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INVENTORY AND PILING WASTE: A COMPUTER VISION APPROACH

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ABSTRACT

Construction sites contain a lot of waste, and eliminating it enables productivity gains and health and safety improvements. Computer vision is a promising technology that is being used in various construction applications. Construction sites with limited human resources could benefit from automated computer vision-based waste analysis. This paper presents preliminary findings related to the algorithm-based waste detection of piling works and explores potential applications from a visual management perspective. An experimental approach was used in the study, and images from a construction site in Finland were used to train the algorithm. The main findings revealed that the amount of waste shown by the images was substantial and that ground-level and drone images could be combined to create a comprehensive view of pile waste inventories. This paper also presents potential applications of image-based pattern recognition for infrastructure sites where the use of drone and ground-level images is standard practice. Several problems emerged when using transfer learning to train the algorithm, the most significant of which were variations in the scenery of images used for training and the limited number of images. The solutions to these problems lie in collecting more data and experimenting with other deep learning-based methods which will be explored in future.

KEYWORDS

Lean construction, waste, visual management, computer vision, piling.

INTRODUCTION

WASTE IN CONSTRUCTION

Since the beginning of the 1990s, the construction industry has been inspired by the manufacturing industry's lean management school of thought and used its tenets as guidance when solving long-term construction problems related to unreliable planning, uncertain production flow and productivity, constant delays, and budget overruns (Koskela, 1992; Koskela et al., 2002). One of the principles of lean management is identifying and eliminating production-related waste, which interrupts production flow and increases operating costs (Ohno, 1988; Shingo, 1985).

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Ohno (1988) identified seven types of waste: overproduction, transportation, stock on hand, idle time, processing, movement, and the production of defective products. The identification of waste in construction industry activities has become a fruitful research field, relating the waste in construction sites, the complexity of construction activities, and production flow interruptions (Koskela, 2004; Koskela et al., 2013; Macomber & Howell, 2004).

Since identifying waste in dynamic environments, such as construction sites, is time consuming and challenging (Lee et al., 1999; Achell et al., 2013), the construction industry once again looked to the manufacturing industry for a supportive tool and identified Gemba walks as an ideal option. The Gemba walks concept was implemented by Ohno (1988) in the car manufacturing industry and described by Womack (2011) as a management practice used to grasp the current situation before acting. Gemba walks can be connected to the visual management (VM) concept of being able to collect the information available at a site with a glance (Galsworth, 1997). The people involved in Gemba walks must know how to correctly identify waste during construction site walkthroughs. Time, training, and team commitment are required to develop this skill (Kerem et al., 2013).

VM was mainly developed to meet the practical needs of the manufacturing industry related to information-based problem solving through the use of simple visual aids and tools (Tezel et al., 2016). In addition to the simple tools of VM, new technologies, such as CV, have been proposed for use in safety management, progress monitoring, productivity monitoring, and quality control (Paneru & Jeelani, 2021; Tezel & Aziz, 2017). CV can support the identification of waste connected to overproduction and inventories. State-of-the-art CV algorithms can detect objects with the help of feature extraction. The use of CV algorithms to identify and reduce construction waste is a promising area of research (Wang et al., 2020). By using CV algorithms to identify objects, construction waste can be significantly decreased.

COMPUTER VISION

CV is the science of recognizing objects of interest with minimal human intervention. CV supports the automation of tasks that require visual assessment. This makes CV an important technology for the automatic detection of critical tasks in construction. One of the growing needs of utilizing CV is rapidly, accurately, and comprehensively understanding a dynamic construction site (Martinez et al., 2019). This visual assessment can have many applications, including construction progress monitoring, construction site safety management, construction waste management, and quality control of building elements.

According to an elaborate review by Martinez et al. (2019), CV has mostly been used to enhance construction site safety by tracking equipment, materials, personnel, and other resources. Next prominent utilization of CV is in productivity analysis by activity monitoring and scan-to-BIM (Building Information Modelling) to obtain an as-built situation from a construction site (Golparvar-Fard et al., 2012; Masood et al., 2020). In addition, CV methods have been developed for inspection and condition monitoring of infrastructure (Bay et al., 20008). No significant research on the combination of CV and construction waste management was conducted before 2019 (Martinez et al., 2019). However, a few research papers after 2019 have focused on construction waste management using CV as discussed in the next paragraph.

Much of the waste-related literature explores the detection of concrete, bricks, plastics, foam, stone, timber, and other types of construction waste (Davis et al., 2021; Na et al., 2022; Seunguk et al., 2022; Song et al., 2022; Zhou et al., 2022). The main objective of previous research was recognizing waste in building construction works through the use of CV and deep learning models. Wang et al. (2019) developed a construction waste recycling robot with the help of CV. The robot used R-CNN (Recurrent Convolutional Neural Network)-based object detection to find scattered nails and screws in real time so that those objects could be collected and recycled. Also, Wang et al. (2020) used SLAM (Simultaneous Localization & Mapping) and instance segmentation to recognize residual pipes and cables. The methodology involved guiding a robot in on-site waste sorting and recycling. Most of the aforementioned works focused on small projects, such as building site construction waste, which includes common building materials. Research on the use of CV in large infrastructure sites and piles is limited.

The present study focused on inventory-related waste accumulated during piling work at an industrial construction site. Furthermore, it explored how CV can be applied for more efficient waste identification and better visualization of the waste problem of providing visual identification of the waste as a VM tool.

DATA COLLECTION AND SETUP

The data was collected from a 70-hectare industrial construction site in Finland. Pile waste inventories (PWI) were observed within a 22,000-square meter area, which included one building. During the observation period, the construction site was mainly in the piling work phase, although work phases in which foundations, concrete frames, and underground pipelines and power cables were built parallel with the piling works.

The data was collected over a 27-week period from March 2021 to September 2021, and the images included spring, summer, autumn, and snowy periods. Each week, ground-level photographs were taken by the site supervisor, and drone images were taken by the measuring team. The approximate distance between the ground-level photographer and the piles varied from a few meters to hundreds of meters. Regarding drone photography, the vertical distance between the camera and the ground varied from 55 meters to about 145 meters. Of the 563 drone images obtained, 21 were included in this study. In addition, 212 ground-level images and 29 combined orthographic images (i.e., a combination of several drone images of the entire site area) were included in the analysis.

The first step in any CV- and artificial intelligence (AI)-related problem is the creation of an annotated dataset that has all classes. For this purpose, the researchers saved the images to a cloud service and then annotated them using a freeware labeling software program called makesense.io. Four categories were used as classes: 0) concrete pile cut-off inventory, 1) steel pile cut-off inventory, 2) concrete pile inventory, and 3) steel pile inventory. The first two consisted of cutting waste or broken piles left after the piling work was completed, while the other two comprised intact piles that had not yet been driven and were in temporary locations on the construction site or next to the pile-driving rigs. Although there was a considerable number of images covering the site area, at the end of the labelling task, only 110 images were used. These were the images that contained one or more of the four categories of classes.

The CV setup was based on transfer learning, which involves initially training a neural network on a small dataset instead of one with thousands of images (Pan et al., 2009). The weights from the pre-trained neural network were improved by using features from ground-level and drone images containing PWIs. YOLO v7 which is a deep learning algorithm was chosen for object detection because of its accuracy and speed (Wang et al., 2022). The YOLO algorithm is originally trained on a set of common objects including a car, a hat, an umbrella, dogs, a door. To detect objects from the construction site, the algorithm parameters were changed based on the features of images with piles. 110 images with a total of 535 labels, including all four classes, were used to change the parameters of the trained YOLO v7 model with the resolution of the images as 4608 × 3456. Processing such a large image for a neural network requires a very high memory and processing power. To avoid CPU and GPU limitations, the algorithm was set up using Google Collaboratory services.

ANALYSIS

During the manual labeling process, 535 PWIs were identified in the images. Specifically, 233 were identified from images taken at ground level, and 302 were identified from drone images. In the ground-level images, 64.4% of the PWIs were concrete PWIs, and 35.6% were steel PWIs. Of the designed and driven piles, 84.6% were concrete piles, and 15.4% were steel piles; the number of steel PWIs was proportionally higher than expected based on the number of designed piles. In the drone images, 63.6% of the PWIs were concrete piles, and 36.4% were steel piles. Furthermore, 54.5% and 37.4% of the PWIs detected in the ground-level and drone images, respectively, were cut-off PWIs. Moreover, temporary pile inventories for piling work purposes (located near piling rigs) comprised 45.5% of the observations in the ground-level images and 62.6% in the drone images. Table 1 shows the observed PWIs.

Table 1: Observed pile waste inventories.

Waste class	Observations from ground-level images	Observations from drone images
0. Concrete pile cut-off inventory	95 (40.8%)	102 (33.8%)
1. Steel pile cut-off inventory	32 (13.7%)	11 (3.6%)
2. Concrete pile inventory	55 (23.6%)	90 (29.8%)
3. Steel pile inventory	51 (21.9%)	99 (32.8%)
Total	233 (100%)	302 (100%)

Figure 1 illustrates examples of classified PWI observations. The top two images are typical pile cut-off inventories after pile driving, while the other examples are typical work-in-progress inventories near pile rigs. Outside of the research location, there was a larger buffer storage area for piles; that area, the size of the buffer inventory, and buffer fluctuations were not explored at this stage of the study.

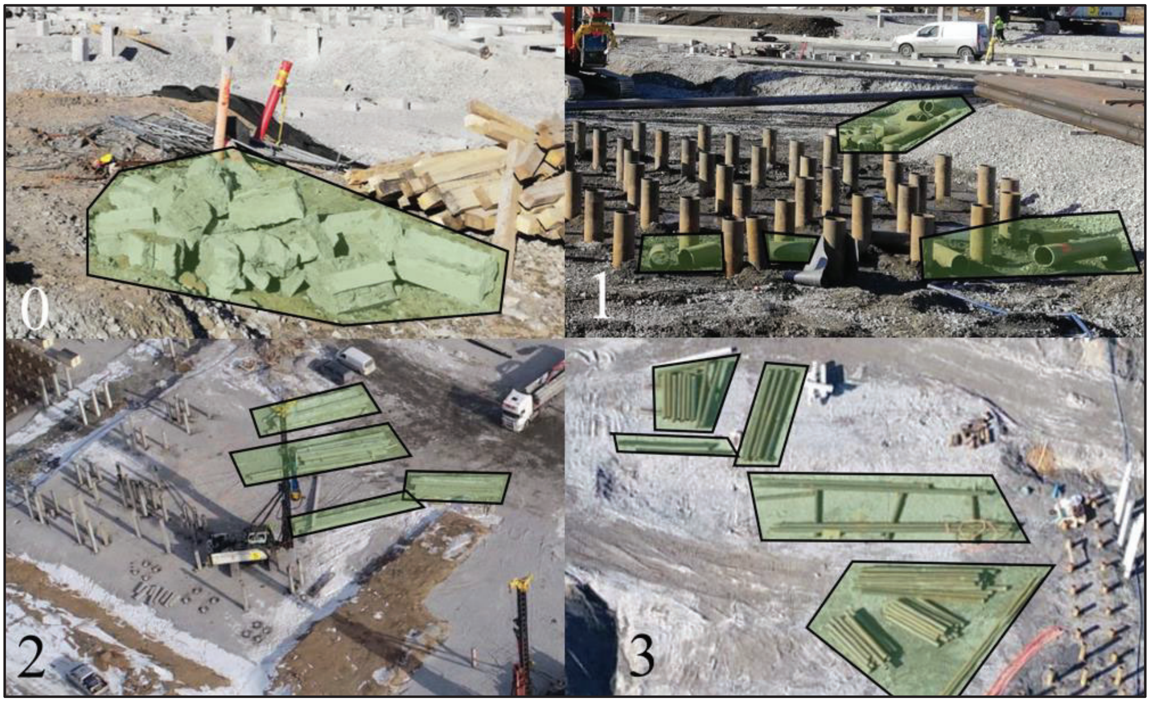

Figure 1: Four Examples of Observed Pile Waste Inventories

The green boundaries shown in Figure 1 correspond to the labeling used to teach the algorithm to identify PWIs. The numbering corresponds to the waste classes in Table 1. Figure 2 shows the observations obtained from the ground-level images of waste inventories over time.

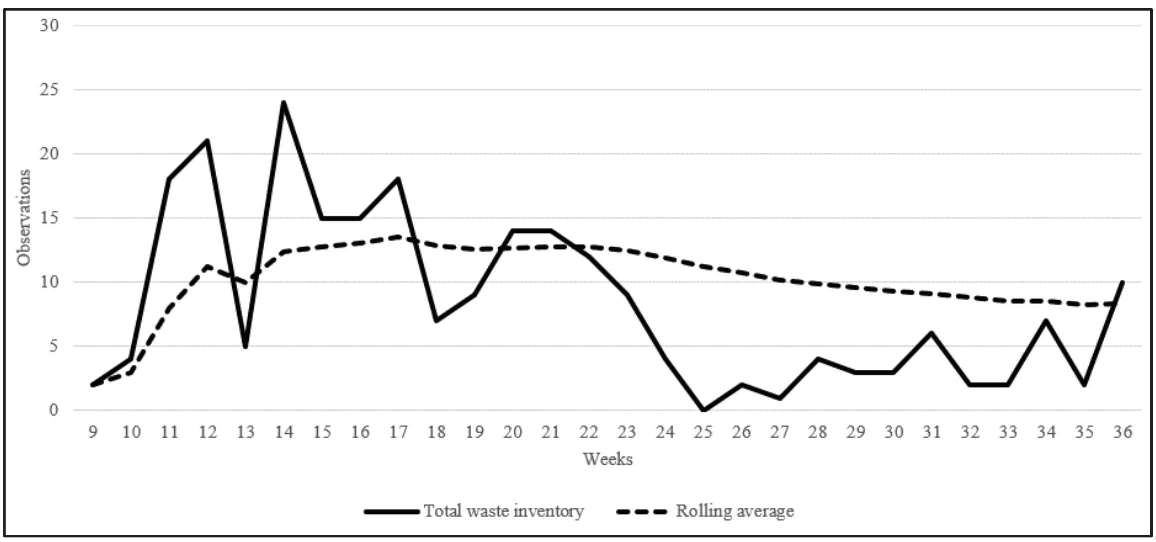

Figure 2: Observed Waste Inventories Over Time: Ground-Level Images

The number of PWI observations in the ground-level images increased after the piling work started and reached an average of 13.9 observations per week between Weeks 11 and 23. Once the summer holiday period started, the number of PWI observations dropped to average of 3 observations per week between Weeks 24 and 35, increasing only at the end of the observation period in Week 36. The average number of observations over the entire period was 8.3 per week. Figure 3 shows the corresponding PWI observations from the drone images.

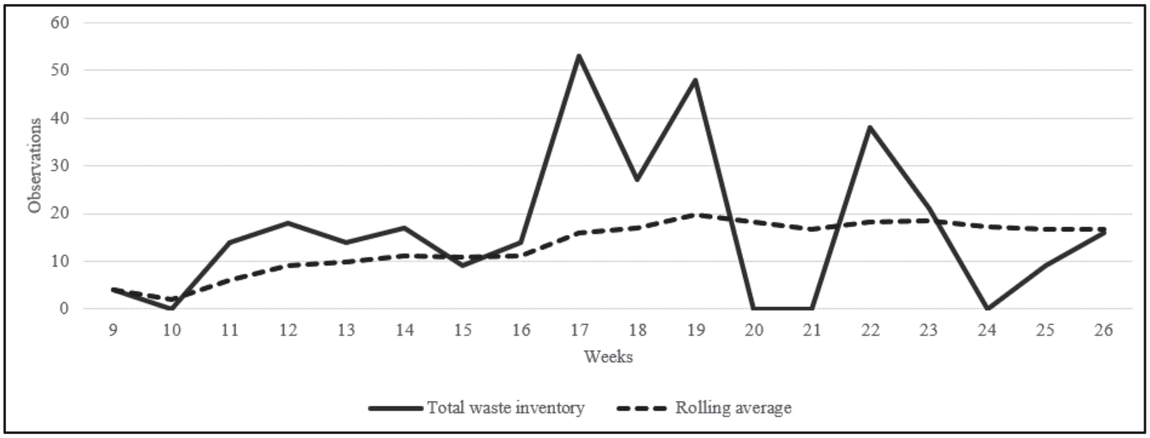

Figure 3: Observed Waste Inventories Over Time: Drone Images

The PWI observations from the drone images differed from those from ground-level images. Between Weeks 11 and 23, the average number of observations was 21 per week. In other words, about twice as much pile waste was observed in the drone images as in the ground-level images. During the summer holiday period, only 2 weeks were observed; there were 9 observations in Week 25 and 16 in Week 26. In Weeks 17–19, there was a clear peak in PWI observations, with an average of 42.6 observations per week during that period. The average number of observations over the entire period was 16.8 per week. Therefore, about twice as many PWI observations were made from the drone images as from the ground-level images.

Figure 4 shows the number of piles driven in pieces and the number of PWI observations. The amount of PWI observations was largely in line with the progress of the piling work.

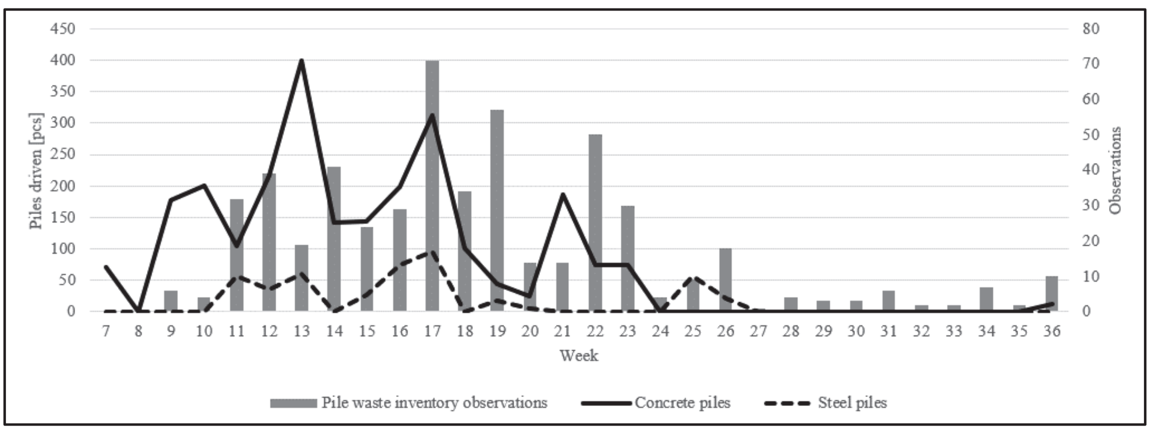

Figure 4: Piling Progress and Pile Waste Inventory Observations

To summarize the waste observation results, the amount of cut-off waste was significant—37,5% to 54,5%, depending on the observation method (a photo taken by a human from the ground level vs. a photo taken by a drone). Twice as many waste piles were detected in the aerial images taken by drones as in the ground-level images taken by supervisors. Regarding the observation area (22,000 m2), the average number of PWI observations was 0.001 per square meter, with a maximum of 0.003 observations per square meter (drone images). Since cut-off waste is smaller in size as compared to full pile, the high altitude of the drone photography may have contributed to the less frequent cut-off waste observations compared to the ground-level photography. Meanwhile, since twice as many PWI observations were made from the drone images, it can be assumed that the high-resolution drone images also included all of the PWI observations made from the ground level. These likely duplicates were not investigated in or removed from the present study because the primary purpose of the images and the waste observations was to train the algorithm; obtaining a large number of images and observations, despite possible duplications, supported the learning of the algorithm.

Observed Challenges in the Setup and Computer Vision

In the first experiment, full-resolution images were taken to train the neural network. The first experiment was conducted for 50 epochs. This means that the algorithm read the images at least 50 times to derive features from them When the images were read in a batch size of eight, Google Colab crashed; however, the image reading process worked for a batch size of four. A recall and mean average precision (mAP) of less than 10% was achieved in the first trial. For the algorithm to detect any relevant information from a new image, a recall and mAP of at least 50% is desired.

For the second experiment, the image size was reduced to 920 × 720, the batch size was 8, and the number of epochs was increased to 100. Although recall in the 93rd epoch increased to 43.5%, the model was unable to detect the PWI while testing on a new image. This result can be attributed to various considerations. One possible reason could be that most images had multiple labels, a large image size, and objects that seemed smaller as compared to other objects in the high resolution imagery; therefore, the algorithm was unable to properly learn the features of these images. Another reason could be that the dataset was too small; for object detection, neural networks are generally trained on about 1,000 images. When we reduced the size of the images, some information was lost from the pixels. Another important challenge was that the site was very dynamic, and the images had variable backgrounds because they were taken during various seasons. For CV, it is desirable to use a training image with some kind of similarity within the features and background of the images, so that the algorithm can better detect the features of objects of interest.

DISCUSSION AND CONCLUSIONS

Waste identification and elimination are the main principles of lean construction (Koskela, 1992). As such, it is essential to visualize waste and identify it properly. VM can provide real-time visualization and support improvements during the construction phase. Given the increasing prevalence of digitalization and efforts to employ it at construction sites (Martinez et al., 2019), technologies can also be incorporated into DVM (Digital Visual Management) devices, providing updated information and real-time understating of the construction site reality leading to decentralized decision-making (Koskela et al., 2018; Reinbold et al., 2020). The present study builds on the contributions of Tezel and Aziz (2017), Li and Liu (2019), and others who have combined VM and drone technology in an infrastructure construction context.

The study data (i.e., the area images) was collected manually by site supervisor during site visits, and differences in the images inhibited the use of CV for data analysis. Manual data collection poses obstacles because it is time consuming and costly; nonetheless, it remains the main form of data collection in construction sites (Kerem et al., 2013). The shift to digitalized means of data collection in construction sites will enable not only the collection of data in a shorter timeframe and with lower costs but also the provision of data that is better suited to the use of CV and other AI technologies in the future.

Since cut-off waste is smaller in size, the high altitude of the drone photography may have contributed to the less frequent cut-off waste observations compared to the ground-level photography. The large number of PWIs observed in the drone images compared to the ground-level images may indicate that supervisors choose a tidier viewpoint because such images are typically used in reports sent to clients. In this respect, drone photography may be a less unbiased way of collecting PWI information from an infrastructure site (Flyvbjerg, 2021). Meanwhile, since twice as many PWI observations were made from the drone images, it can be assumed that the high-resolution drone images also included all the waste observations made from the ground level. These likely duplicates were not investigated in or removed from the present study because the primary purpose of the images and waste observations was to train the algorithm; obtaining a large number of images and observations, despite possible duplications, supported the learning of the algorithm.

The trained model was unable to detect piles in images; however, there was positive foresight as recall went from 10% to 43.5% in the second trial. Reliable pile detection results could be achieved in the future by increasing the training data and employing mid-range image resolution. In addition, dynamic site conditions and background variability may be achieved by obtaining more images per season from different perspectives. Our future work will include training the algorithm with a larger annotated dataset and exploring different algorithms that can handle remarkably high-resolution drone images.

The present study contributes to the development of approaches for determining how CV could be used for achieving lean construction. CV has become a tool for understanding the actual situation in many applications, such as self-driving cars, and construction progress monitoring. The technology can be utilized to improve lean construction practices. For example, CV can be used to streamline the process of observing any construction material inventory or waste which is a subjective process in the construction industry in the current scenario. CV can also be used to generate new types of data for the visual management of construction sites. Furthermore, by comparing both types of datasets (i.e., ground- and drone-based images), we were able to identify challenges in each. For drone images, the coverage is wide; however, the objects appear smaller. For ground-level images, objects are more identifiable in images with a tidy appearance. This work can also be used to determine the most useful dataset for monitoring construction inventories and waste on large infrastructure sites.

One of the lean principles is based on 'maximising value while minimising waste' (Ohno, 1988, p.175). Minimizing waste is essential to enable professionals to deliver increasingly higher value. It is usually difficult to estimate the amount of waste without conducting an inventory. The present study can be used as an example of how waste and excess or misplaced inventory can be identified using CV. This study also demonstrates that it is possible to develop a CV-based tool for inventory management on construction sites alongside existing manual inventory and waste identification methods.

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