach is taken to adjust the learning rate, decreasing from 0.1 towards 10^{-6}, while checking the variance of the loss values in a fixed number of epochs (5 epochs are used in this study). The optimal learning rate for fine tuning of pre-trained models can be found where the loss decreases the least during that learning interval (Smith, 2015). For each model studied, the final training loss after 5 epochs against the learning rate is shown in Figure 6.

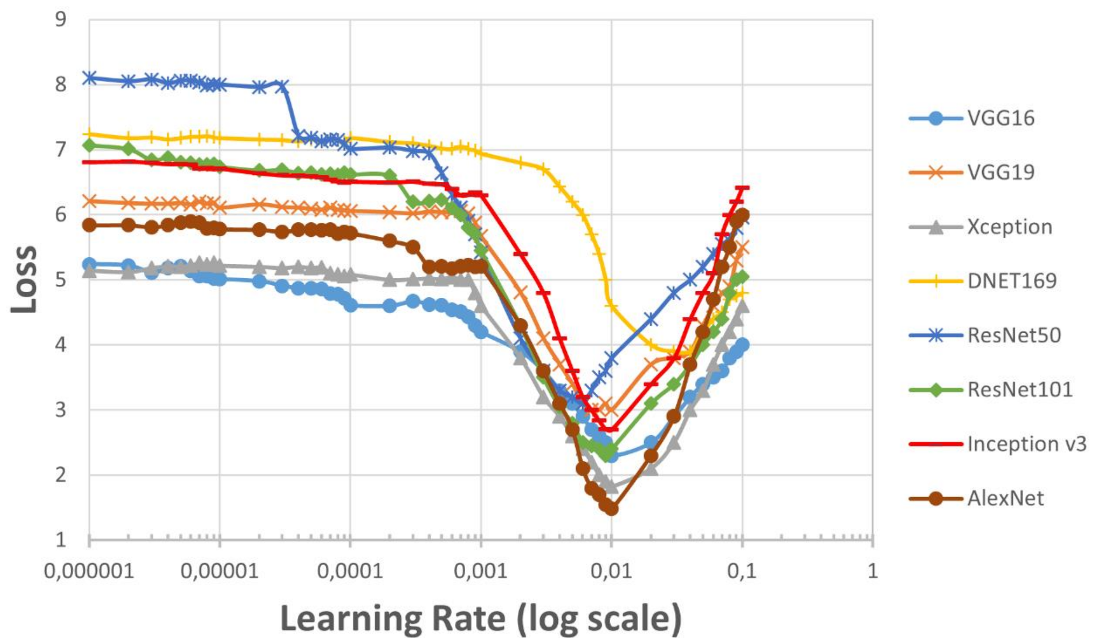


Figure 6. Learning rate optimization results for the models under study.

As observed, most models have a clear decrease in loss value in the interval from 0.001 to 0.01 followed by an immediate increase for learning rates above 0.01. For learning rates smaller than 0.001, the tested models observe small decreases in loss values as the learning rate increases (except the sudden drop in loss for ResNet50 between 10^{-5} and 10^{-4}). As models are already pre-trained, the optimal learning rate aims to vary the weights slowly but gradually in the network. Therefore, the learning rate moving forward for all models is set to 10^{-4}. While an optimum could have been reached for each model individually, a common optimal learning rate is selected as the loss variance is negligeable between values in the selected interval and it simplifies the training process in the following steps.

With the selected learning rate, all the models are trained and validated for 100 epochs. To reduce the computational power required to run the model, minimization of the epoch value is targeted while achieving maximum accuracy. Figure 7 shows the accuracy and loss values obtained during the training and validation processes for all the pre-trained models selected. Note that only the first 25 epochs are illustrated as, by that time, most models had already stabilized, and it permits a clearer visualization.

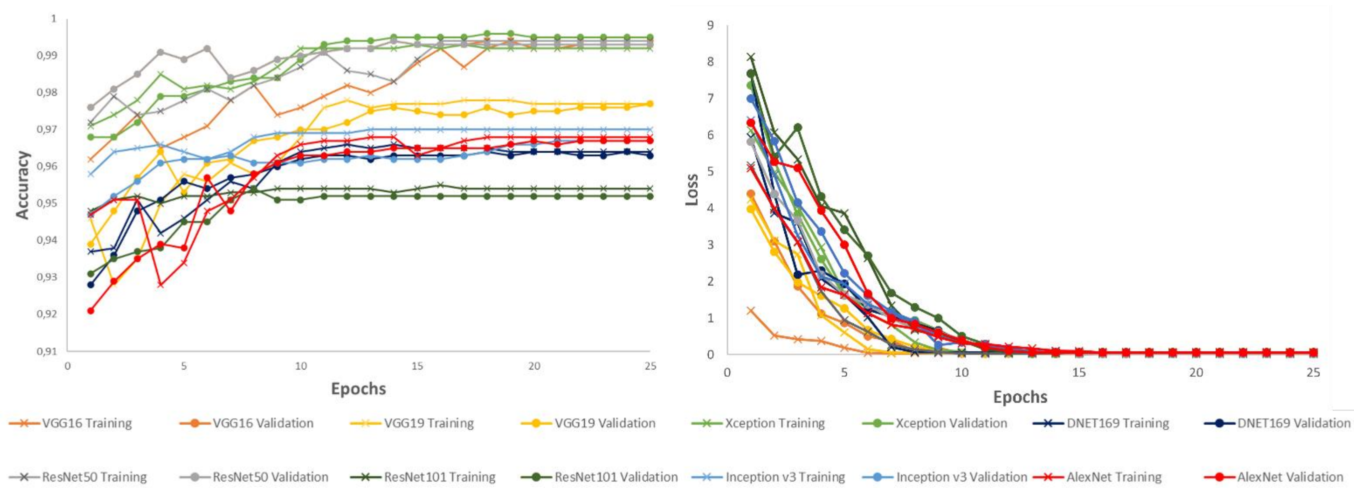


Figure 7. Training and validation results for the models under study. Left: model accuracy against number of epochs. Right: loss value against number of epochs.

The computational performance of the CNN models can be analyzed by comparing accuracy and loss values with respect to epoch count. In this study, the maximum accuracy achieved during training is 99.4%. The VGG16, Xception, and ResNet50 architectures are capable of achieving such accuracy at the 19th, 19th, and 16th epoch, respectively. Similarly, minimum loss is achieved by those models at the 22nd, 13th, and 17th epoch respectively. An overview on the epoch optimization results can be found in Figure 8.

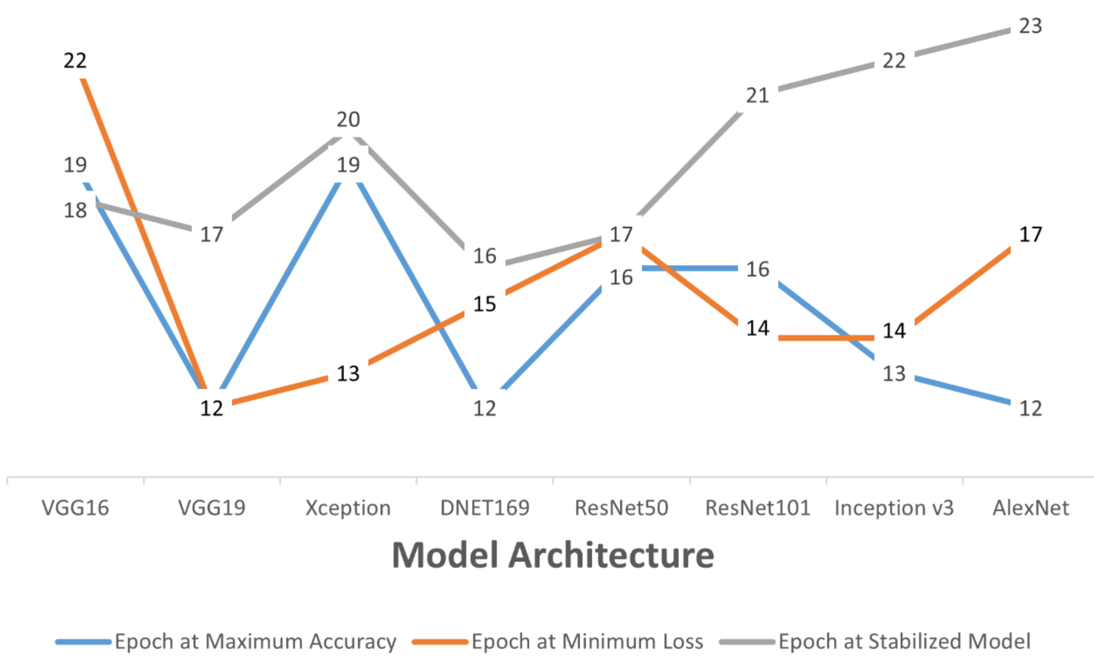


Figure 8. Epoch optimization from validation results for the models under study.

Whereas loss and accuracy for both training and validation results are obtained directly from the libraries used, a more robust metric is needed to evaluate the performance of multi-class classifiers, such as the ones used in this research. For the present study, the micro-averaged F1 score (F_{micro}) and macro-averaged F1 score (F_{macro}) are used and can be calculated directly from the training and validation raw results as shown in Equations 7 and 8. These metrics have been used consistently in academia to measure neural network performance where a small number of positive instances for a label are present, which is the case for this study.

$$F_{micro} = \frac{\sum TP_i}{\sum TP_i + 0.5(\sum FP_i + \sum FN_i)} \tag{7}$$

$$F_{macro} = \frac{1}{n}\frac{2\sum TP_i}{2\sum TP_i + \sum FN_i + \sum FP_i} \tag{8}$$

where (TP_i), (FP_i), and (FN_i) are the true positives, false positives, and false negatives, respectively, for class (i). Table 2 presents the metrics used for analysis of the validation results obtained for each one of the models studied, under the optimized hyperparameters.

Table 2. List of metrics' results for the validation process of the CNN models trained.

Model Architecture	TP	FN	FP	Fmicro	Fmacro
VGG16	521	3	1	0.98	0.98
VGG19	513	8	4	0.96	0.95
Xception	522	3	0	0.98	0.99
DNET169	506	6	13	0.96	0.94
ResNet50	522	1	2	0.98	0.97
ResNet101	501	4	20	0.94	0.95
Inception v3	509	11	5	0.96	0.95
AlexNet	508	9	8	0.95	0.93

As observed, all the models tested have both performance metrics above 90%, showcasing that the use of pre-trained CNN models to accurately classify window profile types is possible. Overall, it has been shown that geometrical features of the profile cross-section can be used to identify window profiles. For that purpose, among the models tested, Xception is the best performing model with a micro-averaged F1 score and a macro-averaged F1 score of 0.98 and 0.99 respectively.

Profile measuring

Based on top-view images of the waste area, image processing techniques are employed to measure the amount of profile waste after a cut has been performed. In this context, as some window profile waste pieces have cuts at a 45-degree angle to facilitate the welding process (Martinez et al., 2020a), the reported waste length of each profile is its longer measurable distance. An algorithm is developed to estimate the length of the window profile contained in the image in a sequential process described in detail below.

1) As this algorithm is dealing with geometric calculations to estimate the profile length, standard camera calibration is required to mitigate the impact of lens distortion on the final measurements (Zhang, 2002).
2) A binary mask is created to focus on the window profile by removing the background using Otsu's threshold filtering (Otsu, 1979).
3) A median blurring filter ($n = 21$) is applied to reduce the impact of profile edges and background noise on the measurement.
4) The boundaries of the profile shape in the binary image are retrieved using OpenCV find contours simple approximation mode.

5) A rectangle is bound over the identified contour to simplify the contour shape to a length and width representable element.
6) The reported waste profile length is assigned as the longer side of the rectangular shape and the value is converted from pixels to millimeters using Equation 9.

$$l_{waste}[mm] = l_{waste}[px] * \frac{w_{dist}}{w_{px}} * \frac{w_{sensor}}{f_{length}} \tag{9}$$

where (w_{dist}) is the camera working distance (or the distance between the camera and the measured object) in millimeters, (w_{px}) is the image width in pixels, (w_{sensor}) is the camera sensor width in millimeters, and (f_{length}) is the focal length in millimeters. An illustration of the profile measuring process for a sample image is shown in Figure 9.

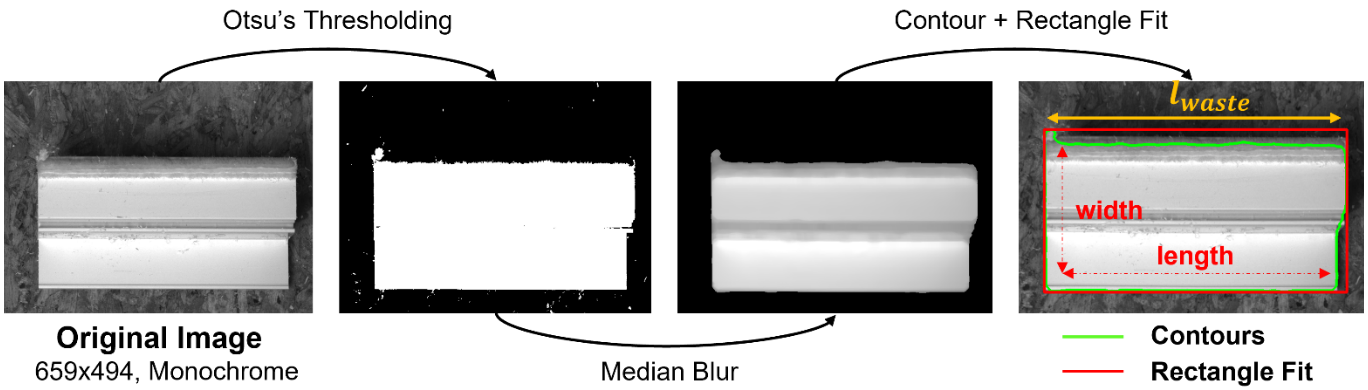


Figure 9. Example of the measurement process for a window profile.

The proposed image processing approach to measure waste profile's length is decided based on two main considerations: (1) a single waste profile is visible at once (as a result of the cutting process patterns – profiles are cut one by one) which minimizes possible noise due to additional elements in the field of view of the camera, and (2) as the waste piece comes out of a saw, the orientation of the profile is not constant, hence the algorithm to measure the waste piece cannot rely on the profile orientation to provide the correct measurement.

5. Test results and discussion

An experiment is undertaken with the aim to validate the proposed system in a real scenario. The waste pieces come from a real production setup in which the machine under study cuts several stock-length profiles from each type mentioned in Section 3.3. The waste pieces obtained for this experimental setup are extracted from four different MWA reports (one per profile type). Due to confidentiality reasons, information provided by the industry partner's ERP system regarding the current percentage of waste in the production line cannot be reported. The experimental setup, then, will solely focus on the information that is required to test and validate the proposed system. Table 3 summarizes the information regarding the number and type of waste pieces studied: a total of 55 waste pieces are used.

Table 3. Summary of the waste pieces information used in the experimental setup.

Profile Type	Number of Profiles	Length Range [mm]	Average Length [mm]
402867	12	[83,116]	94.83
402861	17	[81,131]	100.94
479200	14	[82,114]	93.07
420697	12	[82,127]	95.00

Profile identification

The results obtained by applying the trained Xception CNN model to identify the profile type of the studied waste pieces are presented in this subsection. It should be noted that the data obtained for this experimental setup were not used to train or validate the neural network beforehand. Table 4 presents the confusion matrix as well as the micro- and macro-averaged F1 scores for the Xception neural network.

Table 4. Confusion matrix and performance results for Xception model.

4 Classes (4 profile types) – Classifier: Xception		**Predicted Label**			
		420697	402867	402861	479200
Real Label	420697	11	0	1	0
	402867	0	11	0	1
	402861	0	1	15	1
	479200	0	1	1	12
	Precision	1	0.846	0.882	0.857
	Recall	0.917	0.917	0.882	0.857
	F1 Score	0.957	0.880	0.882	0.857
		Fmicro	0.891	**Fmacro**	0.894

With 0.89 micro- and macro-averaged F1 scores, the profile types are accurately determined using the proposed deep learning approach. Although a drop in performance is observed from the training and validation results, from 0.98 to 0.89, it can be explained by the small number of profiles used for testing in which a false negative or false positive heavily impacts the performance metrics.

Profile measuring

The profile measurement results obtained for all the waste pieces in the experimental setup are presented in this subsection. Table 5 summarizes these profile measurement results. The ground-truth measurements (i.e., real length) are obtained by manual measurement using a tape measure (millimeter precision), following current industrial practice.

Table 5. List of the profile measuring results obtained on the experimental setup.

Waste Piece #	**Profile Type '420697'**		**Profile Type '402867'**		**Profile Type '402861'**		**Profile Type '479200'**	
	Real Length	Inspected Length	Real Length	Inspected Length	Real Length	Inspected Length	Real Length	Inspected Length
1	82	82.22	84	83.48	82	80.18	101	97.63
2	83	82.38	83	83.86	83	84.26	83	84.26
3	94	91.97	84	84.58	86	85.99	85	85.05
4	84	84.74	83	81.43	97	95.27	82	82.53
5	82	80.96	85	86.15	83	83.79	84	85.05
6	83	81.91	99	98.73	81	78.25	83	84.42
7	84	83.01	83	83.95	84	82.69	82	83.16
8	106	106.84	105	103.95	94	93.51	92	93.67
9	98	98.24	107	104.92	104	102.84	94	94.26
10	114	113.4	111	112.04	105	103.48	102	104.58
11	103	104.23	98	98.11	108	108.46	114	115.04
12	127	127.91	116	114.94	117	119.27	104	103.29

13					131	130.01	99	99.67
14					129	127.06	98	97.84
15					108	107.69		
16					125	124.39		
17					99	99.48		

Based on the measurement results obtained, the performance of the proposed algorithm can be statistically analyzed. Table 6 shows the performance analysis of the algorithm for each of the profile types, presenting the mean absolute error (MAE), variance, and root mean square error (RMSE). The algorithm estimates the length of a waste piece of window profile to within an average margin of error of 1.26 millimeters (approximately 1.3% error).

Table 6. Performance statistics of the profile measuring algorithm.

	Profile Type '420697'	**Profile Type '402867'**	**Profile Type '402861'**	**Profile Type '479200'**	**Overall Performance**
MAE	0.8791	0.9367	1.1706	1.1379	1.0476
Variance	0.2309	0.2934	0.5752	0.8569	0.4994
RMSE	0.9923	1.0706	1.3826	1.4458	1.2601

With the goal of an autonomous waste auditing system, measurement error needs to be analyzed and modeled so that the system realizes the uncertainty of its measurements. Based on the statistical results and visual comparison between the error measurements per profile type (see left image in Figure 10), it is assumed that the profile type does not impact the measurement error obtained and that the algorithm behaves independently of the profile type. Considering all the measurement errors, the image on the right in Figure 10 illustrates a Gumbel distribution ($\mu = -0.5025$ and $\beta = 1.1458$) over the data histogram of the measurement error. The Gumbel distribution is selected over other distributions by minimizing the least squares error using Simphony software (AbouRizk et al., 2016).

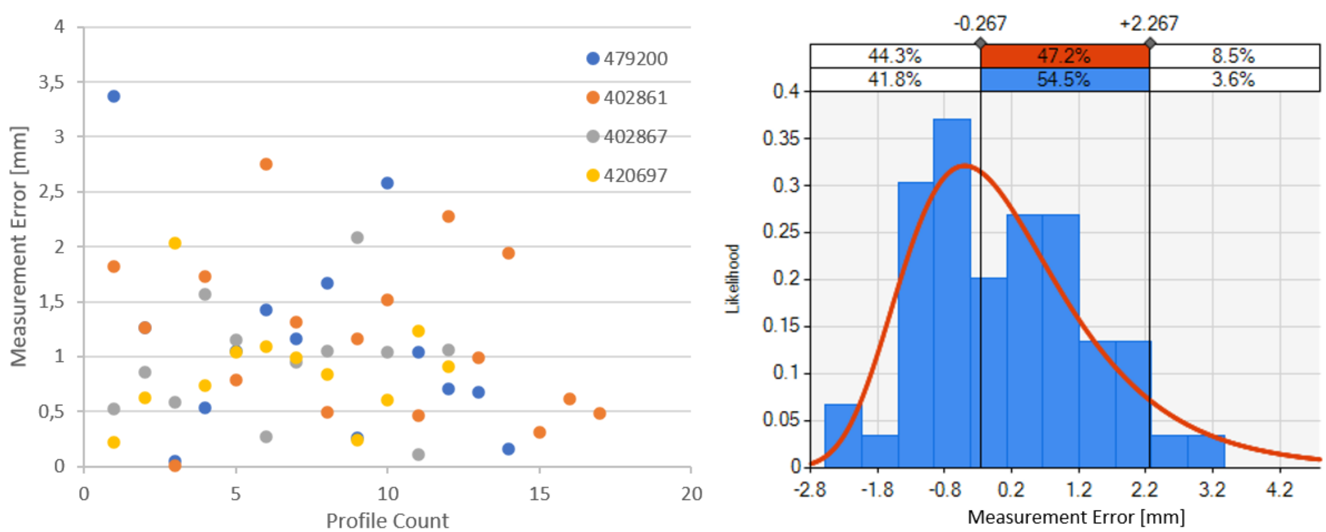


Figure 10. Profile measuring error analysis. Left: MAE scatter plot per profile type. Right: measurement error distribution model fit.

Discussion

In summary, the proposed automatic vision-based system provides a solid method for waste identification and quantification for cutting stations in PVC window production lines. In a manufacturing facility, the potential benefits include savings in terms of time and resources when conducting waste audits and the potential for continuous monitoring of waste generation at specific workstations. The proposed system also eliminates the sampling bias that inherently exists in periodical audits due to potential underperformance or overperformance of operations or workers during the audit. Furthermore, the system produces instantaneous feedback regarding waste generation if changes on the audited workstation are applied, i.e., as in continuous improvement cycles. Nonetheless, the proposed approach is limited by the capability of current deep learning models to identify similar objects; thus, the accuracy of the proposed model improves significantly when material profiles (or more generally, descriptive features) are distinctly different. Also, this approach measures the waste generated at a workstation but cannot provide insight as to the reasons why waste is generated in the amount calculated or regarding potential solutions to minimize waste.

The current system can also be expanded, within the context of window frame cutting workstations, to identify the material used (i.e., aluminum, steel, or PVC) with a similar approach, based on deep learning, by making use of the existing camera setup. Also, one of the current limitations of the proposed approach is that the waste profile measurement is limited to the field of view of the camera, hence hardware is limiting the maximum size of the waste profile that can be accurately measured. Although the main goal is to reduce waste generated thus profile waste should become smaller with time, the proposed approach potentially may end up not being flexible enough to be generalized and adapted to other cutting workstations. Other hardware (sensors) can be explored that can provide the same measurements, for example laser-based measuring devices, or change the image processing approach to a video capture instead so that the field of view of the camera does not impact the system capabilities.

Identification and quantification of waste generated in manufacturing facilities should be the first step of a more comprehensive system aiming to minimize or reduce waste. Future research might be directed towards including additional information from the ERP system and exploring knowledge discovery in database techniques to provide data-driven solutions to waste reduction on production lines. Furthermore, the current approach will be extended to other workstations to complete a full picture of waste generation in the facility and to provide clear estimations of the quantity of waste generated per day (or per hour) of each material used in the facility to facilitate waste management at a higher level (transportation, storage, recycling, etc.). The integration of automation in waste management processes should represent an advancement towards more sustainable manufacturing and a competitive edge for the industrialized construction industry.

6. Conclusions

Waste reduction in construction processes represents a challenge for the industry as it moves towards a more sustainable future. Sizeable efforts have been made in the past decades to reduce waste in the industry. A clear example is the popularization of industrialized construction practices, bringing construction processes into a more controlled environment where waste management practices can be implemented more easily. Decisions to reduce waste are then taken based on sporadic manual audits of the processes, which are not entirely accurate and cannot truly represent the conditions in which waste is continuously being generated. Thus, to provide a robust data-driven approach to waste management, the present study proposes leveraging image processing and deep learning technologies to automatically conduct waste audits on workstations, allowing practitioners to substitute their waste auditing efforts with a continuous data acquisition system. By identifying the material used and quantifying the amount of waste generated, it is possible to make continuous efforts to reduce waste based on data-driven insights obtained from the process. This approach is developed and tested in the context of a window manufacturing production line, aiming at the most upstream workstation, the cutting station. A vision-based algorithm is developed to measure the lengths of the window profiles with an average error of 1.25 millimeters, and a deep learning classification approach is used to identify the window profile type being cut with an overall accuracy around 90% in a real scenario. From these results, waste audits are automatically generated for each profile cut in the workstation, providing a full picture of when and how waste is generated at the cutting station. Future work will investigate extending the current approach to the remaining waste generating processes and researching the integration of waste management into management-level decision-making in industrialized construction facilities.

Declarations

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Conflict of Interests

The authors declare that there is no conflict on interest in the publication of this manuscript.

Availability of data and material

Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions/omissions.

Code availability

The code for the algorithms presented in this manuscript can be obtained by contacting the authors directly.

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

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